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

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Worsening wildfires are one of the most salient impacts of climate change in North America. A large share of the total social costs of wildfires comes from wildland firefighting costs, which in the U.S. are mostly borne by the federal government. We measure the degree to which this arrangement subsidizes development in high risk locations. To do this, we assemble administrative firefighting expenditure data from multiple federal and state agencies, yielding the most comprehensive database of firefighting costs in existence. We merge this to parcel-level data on the universe of western U.S. homes. Our main empirical contribution is to calculate the expected additional future cost to the federal government to protect a home from wildfire, in great spatial detail for the entire western U.S. We use natural variation in ignition locations to measure how firefighting expenditures increase when homes are threatened, and then compile each home's history of fire protection costs in an actuarial calculation of expected future protection cost. We find that a large share of the resources devoted to wildland firefighting are spent to protect homes. Consistent with a model of locally non-rival firefighting benefits, the marginal effect of homes on firefighting costs is rapidly decreasing in development density. Thus, wildland firefighting represents a large implicit subsidy to landowners in high-risk, low-density places. For our highest-cost categories of homes, we find that the expected present value of additional future firefighting costs exceeds 10% of the transaction value.

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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, 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 much larger than within cities. Historical institutions for protecting urban homes did not need to consider disproportionate benefits to 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. Our data show that these differences in risk translate to large differences in fire protection cost.

The institutional structure of firefighting interacts with the ecology of wildfires, with two important economic implications. First, because the federal government bears the large majority of wildland firefighting costs, firefighting represents a transfer of

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

wealth to a relatively small group of homeowners in locations with high fire risk. Second, federal protection interacts with the large spatial heterogeneity in fire risk to generate 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 and land use 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]

In this paper, we quantify the economic consequences of these 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. 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. We first take advantage of variation in ignition locations to measure how incident-level firefighting expenditures increase when homes are threatened. We then use these estimates to construct an actuarial measure of the expected additional future cost to the government to protect each home from wildfires. Finally, we describe the distribution of these expected protection costs and how they vary across space, fire risk, population density, income levels,

[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)".

and housing values.

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. Because the supply of new homes in these areas is relatively elastic (Saiz, 2010), these large implicit subsidies suggest potentially substantial distortions in new home construction. In addition to this extensive margin effect, the failure to internalize fire protection costs may also distort intensive margin behaviors. The promise of an aggressive firefighting response at no cost presumably reduces private incentives to choose fire-proof building materials and clear brush around homes, actions that can reduce the threat to homes from wildfires. At the end of the paper, we discuss how our empirical approach could be used to calculate an optimal fire protection fee that would lead homeowners 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. We find that the annul 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]

Consistent with a previous case study literature, 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. Researchers and policymakers frequently claim that this spending represents a subsidy to homeowners (e.g., Davis, 1995; Loomis, 2004; Stetler et al., 2010; Kousky and Olmstead, 2014), but our paper is the first to measure that implied subsidy empirically.

Perhaps more surprisingly, among fires that threaten homes we find that the number or total value of homes threatened has 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. It also means that policy changes to internalize firefighting costs would encourage more dense development.

[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.

The importance of the issues we consider will continue to increase in the future. Foresters and ecologists predict large amounts of new construction over the next several decades in fire-prone locations that are currently totally undeveloped (Gude et al., 2008). At the same time, climate change is predicted to lead to more severe and more frequent wildfires. In the realm of natural disasters, our results have parallels to flood risk, where economists have long suspected that subsidized insurance through the National Flood Insurance Program may encourage high-risk development. 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 paper contributes to a small economic literature about natural hazards and location choice. Kousky et al. (2006) and Boustan et al. (2012) examine adaption to hurricanes and floods. Champ et al. (2009) considers the salience of wildfire risk to home buyers. Another related working paper is Kousky and Olmstead (2012), which shows that changes over time in federal firefighting policy affected the number of homes built near public lands. We make several novel contributions to this literature. By introducing data on firefighting costs, we are able to quantify the implicit firefighting subsidy. To our knowledge, we are the first to measure this subsidy and to calculate the optimal "fire protection fee" for each home. This focus on incident costs also allows us to measure a strongly non-linear response of firefighting costs to the number of threatened homes, with important implications for the relationship between density and protection costs. Finally, by using parcel-level data on 18 million western homes, we are able to be geographically precise about risks and costs. This specificity represents a valuable advance since fire and other disaster risks can vary

[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.

substantially over small distances.

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 the potential for moral hazard, along with policy alternatives to internalize fire protection costs. Section 8 concludes.

2 Background

2.1 Increasing Costs of Wildland Firefighting

The rapid increase in firefighting cost over the past several decades has been attributed to three primary factors: the lengthening of the fire season as a result of climate change, the buildup of increasingly dangerous fuel loads, and increased human habitation in fire-prone areas. Changes in climate can increase wildland fire activity by either increasing the amount of fuel available for fires or by drying out existing fuel, rendering it more flammable. Prior work estimates that climate change is responsible for an additional 4.2 million acres in burned area between 1984 and 2015, accounting for nearly half of the increase in acres burned (Abatzoglou and Williams, 2016).

However, the increase in available fuels has not been solely driven by climate change. Land use change in beginning in the 19th century and an increase in fire suppression activity in the 20th century have both altered the type and the extent of fuel availability in the Western United States (Stephens et al., 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 the suppression of most fires has led to an increase in the severity in the fires that do escape suppression.

Finally, a rapid increase in the number of homes at possible risk from wildland fires has also contributed to the rising costs of wildland firefighting. Between 1990 and 2000, 8 million homes were added to the Wildland-Urban Interface, or WUI (Hammer et al., 2009). Foresters and planners project that new homes will continue to be built at a rapid pace in these high-risk areas. Gude et al. (2008) projects that huge areas of the WUI that are currently totally undeveloped will be converted to residential housing over the next two to three decades.

2.2 Responsibility for Wildland Firefighting

Broadly speaking, in the United States initial financial and operational responsibility for wildland firefighting is determined by the 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 undertake significant firefighting activity in the West. In addition to USFS, these include several Department of Interior agencies: 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 most notable 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) grant program reimburses states and cities 75% of their firefighting costs. Through this combination of direct expenditures and indirect support, the federal government absorbs most of the expenses associated with wildland firefighting in the United States.

2.3 The Cost of Protecting Homes During Wildfires

Wildland firefighting efforts have multiple objectives, among them safeguarding human lives, protecting publicly-owned natural resources and endangered species, and preventing damage to private property. The incidence and housing market impacts of wildland firefighting depend on the share of expenditures that are devoted to private property protection. What additional firefighting expenses result from locating homes in the path of wildfires? Our paper builds on previous studies of firefighting expenditures in both forestry and resource economics. Previous case studies and expert introspection indicate that the presence of homes increases firefighting costs, as 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 (USDA, 2006). Forest Service personnel report that, heuristically, between 50 and 95 percent of federal firefighting costs is 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 et al., 2007; Liang et al., 2008; Gude et al., 2013). We validate these case study findings for the entire Western United States, and we then extend the analysis to develop novel measures of the resulting implicit subsidy to each homeowner.

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 novel and is thus where we focus the discussion.[5] Section 3.3 relates several additional insights from the model to the empirical analysis. We focus on location choice throughout this section, but it is straightforward to extend the model to intensive margin distortions such as the choice of construction materials.

[5] Among previous theoretical treatments of natural hazards and location choice, our model is probably most similar to Kousky et al. (2006), who develop a model of government protection and private investment primarily focused on flood risk and Albouy et al. (2016), who model the amenity cost of temperature changes due to climate change using a similar framework.

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 also 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 at wage w_i and consume a single unit of housing at the local price. The non-tradable good is perfectly competitively supplied in each location. In addition to their different natural hazards, the risky and safe locations vary in other (exogenous) amenities valued by households (e.g., outdoor recreation, restaurant quality). Each household's relative taste for the amenities in the risky location (not including disaster risk) is given by θ_i. This parameter, which may be positive or negative, is the difference between the household's valuation of non-disaster amenities in the risky and safe locations.

Natural hazard risk in the safe location is zero. The probability of a natural disaster in the risky location is ϕ. Defensive expenditures f made in response to the disaster can reduce expected property damages, 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 $H''(f) > 0$
2. The benefits of defensive expenditures are non-rival within a location.
3. Within a location, homes are geographically homogeneous so that $H(f)$ is constant across homes.

Assumption 1 ensures that defensive expenditures reduce expected damages, and do so with diminishing returns. Assumption 2 matches the facts of our empirical setting, where firefighting efforts are focused on protecting entire communities. Assumption 3 abstracts away from local heterogeneity to focus the analysis on community-level interactions.

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, $f + n_r H(f)$.[6] $f^*(n_r)$ 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, $w_i + \theta_i$. If a disaster occurs, realized household benefit from living in the risky place is, $w_i + \theta_i - \frac{f(n_r)}{n_r} - H(f(n_r))$. The last two terms represent per-capita disaster costs. The sum of these two terms is decreasing in local population.[7] Assuming risk-averse households and perfectly competitive insurance markets, households in the risky place will purchase full insurance covering property losses and defensive expenditures. 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 $w_i + \theta_i - \phi[\frac{f(n_r)}{n_r} + H(f(n_r))]$.

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 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, $\tau = \frac{1}{N} f(n_r)$.

Figure 1 depicts the market for housing in the risky location. The black downward sloping line shows relative demand for non-disaster amenities, θ_i. This line slopes

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

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

downward due to heterogeneity in households' relative taste for the risky location. The 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 in the risky place. 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 r shows the relative price of housing in the risky place, which equals $r_r - r_s$. We assume that the marginal cost of producing housing in both locations is weakly increasing in population. The curve in 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 relative costs.

In equilibrium, households choose the location that maximizes private location benefits net of housing costs. When households pay for defensive expenditures, they choose the risky location if, $\theta_i - \phi[\frac{f(n_r)}{n_r} + H(f(n_r))] \geq r_r - r_s$. The resulting population in the risky place is shown in the figure as n_r^*. 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. The primary contribution of our empirical analysis is to develop novel, spatially-explicit estimates of $\phi\frac{f(n_r)}{n_r}$ in order to quantify this implicit subsidy and thus the amount of wildfire costs that are not internalized.

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, we are able to validate this prediction empirically. This result manifests itself importantly in our final implicit subsidy calculations, where local housing unit density is an important predictor of expected per-capita protection costs.

Finally, this conceptual exercise shows that the resulting distortion in housing construction due to moral hazard depends on the elasticities of housing supply and demand. In Figure 1, the increase in population due to moral hazard is large when the housing market clears on the elastic portion of the supply curve. If instead demand were to intersect the inelastic portion of the supply curve, free provision of defensive expenditures would have large effects on home prices but little effect on quantities. We return to this point when we consider potential welfare effects of these implicit subsidies.

4 Data

We create a novel dataset on wildfire spending by merging administrative data on firefighting expenditures from multiple agencies, parcel-level assessor data for the universe of western U.S. homes, and topographical and weather conditions data. This section provides an overview of the construction of this dataset, with additional details included in the online appendix.

