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

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

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1 Introduction

Driven by climate change, expanded development in high-risk locations, and other factors, annual wildland firefighting costs for the U.S. federal government have more than doubled in real terms over the past 30 years and are expected to continue to grow.[1] Every summer and fall, tens of thousands of firefighters and many millions of dollars worth of equipment and aircraft are continuously dispatched throughout the 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, much of the cost of defending them is borne by the federal and state governments.

This apparent misalignment of incentives 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 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 ex-urban home development starting in the second half of the 20th century increased the number of homes bordering these public lands (Radeloff et al. 2005; Radeloff et al. 2018). Because of the way financial and operational responsibility for firefighting is assigned, federal and state agencies are responsible for fighting many of the wildland fires that threaten these homes.

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

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

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

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

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

In this paper, we consider the consequences of local development decisions for federal and state protection spending. We provide the first estimates of the implicit transfer to homeowners due to fire protection at the individual parcel level for homes throughout the western United States. To do so, we combine parcel-level data on the universe of 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

2. The five most damaging fires during this time period accounted for 55% of all property losses (including the 2017 "Wine Country" fires in Northern California that caused \$13 billion in losses). Unofficial estimates for the 2018 Camp Fire in Northern California project damages of about \$10 billion. Damage data 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 (2017), "Federal Firefighting Costs (Suppression Only)". Monetary values represent 2017 dollars.

dataset on wildland firefighting expenditures in existence. Our empirical approach takes advantage of variation in ignition locations to measure how incident-level firefighting expenditures increase when homes are built in harm's way. We then use these estimates to construct an actuarial measure of the expected additional future cost to the government to protect each home from wildfires. Using a simple theoretical framework, we show how these per capita protection costs can be interpreted as the minimum amount by which residents' average willingness to pay to live in a WUI location must exceed housing costs and insurance premiums in order for new development in a given location to be welfare-improving.

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

These implicit subsidies imply potentially significant efficiency costs. We discuss possible distortions along three margins. The first is the location of new residential development. Because new development is relatively price-elastic in regions with high fire protection costs, there may be substantial excess development in high-cost areas. Second, providing fire protection for free reduces incentives to capitalize on the economies of density that we measure, effectively subsidizing large lot sizes and low-density development. To the extent that sprawl also results from other preexisting market failures, this subsidy exacerbates those inefficiencies. Finally, freely provided fire protection could reduce private construction and maintenance investments that also protect homes. The promise of an aggressive firefighting response at no cost may reduce private incentives to choose fire-proof building materials and clear brush around homes, actions that can decrease the threat to homes during a wildfire. Similarly, federally financed firefighting limits incentives for cities and states to create and enforce wildland building codes and defensive space regulations.

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

One way to mitigate these distortions is to adopt policies that lead individuals and localities to internalize a larger share of the firefighting costs imposed by new construction in currently undeveloped areas. We discuss how the empirical approach that we develop can be used to calculate a differentiated fire protection fee for this purpose.

From a fiscal perspective, our results imply that wildland firefighting is a previously unappreciated mechanism for redistribution to particular geographic areas. For example, we find that the annual implicit subsidies to homeowners in Montana and Idaho via firefighting are larger than federal transfers to those states under the Temporary Assistance to Needy Families program (TANF).[3] Contrary to conventional wisdom (e.g., Davis 1995), we do not find that federal fire protection spending is regressive. This is because fire protection costs are highest in rural and ex-urban parts of the West where incomes and land values are generally low.

More broadly, this study underscores 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

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

4. For a review of natural disasters and climate change, see IPCC, 2012 (2012).

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 setting has some particular parallels to the literature on flood risk. Economists have studied behavioral responses to subsidized federal flood insurance and ex post rebuilding assistance (Kousky, Luttmer, and Zeckhauser 2006; Smith et al. 2006; Boustan, Kahn, and Rhode 2012; Deryugina 2017; Gregory 2017). Several of these studies find that such policies encourage rebuilding in high-risk areas following losses, which is also an issue for fires. However, development in high fire-risk WUI areas includes substantial new construction, including in currently undeveloped areas (Radeloff et al. 2005; Gude, Rasker, and Noort 2008; Mann et al. 2014). The demand for construction in new areas is likely to be more price-elastic than the demand for rebuilding where one already lives, implying potentially larger behavioral responses to subsidies. Another difference between fires and flooding is that one home's expected losses in a flood (and thus, the value of insurance subsidies) do not usually depend on the number of nearby homes, while we show that the per capita costs of protecting a home from wildfire depend strongly on density.