4.1 Wildland firefighting expenditures

We compile fire suppression and preparedness cost data from six different sources, including five federal agencies and one state firefighting agency. The federal agencies we include 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 Freedom of Information Act (FOIA) requests (or similar records requests for state data). In some cases we have augmented these data with publicly available records, as we describe. Our geographical focus is the western United

States (Arizona, California, Colorado, Idaho, Montana, New Mexico, Nevada, Oregon, Utah, Washington, and Wyoming), where wildfires are most frequent and costly to suppress.[8] We discuss each source of data in detail below, as well as the process by which we harmonize these datasets.

4.1.1 US Forest Service

The Forest Service (USFS) accounts for the largest share of fire suppression expenditures of any federal agency. We obtain historical by-incident suppression costs for fires managed by the USDA Forest Service from 1995 to 2014 from the National Interagency Fire Management Integrated Database (NIFMID). These data are compiled by the Kansas City Fire Access Software (KCFAST) and include data on suppression expenditures and fire locations. USFS is primarily responsible for fires that ignite in or near the boundaries of National Forest areas. As discussed in Section 4.1.5, suppression expenditures in these data represent wage and equipment costs incurred by USFS during a given wildfire incident.

We also obtained separate US Forest Service accounting data on incident level expenditures. Gebert et al. (2007) argues that these accounting records capture incident costs more accurately than the NIFMID data. However, USFS was only able to provide these records for the period 2004–2012. We use the NIFMID data in our main analysis because of the greater temporal coverage. In the online appendix, we compare the NIFMID data and accounting data during 2004–2012. We find that for our purposes, both datasets generate similar results. Our final NIFMID dataset includes 2,563 fires exceeding 300 acres, which is the minimum size for which suppression costs are accurately reported.

Most ignitions are quickly suppressed at low marginal cost by carefully positioned "initial attack" resources. These incidents are not included in our dataset of large fires.[9] We address this in Section 6 by incorporating data on preparedness costs for the USFS and other agencies. These preparedness costs represent the cost of maintaining initial attack readiness and other fixed costs of the wildland firefighting system. For USFS, we compile preparedness expenditures from the agency's annual

[8] Specifically, we consider homes located in and fires started in these 11 states.

[9] NIFMID includes location and size information for these fires, but not accurate suppression costs.

budget justifications for fiscal years 2007–2019. Section 6 describes how we allocated these costs over ignitions.

4.1.2 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. 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 (e.g., BLM's cost data come from the Federal Financial System (pre-2008) and Financial and Business Management System (post-2008) databases). Our final DOI suppression dataset includes 3,003 BLM fires, 418 BIA fires, and 240 NPS fires larger than 300 acres.

As for 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. Our data on DOI preparedness costs come from the fiscal year 2012–2018 versions of these documents.

4.1.3 California Department of Forestry and Fire Protection

We also collect fire suppression cost data for California, which includes over 50% of the West's population 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 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.[10] 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.

4.1.4 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 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.

4.1.5 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,

[10]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.

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 et al. (2007), who argue that USFS bears at least 90% of the costs of these fires.[11]

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, BLM told us that they assign mileage costs for regular vehicles and engine-hour costs for fire engines to each incident, while NPS told us 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.

4.2 Fire covariates

Using the harmonized location data, we obtain elevation, slope, aspect, and fuel model data for the ignition point of each fire from LANDFIRE (United States Department of Interior, 2013). The former three products are derived from the high-resolution National Elevation Dataset; elevation represents 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 (Anderson, 1982) and describe the fire potential of surface fuel components (e.g., the type of foliage in the

[11]Ideally, we would sum each agencies expenditures on each individual incident. Unfortunately, despite repeated attempts to adopt consistent formats, USFS and the DOI agencies do not reliably use consistent incident identifiers, making such a merge impossible.

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 (Group, 2004).

4.3 Parcel data

The homes data include information on home locations, values, year built, and other property characteristics for the universe of 17,700,000 single-family homes in the western United States. These data are provided by CoreLogic and represent a compilation of tax assessor data from individual counties. We limit the sample to include only homes in partially vegetated areas that would be threatened by wildland fires, based on wildland-urban interface categories identified in Radeloff et al. (2005) (see appendix for details). 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 that restrictive. Our analysis dataset includes 8,046,957 homes (about 47% of all single-family homes in the West).

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,

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

$Cost_{ift}$ 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 $f()$ 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 month of the 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. 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 the distance to the nearest home, 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. We calculate this variable by merging ignition point data from the firefighting data to the geographic coordinates of all the homes in the real estate dataset. If, in the absence of suppression effort, wildfires are more likely to destroy homes that are close by, we might expect to find that firefighting effort is higher for fires that start near areas of private development.

Figure 3 shows regression estimates. We consider the total cost of Forest Service fires as a function of the distance from the fire's ignition point to the nearest home. The figure includes three different 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, steep 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 costs of a fire less than five kilometers from homes are higher by about 3. 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.[12]

Table 1 estimates alternative models. Column (1) matches the figure. Column (2) adds additional controls for pre-determined fire characteristics. In general the signs and magnitudes of the included covariates match expectation. 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.[13] 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 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 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)

[12] 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 $e^{\beta - 0.5V(\hat{\beta})} - 1$, where β is the regression coefficient.

[13] 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).

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.

Table 2 shows the effect of home density on fire costs. We report results from the binned step function specification.[14] The reference bin is fires with zero homes within 30 km, and the other bins evenly divide the remaining fires.[15] We define bins by quantiles instead of equal intervals for this table because of the long right tail of the number of homes variable; however, our results are robust to the use of equal intervals as well . The estimates show that the presence of up to 127 homes increases log costs by 0.97. For up to 826 homes, the cost effect increases to 1.74. Beyond that, costs change very little with additional homes, 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

[14]An alternative specification is a constant elasticity model (a log-log specification). The average elasticity from a regression of log costs on log threatened homes is 0.17, with a t-statistic of 3.9. This linear relationship in log-log space maps closely to the concave relationship that we measure in log-linear space. We focus on log-linear models in the text because we are interested in the effects of one additional home, as opposed to the effects of proportional increases in homes. The log-log model also does not accommodate fires with zero nearby homes.

[15]To reconcile these results with the proximity results, note that the average of the coefficients in the first five rows of Table 2 gives the average cost difference between fires with homes within 30 km, and those without. This is conceptually similar to the sample-weighted average of the coefficients for the 0-10 , 10-20 , and 20-30 km bins minus the sample-weighted average of the 30-40 and 40+ km bins in Table 1. Both exercises yield about 1.5.

protection costs are decreasing in population density.

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 Table 2 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.

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 or dry weather). This selection would result in an upward bias in a naive regression of firefighting costs on distance to homes.[16] 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 et al., 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

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

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 about 0.06 additional fires per year. The finding that human presence increases fire frequency is consistent with work by ecologists (Syphard et al., 2007; Massada et al., 2012; Faivre et al., 2014). This implies that we slightly underestimate the additional firefighting cost created by new homes.

6 The Implicit Subsidy To Homeowners

Having demonstrated that a disproportionate share of wildland firefighting expenditures are dedicated to protecting private homes, we turn our attention to calculating the incidence of this implicit subsidy. For every individual home in the western United States, we calculate an actuarial measure of the expected net present value of the additional cost incurred by the federal and state governments in order to protect the home during future wildfires.

While we limited the dataset to USFS fires in Section 5.1, this section brings in additional historical expenditure data from other agencies. We use these data to construct three different measures which vary in precision and completeness. The first, which we refer to as "suppression only", reflects expected 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. The second measure, which we call "suppression plus", also accounts for the annual fixed costs of maintaining fire response capabilities ("preparedness" expenditures), and federal reimbursements to state firefighting agencies through the Fire Management Assistance Grant (FMAG) program. Finally, our third measure is specific to California and includes "suppression plus" expenses as well as Cal Fire direct firefighting expenditures (subtracting FEMA reimbursements to avoid potential double counting).

6.1 The implicit subsidy due to federal direct suppression expenditures

In the first step of this calculation, we use the estimated model in Equation 1 to predict the amount of firefighting expenditures on each historical fire that were due to the presence of homes. To do this, we estimate the difference between the observed fire cost and the predicted cost for the incident if there had been no homes within 40 kilometers of the ignition point. For each fire i we call this difference Δ_i.[17]

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 40 kilometers 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 assign a larger share of Δ_i to homes closer to the ignition point. We use two approaches to this weighting, an inverse-distance weighting (IDW) algorithm and an empirical estimate based on the results in section 5.1. For the IDW algorithm, houses within 40km are assigned a weight of $\frac{1}{d}$, weights are normalized to one within each fire, and home protection expenditures by fire are divided using the normalized weights. Our second and preferred approach is identical except that the weights assigned to each fire-parcel combination are the estimated coefficients from Equation 1 for 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} 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 add up 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.

Our estimate of interest is not past expenditures, but expected future expenditures.

[17] See Appendix Section 2.1.2 for the construction of Δ_i.

The observed history of firefighting costs is 20 years or less, which in many regions may not be a long enough period to accurately describe the underlying fire risk. To estimate expected firefighting costs, we group regions with similar ecological and fire risk characteristics together into actuarial groups, much like a private insurer would be expected to do when calculating risk. We calculate expected cost for homes in each group as,

$$\mathop{\mathbb{E}}_{h,d,s}[\rho_j]$$

This calculation takes expectations over bins of wildfire hazard h, housing 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. The appendix includes more information on this physical risk measure as well as a map of wildfire hazard potential. Housing density (population per square meter) comes from the Gridded Population of the World dataset (GPWv4), which reports population density within 1 km grid cells (Doxsey-Whitfield et al., 2015). 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.

6.2 Adding preparedness costs

Next, we add federal preparedness spending from both the USFS and from the DOI agencies to calculate the "suppression plus" measure. 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.[18]

[18]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

After this even division, we then calculate the share of preparedness costs due to homes using the same model as for suppression expenditures.[19] 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 should be attributed to homes. Finally, we allocate these per-fire costs across nearby homes using the same distance weights used for suppression spending.

6.3 Adding FEMA reimbursements

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.[20]

6.4 Estimating the implicit subsidy for California

Our final measure focuses on California, the largest state in the West. In this scenario, we estimate the subsidy from suppression spending following the previous three sections, but we eliminate the FEMA reimbursements to California. Instead, we include

by annual number of fires.

[19]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.

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

Cal Fire suppression costs. 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.[21]

6.5 Exploring Expected Protection Costs

Table 3 shows the distribution of expected parcel protection costs using the "suppression only" and "suppression plus" measures. These costs were calculated using 210 actuarial groups of homes created by crossing six bins of physical fire risk, five bins of housing density, and the seven wildland firefighting regions. 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 homes). The first two columns describe the upper half of the distribution of the expected present value of additional firefighting costs due to each home, using the two measures. Using the "suppression only" measure, most western homes have expected protection costs of a few hundred dollars or less, while the highest-risk homes have costs that are much larger. Five percent of homes have "suppression only" costs exceeding $4,000. These homes belong to 34 separate actuarial groups throughout the West. One percent of homes have expected protection costs exceeding $11,000 or about 8% of home value. These homes belong to 11 actuarial groups. 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.

The right-hand column of Table 3 reports the "suppression plus" measure as a share of the transaction value of the property. These implicit subsidies are large compared to housing values. For the highest-cost 5% of homes, the present value of expected future firefighting costs is more than 7% of property value. For the highest 1% of homes, it exceeds 18%. It should be emphasized that these are not estimates of ex post

[21] 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.

historical costs, which would be expected to have a long right tail due to unlucky households experiencing bad realizations. Instead, these are ex ante measures of expected future costs for homes located in high-cost actuarial regions.

Figure 4 shows the broad geographic distribution of expected protection costs. This map shows the average expected protection cost for homes in each 30 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. Gray areas represent unpopulated regions and populated regions with no wildland vegetation (e.g., cities). Average expected protection costs are highest in Northern California, central Oregon and Washington, and Idaho and western Montana.

Figure 5 explores this variation in expected protection costs in more detail. The four panels in the figure show how protection costs vary along four different margins, using the "suppression only" measure of expected protection cost. Panel A shows that protection costs are increasing in our physical measure of underlying fire risk. On average, expected protection costs for homes in the highest category of fire risk are about six times higher than for the lowest category. This relationship is intuitive, but it is also a reassuring validity test on our calculations. Panel B shows that expected parcel protection costs are strongly decreasing in housing 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. Increases in density are strongly associated with decreasing per-home costs, with expected costs in the lowest decile of density higher than the highest decile by a factor of ten or more.

Panels C and D consider 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)). The opposite appears to be true. Panel C shows that homes in low-income areas receive substantially more benefit from government firefighting efforts on average, compared to 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. Wildfire protection costs are lowest in cities, where incomes are higher. 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 relationship between average expected cost and home value is U-shaped, with increasing costs for high-value homes. This may reflect greater government efforts to protect high-value homes during wildfires, or high-value second homes located in areas where permanent residents have low incomes ("tourist towns").

Significant local variation in wildfire risk and development density in the West means that expected protection costs vary substantially over small distances. Figures 6A and 6B illustrate this local variation for two areas in California. These maps show the net present value of per-home expected protection costs, averaged at the Census block level for plotting. Figure 6A shows Shasta and Tehama counties in Northern California. This part of California experiences frequent wildfires every summer. Expected protection costs are several hundred dollars per home or less in the more densely-developed areas of Redding and Anderson. Outside of these urban areas, protection costs increase quickly. In some of the more remote Census blocks that border national forest lands or other public wildlands, costs reach 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 6B 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.

7 Discussion

This section considers the implications of large implicit subsidies via wildland firefighting. Section 7.1 considers the potential for moral hazard in the location of new construction and in risk-reducing activities for already-constructed homes. Section 7.2 considers potential policy solutions aimed at internalizing these costs.

7.1 Moral Hazard

The welfare implications of this subsidy depend on the degree to which it distorts decisions. In this section we consider the potential for moral hazard along two margins. First, we consider the extensive margin choice by a municipality to allow new development or by an individual to build a home. Then we consider intensive margin choices about risk-reducing activities such as maintaining vegetation and using fire-proof building materials.

As illustrated in Section 3 and Figure 1, the housing market effects of this implicit subsidy depend on 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). On the other hand, in regions with elastic demand and supply, subsidies generate larger distortions.

We measure large subsidies in low-density ex-urban and rural areas in which supply, at least, is likely to be quite elastic. Development in these areas is not likely to be limited by land availability or regulation. Saiz (2010) reports that supply elasticities in the metropolitan statistical areas around Denver, Colorado Springs, and Albuquerque are 1.53, 1.67, and 2.27, respectively. This includes homes in more urban parts of the MSA and thus may understate supply elasticities in wildland-urban interface areas. 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. Furthermore, because prices are low in these areas, firefighting costs for these homes are large in percentage terms. Together, these factors would seem to imply potentially significant quantity changes.

We note here that 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 households via wildland firefighting. It is also the appropriate value for understanding the external cost of new development in currently undeveloped areas. There are many such areas. Gude et al. (2008) reported that just 14% of the wildland interface in the western United States was developed at the time of their study. Their study considers scenarios involving eventual development of as much as 50% of wildland interface areas over the coming decades.

In areas with significant existing development, a more appropriate measure of external cost may be the marginal expected firefighting cost associated with additional homes. Our results in Section 6 suggest that marginal cost may be substantially lower than average cost. We find that beyond a small number of homes within 30 km of the ignition point, increases in density lead to little or no increase in firefighting costs. The non-rival nature of firefighting benefits implies low marginal expected costs for "infill"-type development.[22] This implies that if fire protection costs were to be internalized starting today, one consequence would likely be increased density in these areas with existing homes (and less construction in undeveloped areas).

In addition to changing incentives about where to build, the firefighting guarantee 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 fire-proof roofing materials instead of wood roofs. Once the home is built, residents can protect the home by trimming vegetation around the home to create "defensible space". If these investments in home protection are partial substitutes for firefighting (because they 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 on these other margins.[23]

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

[22] Our empirical approach could be used to calculate direct estimates of marginal expected cost. Holding constant wildfire hazard class and geographic region, one could compare total expected cost across density groups to construct region- and hazard-specific estimates of marginal expected cost.

[23] One more subtle manifestation of this type of moral hazard may be local opposition to prescribed burns, which can reduce the risk of future large fires but are often unpopular with homeowners.

when building a new home. This policy leads homeowners to internalize firefighting costs in expectation. Our empirical analysis provides a road map for calculating this spatially-specific optimal firefighting tax.[24]

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.[25] Yet another alternative that would internalize costs in principle would be to recover ex post firefighting costs directly from insurers holding homeowners insurance policies near the ignition point of the fire.[26]

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 in high-risk locations fail to internalize a substantial fraction of expected wildfire costs when choosing where to live. Interestingly, we also find that firefighting expenditures vary only slightly with the total number or value of homes threatened, conditional on any homes being threatened. This means development density is an important predictor of per-home protection costs, consistent with a conceptual model of locally non-rival benefits from firefighting.

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

[24] 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. Our results suggest that this fee would need to be much more differentiated in order to correct incentives (as opposed to simply raising revenue for firefighting). The fee was unpopular in rural areas and was suspended in 2017.

[25] There are clear economies of scale in supplying wildland firefighting services for very large incidents. In principle, one could imagine that the existing federal system could continue to supply firefighting, while collecting payment from cities and counties for this service.

[26] Given the large increases in insurance premiums that would be expected under such a policy, it may have to be coupled with a mandate to purchase homeowners insurance in order to be effective.

expected NPV of the implicit subsidy is over 10 percent of total property value. This spending will continue to increase as climate change worsens the fire problem. Meanwhile, in the absence of policies to make homeowners internalize fire costs, the rate of new home construction in high-risk places is likely to continue unabated, implying substantial under-adaptation to this particular impact of climate change. Our empirical analysis provides a road map for calculating the optimal "fire protection fee" to internalize wildland firefighting costs. More broadly, our results emphasize the importance of considering the role of public institutions and expenditures in climate change adaptation, including for flooding, sea level rise, drought, and other impacts.

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Figure 1: The Market for Housing in a Risky Place