This paper makes several contributions. Introducing administrative data on firefighting expenditures allows us to provide the first quantitative estimates of the spatially differentiated implicit subsidy, and thus the optimal "fire protection fee" for every home in the western United States. Researchers and policymakers have long suspected that federal firefighting affects local incentives, but ours is the first study to measure these subsidies.[5] We also present novel evidence of a non-linear response of firefighting costs to the number of threatened homes, with important implications for the effect of freely provided firefighting on development density. From a methodological perspective, the introduction of parcel-level data on 18 million western homes allows us to be geographically precise about risks and costs relative to existing work

5. Examples of many academic studies that speculate about the importance of moral hazard in this setting include Davis (1995), Loomis (2004), Stetler, Venn, and Calkin (2010), Lueck and Yoder (2016), and Wibbenmeyer (2017). Policy examples include U.S. Department of Interior and Department of Agriculture. 1995. "Federal Wildland Fire Management Policy & Program Review"; California Legislative Analyst's Office. 2005. "A Primer: California's Wildland Fire Protection System"; and USDA (2006).

on wildfires that relies on spatially coarse aggregate data. This specificity represents a valuable advance since fire and other disaster risks can vary substantially over small distances. Finally, we embed our empirical results in a simple economic model that demonstrates the economic and policy implications of the expenditures that we measure.

The paper is organized as follows: Section 2 provides an overview of wildland fire institutions and explains how they motivate our empirical approach. Section 3 establishes the economic context for our empirical analysis through a simple conceptual framework, and Section 4 discusses the data. Section 5 measures the cost of saving homes during wildfires, Section 6 calculates implicit subsidies to homeowners, Section 7 considers efficiency costs along with policies to internalize fire protection costs, and Section 8 concludes.

2 Wildland Firefighting in the United States

Wildland firefighting in the United States is provided by a patchwork of federal, state, and local government agencies. Broadly speaking, financial and operational responsibility for a wildfire is determined by its ignition location and the area affected (Hoover and Lindsay 2017). For fires that affect multiple jurisdictions, these responsibilities are governed by local, state, and federal laws, as well as cooperative agreements in place between the affected jurisdictions.[6] For fires on national forest land, for example, primary responsibility rests with the USFS. A handful of federal government agencies manage large amounts of public land and thus oversee significant firefighting activity in the West. In addition to USFS, these include the Bureau of Land Management, the National Park Service, the Bureau of Indian Affairs, and the Fish and Wildlife Service. Individual states also maintain large investments in wildland firefighting capacity and have primary responsibility for incidents on state-owned lands and private unincorporated areas. The largest state fire service is the California Department of Forestry and Fire Protection (Cal Fire), which provides fire protection for large areas of mostly private land in California. Incidents that start

6. An example of such agreements is the California Master Cooperative Wildland Fire Management and Stafford Act Response Agreement, which involves the USFS, several Department of Interior agencies, and California.

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 lands where federal or sometimes state agencies bear the primary financial responsibility for firefighting. The federal government also bears a portion of costs incurred on incidents “owned” by state and local governments through grants from the Federal Emergency Management Agency (FEMA). For qualifying large fire incidents, the FEMA Fire Management Assistance Grant (FMAG) program reimburses states and cities 75% of their firefighting costs. Through this combination of direct expenditures and indirect support, the federal government absorbs a majority share of wildland firefighting expenses.

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

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

The increase in available fuels is in part due to forest management decisions. Land use change and a policy of fire suppression have altered the type and extent of fuels in the western United States (Stephens et al. 2016). Although the precise impacts of these changes on the costs of fires are the subject of continuing research, the majority view is that aggressive fire suppression efforts have led to an increased risk of large, damaging fires. Many ecologists argue that greater use of prescribed and managed fires, as well as mechanical thinning of vegetation, would reduce the risk of dangerous wildfires and lower overall required expenditures on fire management. Efforts to implement these recommendations have proven politically unpopular and have met with limited success. Prescribed fire is particularly difficult to use in areas with private home development because of concerns about threat to homes.