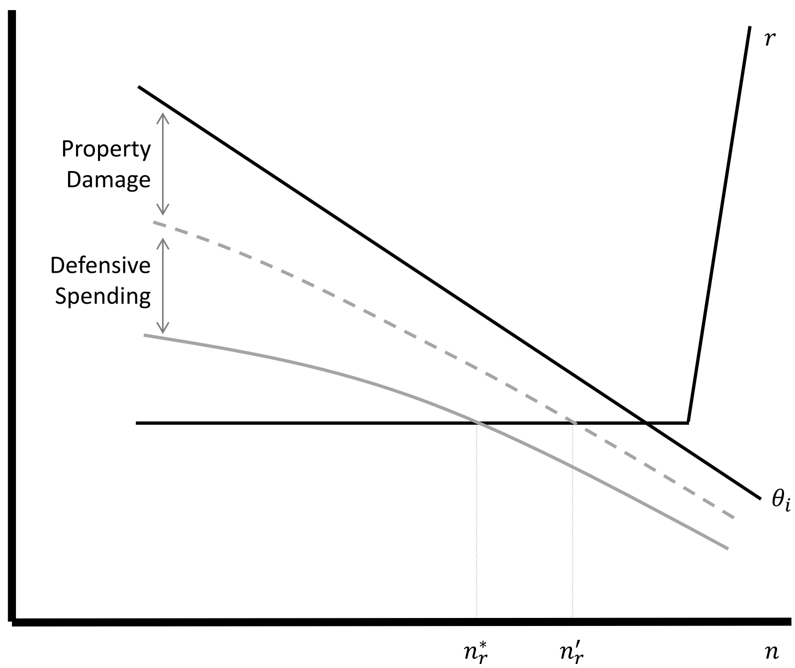
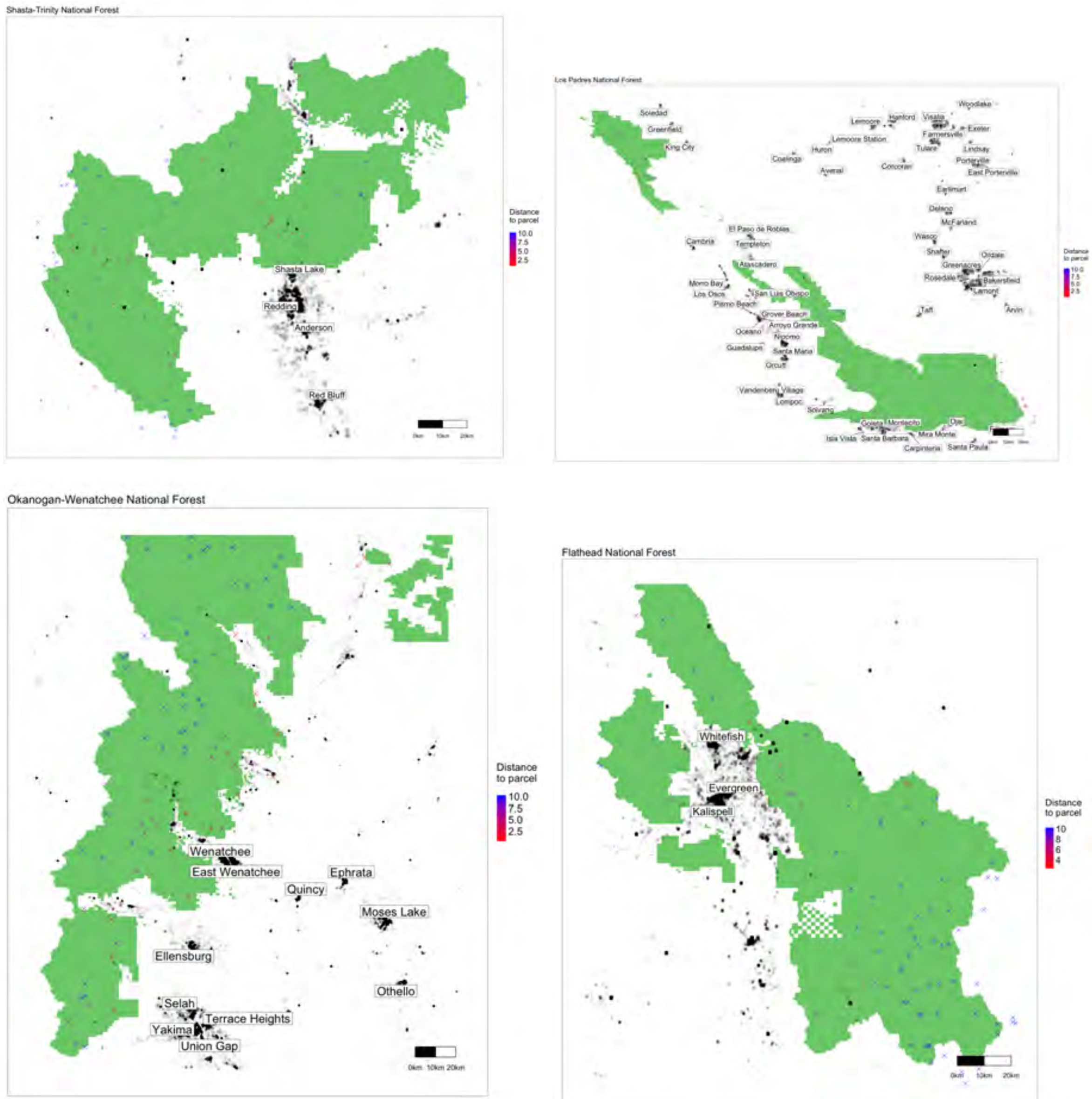
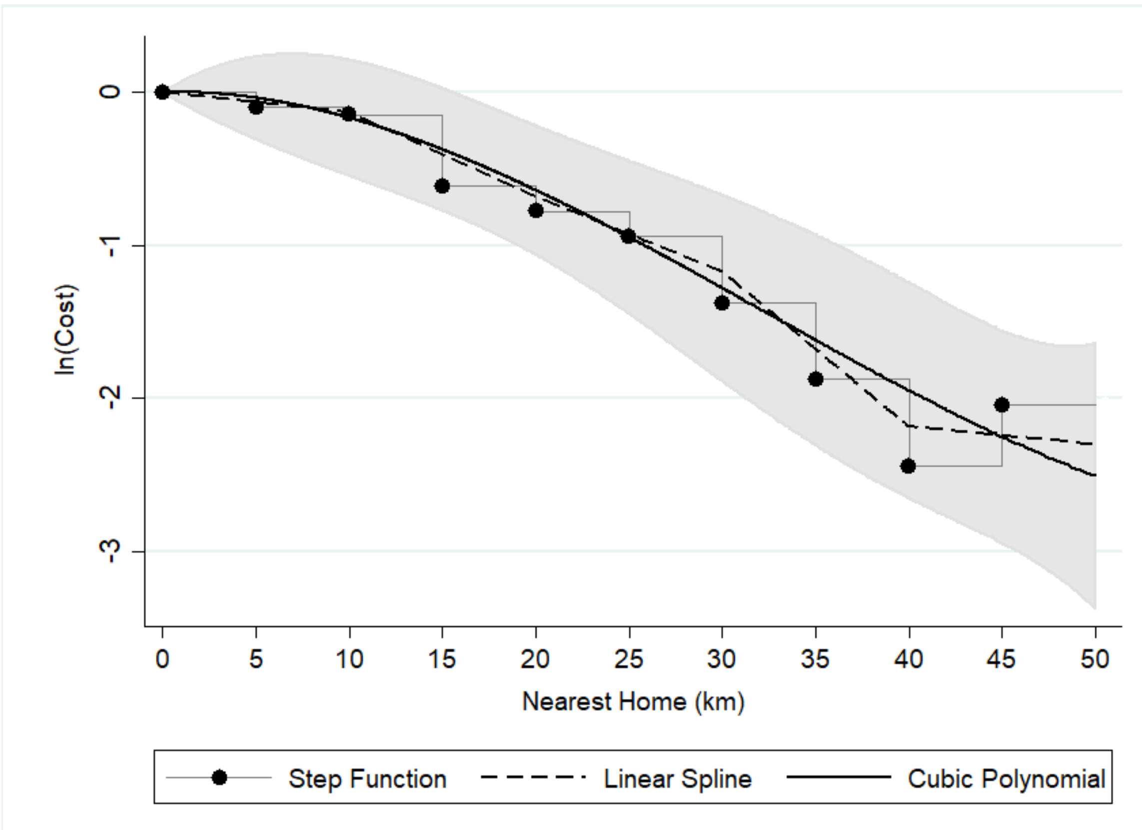


Figure 2: Example National Forest Units



Each panel shows a single national forest area in green. The X's represent individual wildfires, colored according to the distance to the nearest home. Black dots indicate private homes. 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).

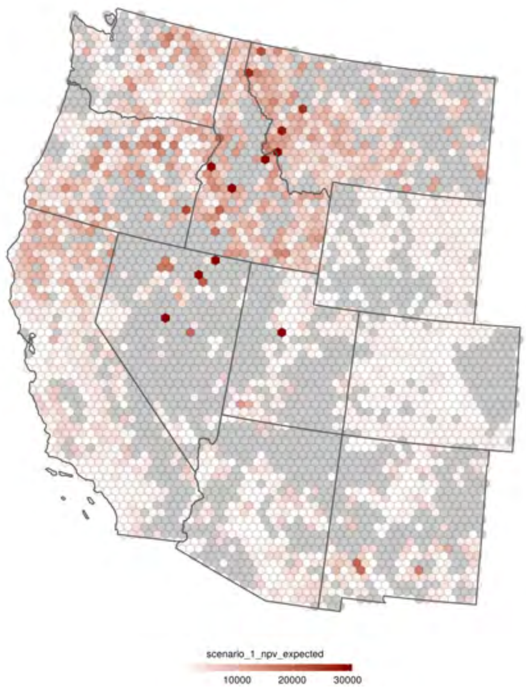
Figure 3: The Effect of Homes on Firefighting Costs



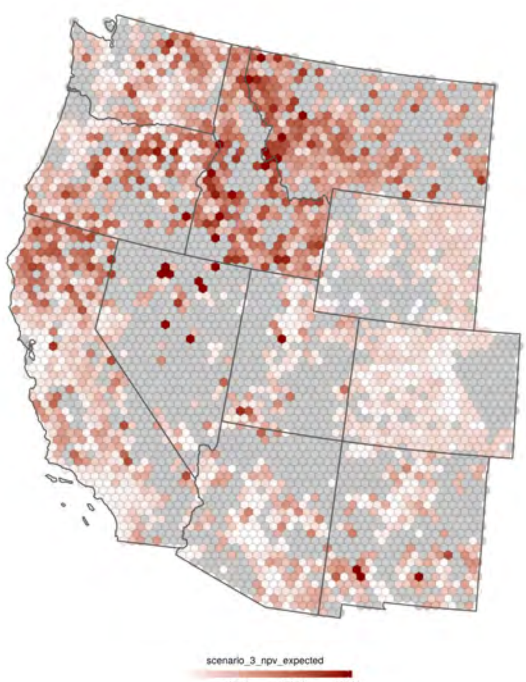
This figure reports results of three separate regressions of log firefighting cost on distance from the ignition point to the nearest home. The step function plots coefficients from a regression of log costs on indicators for 5 km distance bins. The linear spline is a piecewise linear regression with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

Figure 4: Expected Protection Cost by Region

Panel A. USFS and DOI Firefighting Costs Only



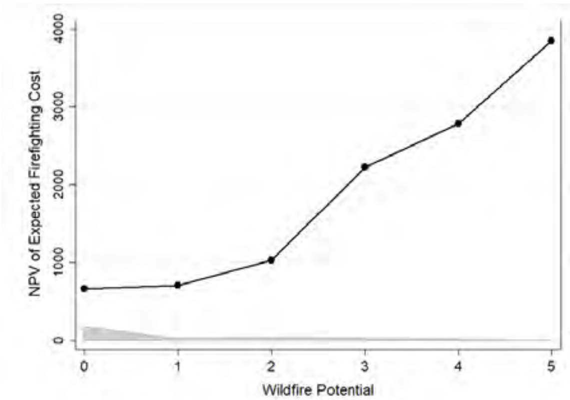
Panel B. "Suppression Plus" Cost Measure



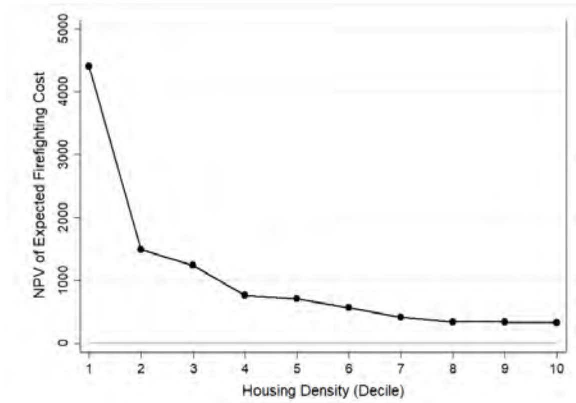
Notes: This figure shows the net present value of the additional future costs incurred by the federal government to protect a home from wildfires, averaged across 30 km hex cells. The sample includes 8 million homes near wildland vegetation areas (47% of all western homes). Panel A includes only USFS and DOI direct suppression expenditures. Panel B also includes preparedness costs for USFS and DOI, 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.

Figure 5: Expected Parcel Protection Cost by Fire Risk, Housing Density, and Wealth

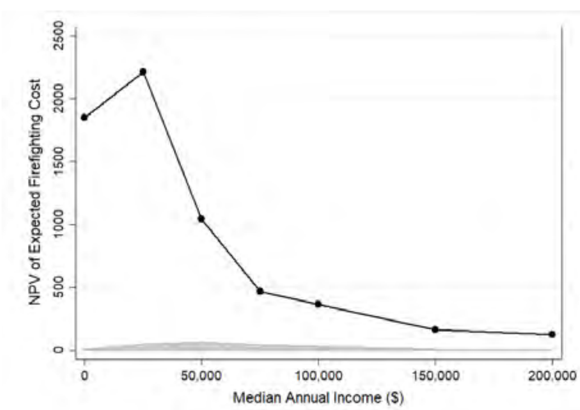
(a) Wildfire Hazard Potential



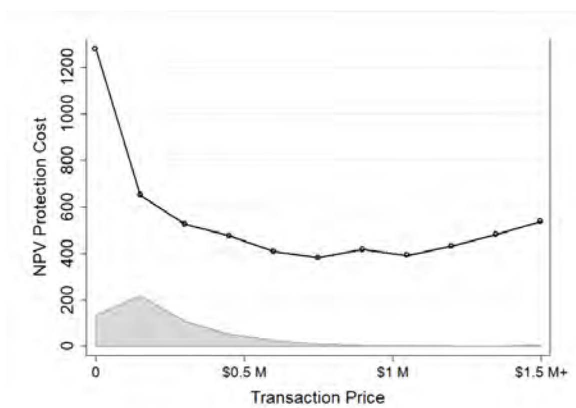
(b) Housing Density



(c) Income

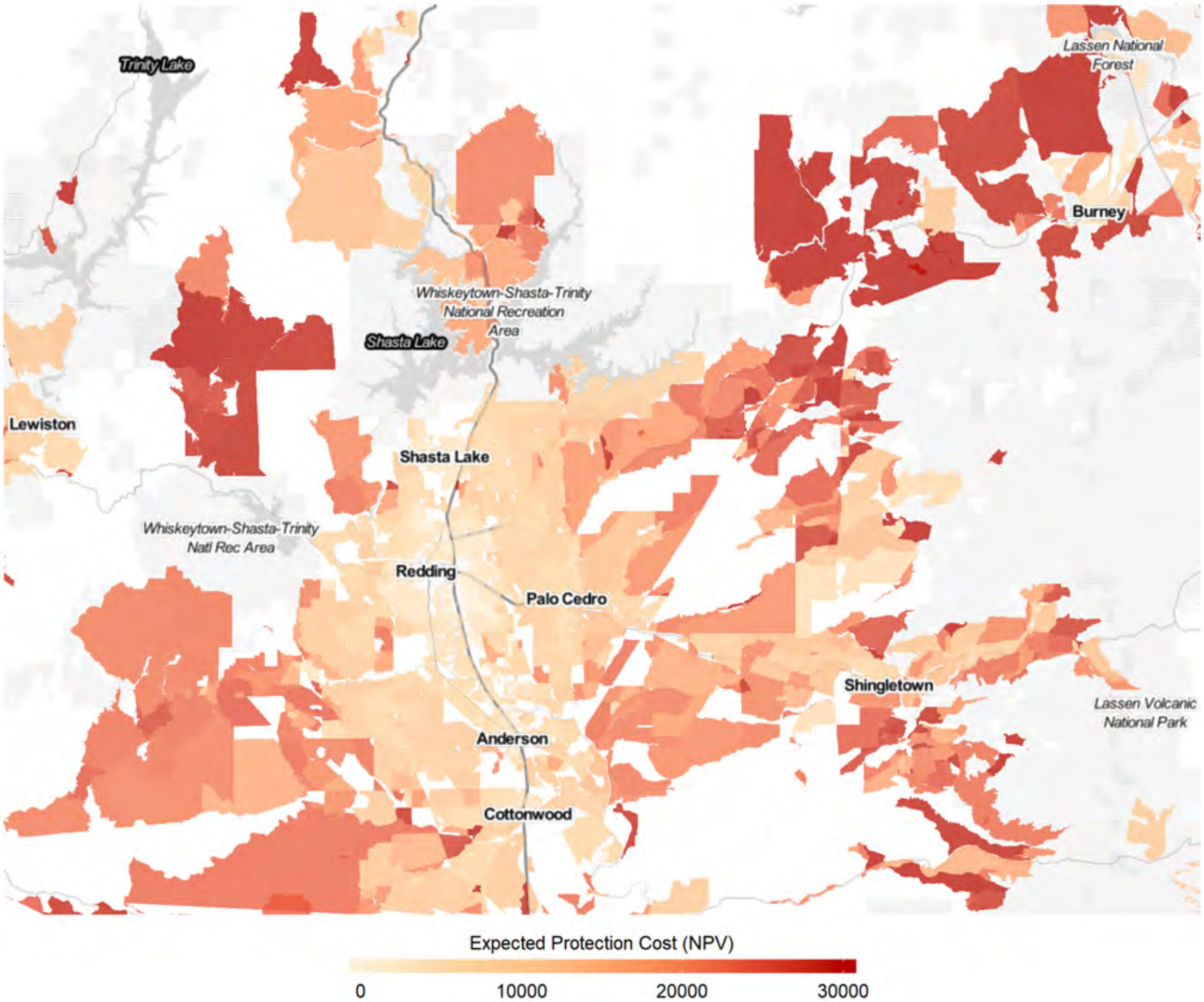


(d) Transaction Value



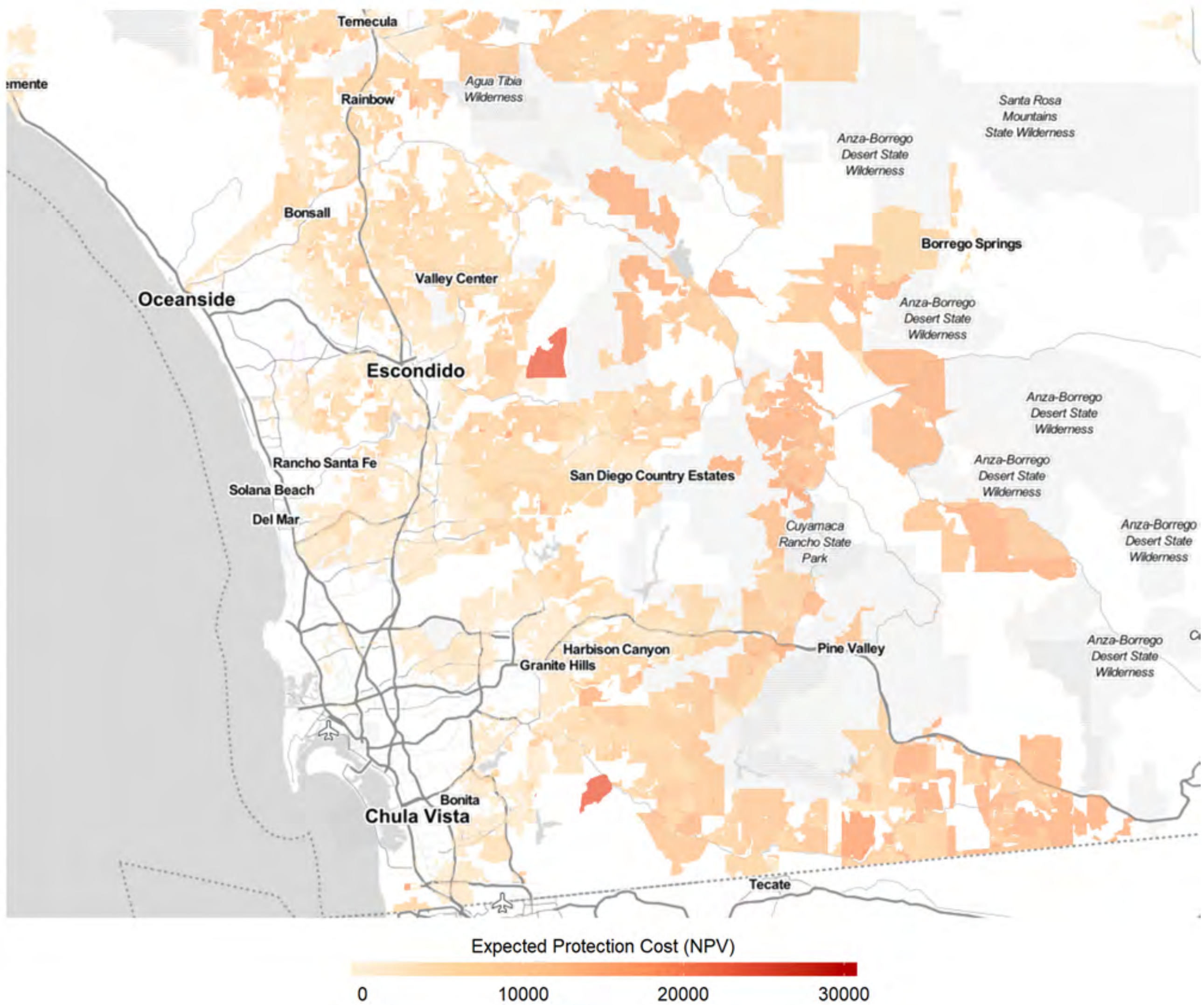
Each panel shows the variation in the net present value of expected protection costs along a single margin of interest. The black line in each panel shows average expected protection costs. The gray density shows the distribution of homes. Panel (a): The six categories correspond to wildfire hazard potential risk categories in Dillon (2015). Panel (b): Costs are plotted according to deciles of pixel-level population density for the study area from the Gridded Population of the World database Columbia University CIESIN, 2017. Panel (c): Each home is assigned the median annual income for its Census block group from the 2015 American Community Survey.

Figure 6A: Local variation in Expected Cost



This map shows expected protection costs averaged by Census block for Shasta and Tehama counties in Northern California. The color scale indicates the average expected NPV of a home's protection cost, and is top-coded at $30,000. Crosshatched areas are public lands. White areas have no wildland vegetation (e.g., urban areas) or no homes. The online appendix includes example maps for additional areas throughout the West.

Figure 6B: Local variation in Expected Cost, Continued



This map shows expected protection costs averaged by Census block for San Diego County, California. The color scale indicates the average expected NPV of a home's protection cost, and is top-coded at $30,000. Crosshatched areas are public lands. White areas have no wildland vegetation (e.g., urban areas) or no homes. The online appendix includes example maps for additional areas throughout the West.

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

	(1)	(2)	(3)	(4)	(5)
Distance to Homes (km)					
10–20	-0.28	-0.24	-0.25	-0.40*	-0.64*
	(0.20)	(0.19)	(0.22)	(0.22)	(0.35)
20–30	-1.17***	-1.08***	-1.11***	-1.23***	-1.52**
	(0.29)	(0.27)	(0.36)	(0.33)	(0.64)
30–40	-1.80***	-1.75***	-1.73***	-1.83***	-2.72***
	(0.51)	(0.50)	(0.60)	(0.56)	(0.78)
40+	-2.201***	-2.162***	-2.032***	-2.371***	-2.169***
	(0.360)	(0.321)	(0.409)	(0.352)	(0.772)
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	1,509	1,509	1,509	1,154	574
R^2	0.41	0.43	0.52	0.46	0.57

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: Firefighting Costs by Number of Nearby Homes

Number of homes	
1-127	0.97***
	(0.31)
128-826	1.74***
	(0.34)
827-2,871	1.53***
	(0.43)
2,872-10,245	2.06***
	(0.36)
10,246+	1.79***
	(0.51)
Controls for Weather, Topography, and Vegetation	X
National Forest FE	X
Year by State FE	X
Month-of-Year by State FE	X
Fires	1,503
R^2	0.42

This table reports results from an OLS regression. The sample includes western U.S. fires managed by the Forest Service during 1995-2014 larger than 300 acres. The dependent variable is the natural log of suppression cost. We report coefficients and standard errors on dummy variables corresponding to equal-observation bins of number of homes within 30 km. The omitted category is fires with zero homes within 30 km of the ignition point. See Table 1 for details on controls for weather, topography, and vegetation. Standard errors are clustered at the national forest level.