2.1 Potential Market Failures

The complexity of the wildfire problem and the institutions designed to address it give rise to a number of potential inefficiencies. These could include spillovers in protection benefits between adjacent landowners, dynamic tradeoffs of suppression today with fuel loads tomorrow, and inefficient dispatch of firefighting resources for political economy reasons.[7]

Several studies have asked whether individuals are fully informed about the private costs of future wildfire damages. Home prices in wildland areas decrease after nearby fires or wildfire information campaigns, suggesting this risk is imperfectly salient (Loomis 2004; Donovan, Champ, and Butry 2007; McCoy and Walsh 2018). Inattentiveness to private wildfire costs may affect individuals' location decisions by reducing

7. See Lueck and Yoder (2016) for a review of economic issues in wildland fire management.

perceived private costs in high-risk areas. In contrast, our study addresses the *external* costs of individuals' location decisions. The incentive effects of this externality do not depend on the salience of protection costs. Under the current regime, protection costs should not be expected to affect private decisions regardless of what individuals believe these protection costs to be.[8] Moreover, a corrective tax levied at the time of construction and equalling expected future protection costs would presumably be highly salient. Section 7.2 discusses such a policy.

As noted above, economists and policymakers have long suspected that the external costs of fire protection have distortionary effects (see citations in Footnote 5). Qualitative case studies in geography have documented how municipal governments realize property tax revenues from development in high fire-risk areas while federal and state sources subsidize fire protection (Simon 2017). In 2006, the USDA Inspector General expressed similar concerns. "Assigning the financial responsibility for WUI wildfire protection to State and local government is critical because Federal agencies do not have the power to regulate WUI development. Zoning and planning authority rests with State and local government", and that, "Homeowner reliance on the Federal government to provide wildfire suppression services places an enormous financial burden on FS, as the lead Federal agency providing such services. It also removes incentives for landowners moving into the WUI to take responsibility for their own protection and ensure their homes are constructed and landscaped in ways that reduce wildfire risks" (USDA 2006).

2.2 Implications for Measurement

The empirical portion of this paper uses administrative expenditure data along with plausibly-exogenous variation in ignition locations to estimate the amount of money that is spent to protect homes from wildfires. This approach quantifies the implicit subsidy to wildland homeowners, a parameter that is directly useful for economic and policy analysis. An alternative empirical approach would be to measure changes in construction and prices in response to policy differences over time or space, yielding direct reduced form estimates of past policy variation on housing markets. Our ex-

8. This is true for any externality. For example, the effects of an unpriced pollution externality do not depend on whether polluters know the external costs of pollution.

penditure approach has two major advantages over this alternative. First, there is little credible identifying variation in existing firefighting policies. We are not aware of any part of the U.S. where no effort is made to protect homes during wildfires. Existing policy differences generate only small, difficult-to-interpret differences in perceived protection.[9] Given the evidence that overall wildfire risk is imperfectly salient, it seems strong to assume that home buyers perceive small *differences* in the risk of property damage when firefighting rules shift across time or borders. A second and related point is that responses to observed policy differences have limited applicability to our research question. Since our focus is on the effects of providing fire protection for free, the welfare-relevant counterfactual is a scenario where homeowners or local governments internalize this cost (for example, through a tax at the time of construction that equals expected future fire protection costs in that area). The responses to a transparent up-front cost would presumably be different than responses to the opaque minutiae of firefighting dispatch rules.

In contrast, our approach using expenditure data is more interpretable and generalizable. Combined with existng estimates of supply and demand for new residential construction, our implicit subsidy estimates can be used to calculate expected quantity changes relative to optimal pricing of fire protection, and the resulting deadweight loss. Our estimates also directly reveal the fiscal and distributional consequences of federal firefighting policy. Furthermore, our estimates are calculated for the entire Western U.S., as opposed to the place and time of a particular policy change or boundary.[10]

3 Conceptual Framework

This section presents the stylized model that guides our empirical analysis. The model illustrates how potential distortions in the housing market depend on the relative

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

10. We see research that leverages spatial and time-series variation in protection policy in special instances where it exists as a potentially useful complement to our approach. The one relevant paper that we are aware of is a 2012 working paper that studies construction adjacent to public lands after the 1988 Yellowstone fires led to changes in federal firefighting policies (Kousky and Olmstead 2012).

magnitudes of government defensive expenditures and private property damages, the severity of disaster risk, and the elasticities of supply and demand for residential construction. We focus on location choice and development density, but the model could be extended to include private protective investments.

3.1 Setup

There are N households indexed by i that 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 housing (a locally-produced non-tradable good). We impose several stylized assumptions in the spirit of Rosen (1979) and Roback (1982) to simplify exposition and focus on the elements of the model related to our research question. Households move frictionlessly between locations to maximize their utility, supply a single unit of labor inelastically at a fixed wage, and consume a single unit of housing at the local price. Housing is supplied in a competitive market. The risky and safe locations also vary in other (exogenous) amenities valued by households (e.g., outdoor recreation). Each household's willingness to pay (WTP) to live in the risky place instead of the reservation location (not including disaster costs) is θ_i. This WTP simply reflects taste for risky place amenities, since wages are assumed to to be equal. We adopt a static framework in which development in the risky place happens all at once.

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

1. $H'(f) < 0$ and $H''(f) > 0$. That is, defensive expenditures reduce expected damages, and do so with diminishing returns.
2. Benefits of defensive expenditures are non-rival within a location.
3. Within a location, $H(f)$ is constant across homes.

In the event of a disaster, the government chooses the optimal level of defensive expenditure given population in the risky place, n_r. This value $f^*(n_r)$ minimizes the sum of defensive expenditures and total expected property damage, $f + n_r H(f)$.[11] $f^*(n_r)$ 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 how the financing of defensive expenditures affects population in the risky place. One intuitive benchmark is a policy that requires households to reimburse the central government for their per capita share of defensive expenditures after a disaster. In the absence of a disaster, realized household benefit from living in the risky place is θ_i. If a disaster occurs, realized household benefit in the risky place is $\theta_i - \frac{f(n_r)}{n_r} - H(f(n_r))$. The last two terms represent per capita disaster costs. The sum of these two terms is decreasing in local population.[12] 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 $\theta_i - \phi[\frac{f(n_r)}{n_r} + H(f(n_r))]$.

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

Figure I depicts the market for housing in the risky location under each policy. The black downward sloping line indicates demand for non-disaster amenities, θ_i. This line slopes downward due to heterogeneity in households' WTP to live in the risky location. The solid gray line shows demand net of expected per capita disaster costs

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

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

$\phi[\frac{f(n_r)}{n_r} + H(f(n_r))]$. As discussed above, the vertical distance between these two lines is larger at lower population levels because per capita disaster costs decrease with population. The dashed gray line shows demand net only of expected property damages, $\phi H(f(n_r))$, corresponding to the case where households are not required to pay for defensive expenditures. The black line labeled s shows the marginal cost of housing in the risky place. This example is drawn to reflect elastic housing supply up to a capacity constraint (perhaps due to land availability or land use regulations). The supply elasticity of housing has important implications that we revisit in Section 7.

When households pay for defensive expenditures, the equilibrium population n_r^0 equates demand and supply in the risky place. If the government pays for defensive expenditures, housing demand is higher and population is n_r'.

3.3 Optimal level of development

Having shown how the financing of defensive expenditures affects individual decisions, we now consider the optimal amount of development in the risky place and the efficiency costs of deviations. The total net benefit of development in the risky place is,

$$\int_0^{n_r} \theta_i dn - \int_0^{n_r} s(n)dn - \phi f(n_r) - \phi H(f(n_r))n_r \tag{1}$$

The first term is total WTP of risky place residents; the second is the total cost of housing; the third is expected defensive expenditures; and the fourth is total expected property damage. A necessary condition for a non-zero optimal population is given by the first order condition,

$$\theta_{n_r} = s(n_r) + \phi f'(n_r) + \phi \left[H(f(n_r)) + \frac{\partial H}{\partial f(n_r)} f'(n_r)n_r \right] \tag{2}$$

This expression equates the WTP of the marginal risky place resident with the sum of the marginal housing and disaster-related costs. The second term on the right hand side shows that increasing development increases optimal defensive expenditures in the event of a disaster (because the value at risk has increased). The final expression in brackets is the change in property damage. This change includes expected damages to one more home, plus decreased damages for all inframarginal homes as a result of the increase in defensive expenditures in the event of a disaster.