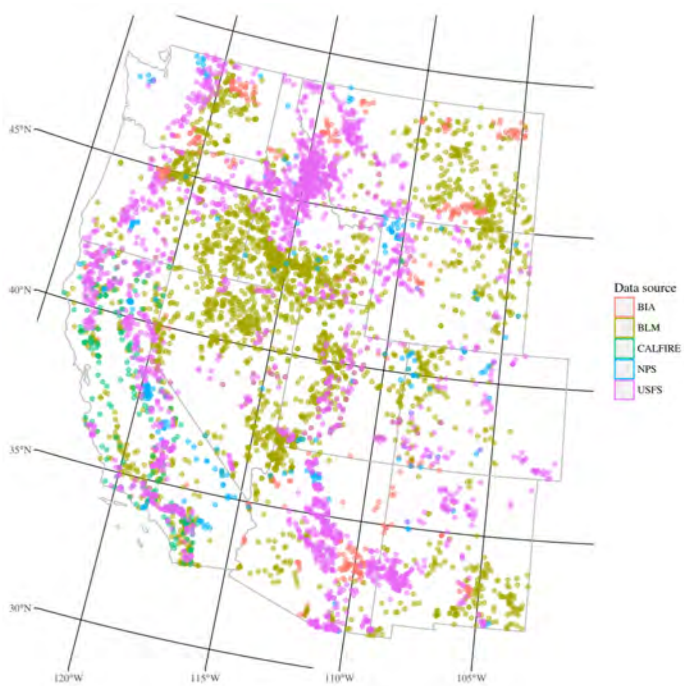
Table 3: Expected Parcel Protection Costs for 8 Million Western Homes

	Federal Suppression Only ($)	**Suppression Plus ($)**	**Share of Transaction Value (%)**
Mean	1,054	2,437	1.9
p50	644	1,435	0.7
p90	2,221	5,374	3.7
p95	3,946	8,346	7.3
p99	10,251	19,446	18.3
N	8,046,957	8,046,957	8,046,957

This figure describes the distribution of expected future 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 of similar-risk homes. Actuarial groups were created by crossing 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. "Suppression only" includes federal agency direct suppression expenditures. "Suppression plus" also accounts for federal preparedness costs and state suppression costs reimbursed by FEMA. "Share of Transaction Value" is the "suppression plus" measure divided by the transaction value of the property. Values are in 2014 dollars. See text for details.

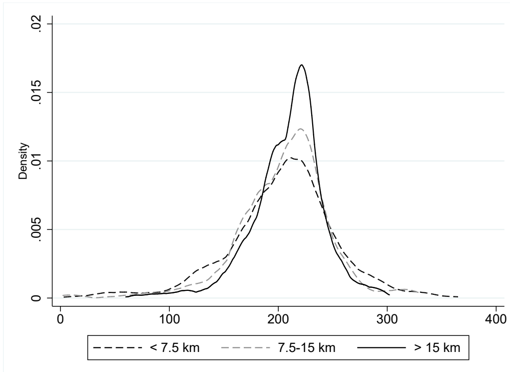
1 Additional Results and Robustness Checks

Appendix Figure 1: Western Wildfires, 1995–2004

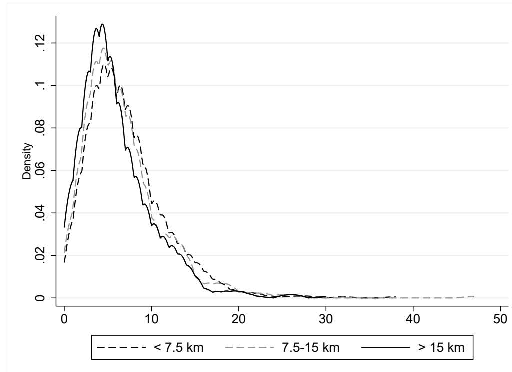


Appendix Figure 2: Covariate Overlap by Distance from Ignition Point to Nearest Home

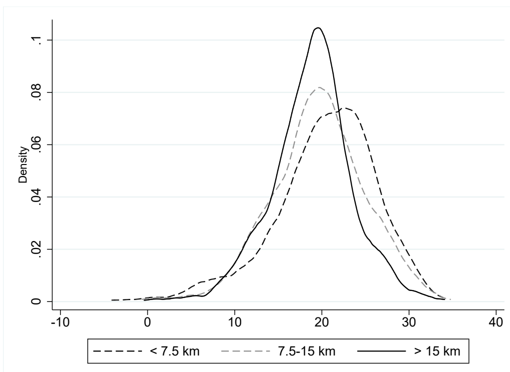
(a) Day of Year (Ignition)



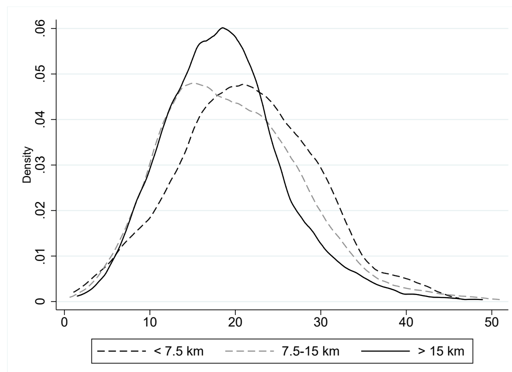
(b) Wind Speed (mph)



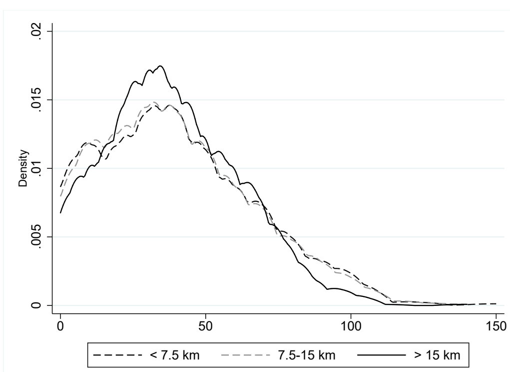
(c) Temperature (F)



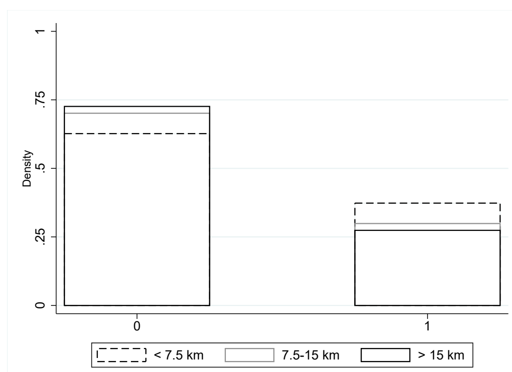
(d) Vapor Pressure Differential



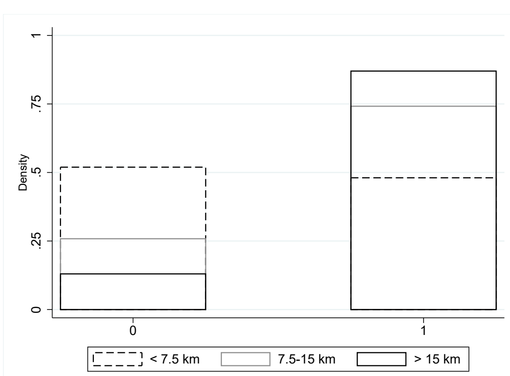
(e) Terrain Slope



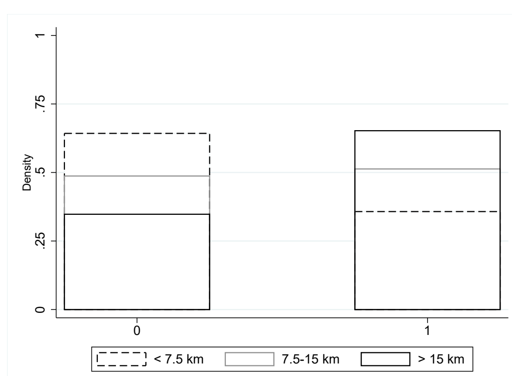
(f) South/southwest-facing



(g) Lightning-caused

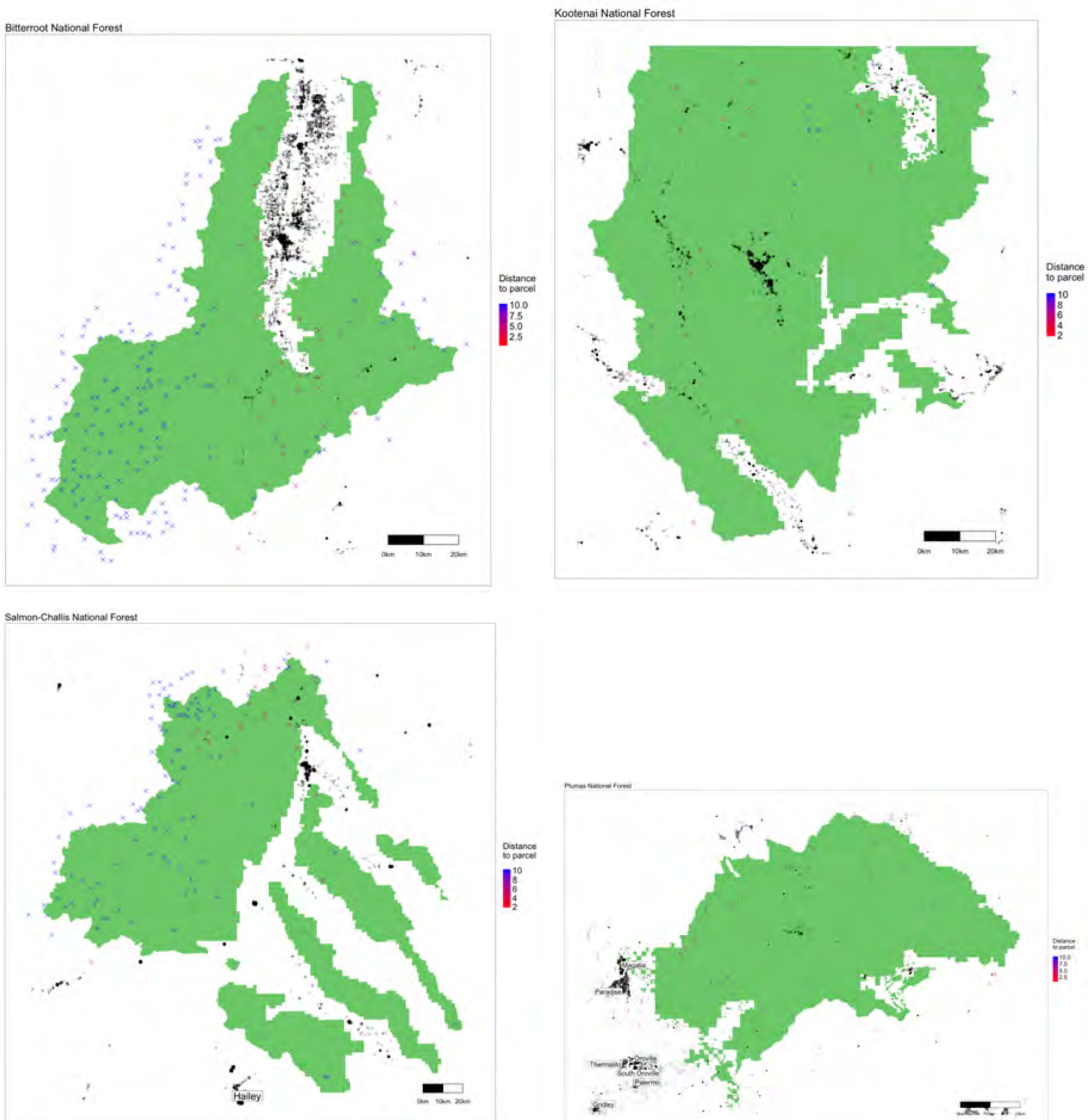


(h) “Timber” fuel model



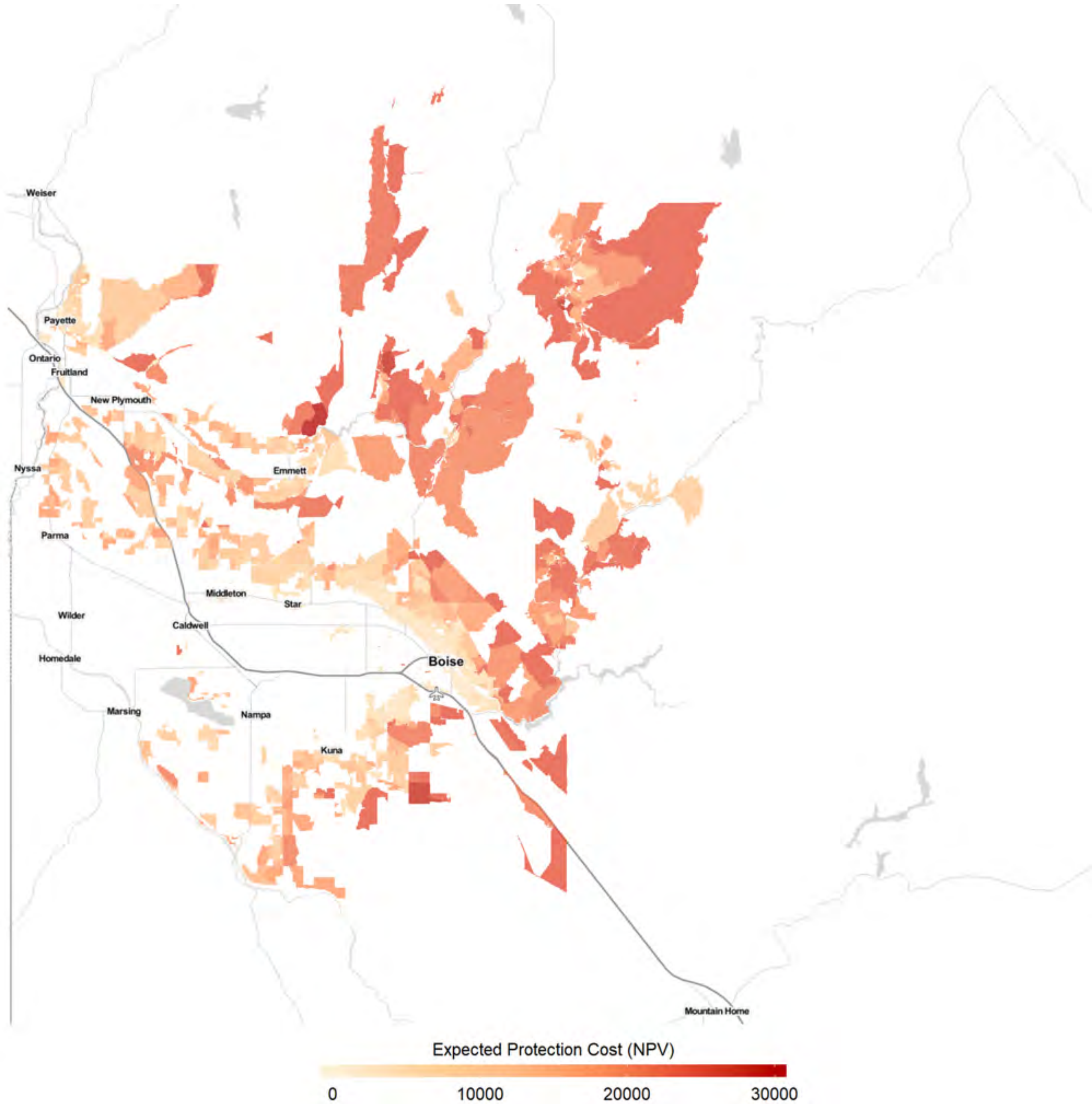
This figure shows covariate distributions for the US Forest Service fires analyzed in Tables 1 and 2. Panels (b), (c), and (d) report weather on the day of ignition. Wind speed is average wind speed from the reference weather station reported in NIFMID. Temperature and vapor pressure differential are 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 are National Fire Danger Rating System fuel models E, G, H, P, R, and U.

Appendix Figure 3: Additional National Forest Examples



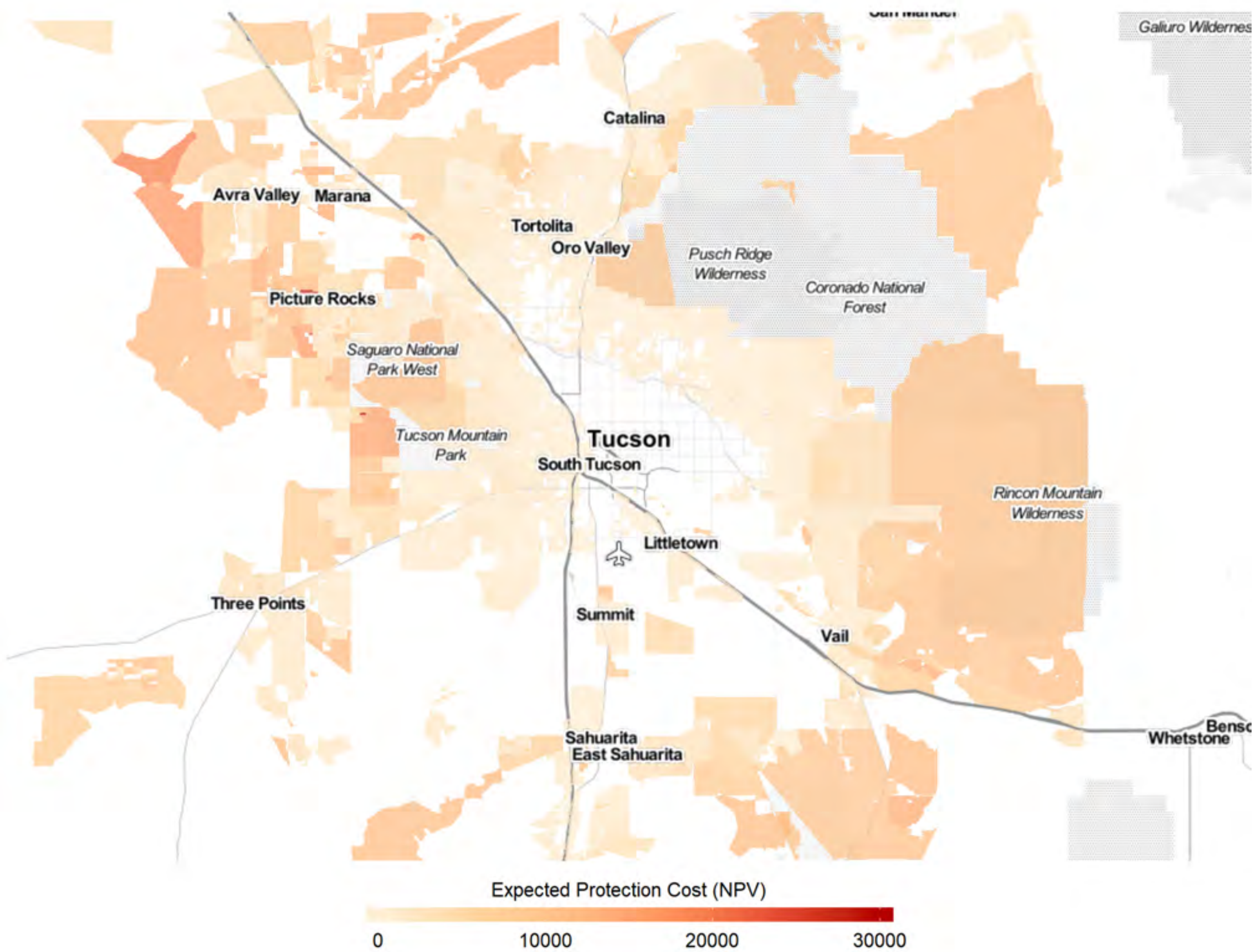
Each panel shows a single national forest area in green. The X's represent individual wildfires, colored according to the distance to the nearest home. Black dots indicate private homes. Clockwise from upper left, the forests are Bitterrroot National Forest (Montana), Kootenai National Forest (Montana), Salmon-Challis National Forest (Idaho), and Plumas National Forest (California).

Appendix Figure 4A: Local variation in Expected Cost, Additional Examples



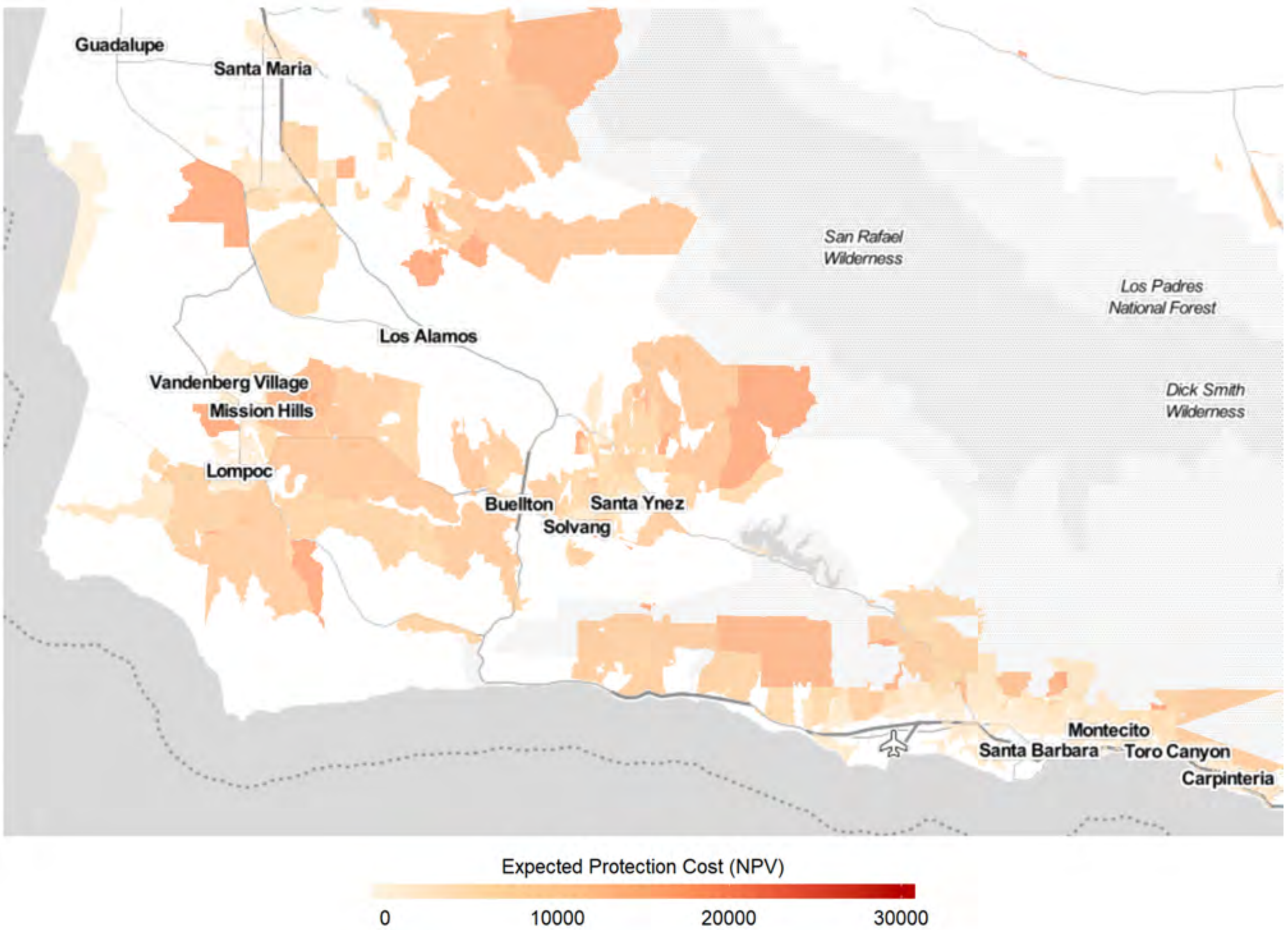
This map shows expected protection costs averaged by Census block for the Boise, Idaho area. The color scale indicates the average expected NPV of a home's protection cost, and is top-coded at $30,000.

Appendix Figure 4B: Local variation in Expected Cost, Additional Examples



This map shows expected protection costs averaged by Census block for the Tucson, Arizona area. The color scale indicates the average expected NPV of a home's protection cost, and is top-coded at $30,000.

Appendix Figure 4C: Local variation in Expected Cost, Additional Examples



This map shows expected protection costs averaged by Census block for the Santa Barbara, California area. The color scale indicates the average expected NPV of a home's protection cost, and is top-coded at $30,000.

1.1 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 Table 3 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 table row shows coefficients for five 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., in the 40 km column, 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	-0.2048	-0.2387
	(0.2281)	(0.1907)
20–30 km	-1.3124***	-1.0777***
	(0.3221)	(0.2680)
30–40 km	-2.4601***	-1.7505***
	(0.3857)	(0.5000)
40+ km	-2.6890***	-2.1617***
	(0.3886)	(0.3214)
WindSpeed		0.0961**
		(0.0407)
WindSpeed^2		-0.0031*
		(0.0016)
TerrainSlope		0.0533**
		(0.0210)
TerrainSlope^2		-0.0009*
		(0.0005)
VaporPressureDifferential		0.0882
		(0.0588)
$\text{VaporPressureDifferential}^2$		-0.0019
		(0.0013)
Precipitation		-0.2071**
		(0.0956)
Precipitation^2		0.0271**
		(0.0106)
South/SW Aspect		0.0894
		(0.1620)
Shrub Fuel Model		-0.1541
		(0.1717)
Timber Fuel Model		-0.0968
		(0.1449)
Urban/Barren Fuel Model		0.0846
		(0.3498)
Constant	13.2532***	11.1949***
	(0.2069)	(0.7473)
National Forest FE		X
Year by State FE		X
Month-of-Year by State FE		X
N	1,509	1,509
R^2	0.12	0.43

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 NIFMID (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***	0.97***	0.95**	1.01***	1.33**	0.88***
	(0.30)	(0.31)	(0.38)	(0.33)	(0.64)	(0.33)
2	1.76***	1.74***	1.61***	1.75***	1.67***	1.52***
	(0.36)	(0.34)	(0.38)	(0.37)	(0.58)	(0.33)
3	1.56***	1.53***	1.31**	1.41***	1.70***	1.96***
	(0.47)	(0.43)	(0.50)	(0.45)	(0.58)	(0.37)
4	2.07***	2.06***	1.94***	2.07***	2.73***	1.66***
	(0.38)	(0.36)	(0.47)	(0.37)	(0.62)	(0.35)
5	1.88***	1.79***	1.52**	1.81***	2.20**	1.99***
	(0.53)	(0.51)	(0.60)	(0.66)	(0.93)	(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	
Fires	1,503	1,503	1,503	1,151	574	1,503
R^2	0.41	0.42	0.52	0.45	0.57	0.42

Columns (1) through (5) reproduces Table 2 from 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 Table 2 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 Table 3: Costs by Number of Homes: Alternative Radii

Bin	20 km		30 km		40 km	
	Number of homes	Log Cost	Number of homes	Log Cost	Number of homes	Log Cost
0	0	0.00	0	0.00	0	0.00
1	1	0.65**	1	0.84***	1	0.86***
		(0.26)		(0.28)		(0.14)
2	36	1.11***	115	1.35***	300	1.74***
		(0.29)		(0.33)		(0.31)
3	185	1.20***	626	1.55***	1,336	1.67***
		(0.34)		(0.39)		(0.24)
4	859	1.05***	2,499	1.68***	4,983	1.85***
		(0.29)		(0.33)		(0.24)
5	3,257	1.32***	8,524	1.69***	15,529	1.66***
		(0.31)		(0.38)		(0.34)
Fires with Homes		1,806		2,082		2,233
Fires Without Homes		528		252		101

This table reproduces Table 2 from the main text using alternative radii. Each table row shows coefficients for five 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., in the 40 km column, 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.

1.2 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.[27] 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 4 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%.[28] 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.

[27]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.

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

Appendix Table 4: 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*** (0.005)	0.035*** (0.007)	0.029*** (0.008)	0.037*** (0.008)	0.033*** (0.007)	0.030*** (0.008)	0.021* (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

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.

1.3 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.[29] 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 et al., 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.[30]

Table 5 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 6 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

[29]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).

[30]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 5: 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

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 6: 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
National Forest Dummies			X	X
Year Dummies				X
N	1,491	77,484	77,484	77,484

2 Construction of the Dataset

2.1 Homes data

2.1.1 Sample restrictions

The initial dataset includes nearly 18 million single-family homes in the 11 western states.[31] We restrict the sample to include 8,117,482 homes at risk from wildland fires due to the presence of wildland vegetation, based on geographic classifications in Radeloff et al. (2005). The vegetation categories we include are 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. Finally, we exclude homes in areas without wildland vegetation, including high density no vegetation, medium density no vegetation, low density no vegetation, very low density no vegetation, and uninhabited no vegetation.

2.1.2 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 12 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 $\hat{p}_d$:

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

[31] Arizona, California, Colorado, Idaho, Montana, New Mexico, Nevada, Oregon, Utah, Washington, Wyoming.

2.2 Additional Data

We assign both a categorical and a continuous measure of wildfire hazard potential to nearly every parcel[32] in our dataset using data from Dillon (2015).

[32] 156 parcels lie outside the boundaries given by the spatial data in Dillon (2015).

3 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 et al. (2007) write that the publicly available data on costs in NIFMID represents an underestimate of the total USFS fire suppression costs and that the "only accurate data on suppression expenditures are the actual expenditures obtained from the Forest Service accounting system." Since the time of their writing, the addition of an accounting code (known as a "P-code") to the NIFMID 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 NIFMID data presented in FAMWEB and the accounting dataset we obtain.

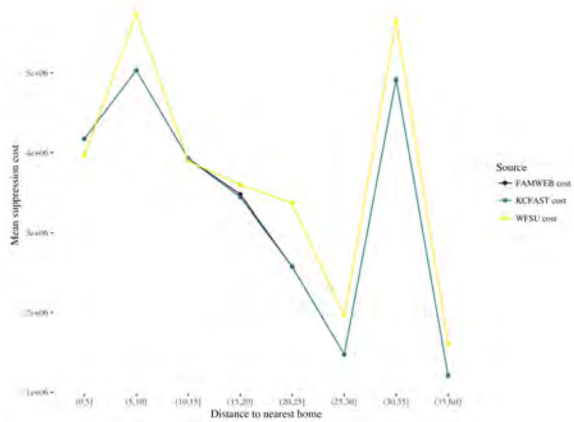
Year	FAMWEB	FAMWEB West	WFSU valid	WFSU all
2004	247	236	471	679
2005	271	262	440	768
2006	828	799	1,142	1,355
2007	978	923	977	1,263
2008	708	694	1,070	1,464
2009	401	394	682	840
2010	239	224	373	662
2011	475	436	623	1,251
2012	975	952	917	1,161
Total	5,122	4,920	6,695	9,442

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. [33]

Next, we match the costs in the accounting dataset to the NIFMID data using the P-code to identify whether the relationship between suppression costs and distance from homes is stable across the use of either source of cost data. We match from the

[33] 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.

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

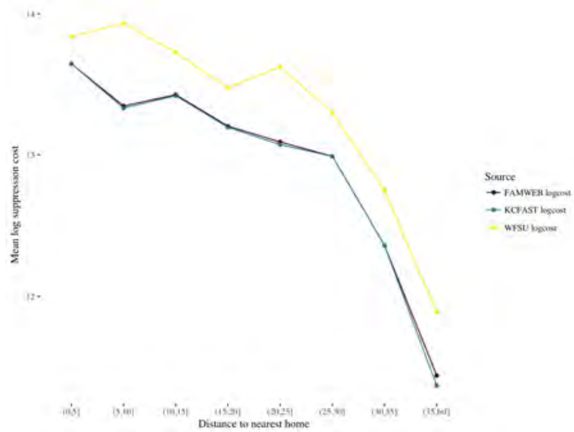


P-code and year to the suppression expenditure data from NIFMID. This match is not entirely straightforward: the guidelines over the issuance of P-codes and the proper accounting procedures have changed over the years, and many fires are submitted under the same P-code. In particular, large complex fires are often accounted for using the same P-code.[34] For the 974 fires in our NIFMID dataset from 2004-2012, we are able to match 782 of these to the accounting dataset.

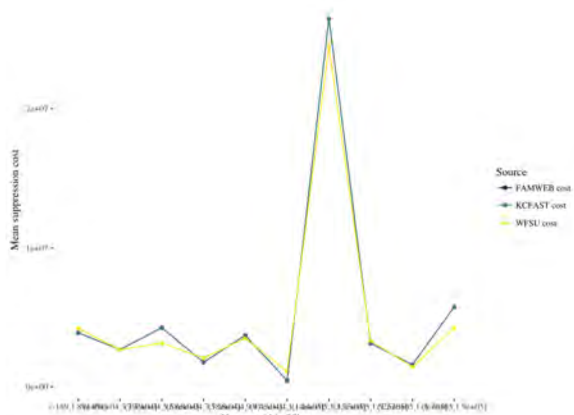
For the 1,234 fires from 2004-2012 in our NIFMID dataset, we successfully match 673 from the accounting dataset after accounting for the issues above. We estimate the relationship between fire cost and nearby homes for four sets of costs: A) NIFMID costs for all fires in NIFMID, B) NIFMID costs for all 2004-2012 fires in NIFMID, C) NIFMID costs for fires that match to the accounting data, and D) accounting data costs for all fires that match to NIFMID 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.

[34]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 NIFMID and accounting data: mean log suppression costs and distance to nearest home



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



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