Public provision of defensive expenditures creates moral hazard, which can distort development. The first potential distortion is on the intensive margin. When individuals do not internalize $\phi f'(n_r)$, private costs are below social costs and the amount of development in the risky place exceeds the socially optimal level. The magnitude of this distortion depends on the *marginal* increase in defensive expenditures with population.

The second potential distortion concerns whether development occurs at all. The necessary condition in Equation (2) yields the optimal population in the risky place conditional on development, but it does not guarantee that the total benefits exceed the total costs. If the marginal cost of supplying fire protection is substantially below the average cost, it may be that development at the population implied by Equation (2) would yield negative net benefits. In such cases, the socially optimal amount of development in the risky place is zero. One example might be an extreme case where defensive expenditures include only a large fixed cost.

When rational households internalize all disaster-related costs, development occurs only if total WTP among risky place residents exceeds the sum of housing costs, expected property damages, and expected defensive expenditures.[13] When the government pays for defensive expenditures, development proceeds whenever total WTP exceeds housing costs and expected property damages. When development passes this latter private cost test but fails the former social cost test, development proceeds inefficiently. The magnitude of this distortion depends on *average* defensive expenditures at the observed level of development.

13. Defensive expenditures need not be divided equally among risky place households. In fact, welfare is highest when costs are allocated in proportion to WTP, since that may enable some low-WTP households to locate there. Such differentiation makes it possible to satisfy Equation (2), balancing the marginal household's WTP against marginal (instead of average) defensive expenditures. Absent contracting frictions, households could reproduce this efficient allocation of protection costs through private contracts regardless of the statutory assignment of costs.

3.4 Implications for the empirical analysis

The share of total expected disaster costs that risky-place residents internalize depends on the relative magnitudes of publicly provided defensive expenditures and privately borne property damages. When defensive expenditures make up a large share of total disaster costs, as in our empirical application, private location decisions ignore a large component of disaster costs. This study derives spatially explicit measures of expected firefighting expenditures that directly quantify the implicit subsidy in this model. The per capita expected protection costs in our analysis map directly to average defensive expenditures, $\phi\frac{f(n_r)}{n_r}$. From a welfare perspective, these per capita expected cost estimates can be interpreted as the minimum amount by which average WTP to live in a WUI area must exceed housing costs and insurance premiums in order for development to be efficient. We also explore marginal expected firefighting costs, which allows us to compare the relative importance of the two distortions in the model.

The model also shows how the size of the subsidy depends on the equilibrium population in the risky place. Per capita disaster costs decrease with population, so that the marginal increase in total disaster-related costs from locating in the risky place is higher at low populations. Because we observe responses to a large number of wildland fire incidents in areas with varied population density, we are able to validate this relationship between local population density and per capita disaster costs empirically.

4 Data

We construct a dataset that combines administrative data on firefighting expenditures from federal and state agencies with assessor data for nearly all homes in the western United States, defined as the states of Arizona, California, Colorado, Idaho, Montana, New Mexico, Nevada, Oregon, Utah, Washington, and Wyoming. Our dataset also includes topographical information, wildfire risk assessments, and weather conditions from the time and location of the fire ignition. This section provides an overview of the dataset, while a comprehensive account of dataset construction can be found in Section B in the appendix.

We collect fire suppression and fire preparedness data from five federal agencies and one state agency. Fire suppression refers to expenditures made in the act of fighting a fire, while preparedness expenditures are costs incurred in order to reduce or mitigate damage from future fires. The federal agencies are the U.S. Forest Service (USFS), the National Park Service (NPS), the Bureau of Land Management (BLM), the Bureau of Indian Affairs (BIA), and the Federal Emergency Management Agency (FEMA). The state agency is California's Department of Forestry and Fire Protection (Cal Fire), which is unique among state agencies in the magnitude of its firefighting spending. Incident-level expenditures for each agency come from a combination of Freedom of Information Act requests (Public Records Act requests for California) and publicly available sources. Because fire costs are only reported consistently for large fires and because large fires comprise the bulk of fire suppression expenditures, we focus our analysis on fires that are 300 acres or larger. The regression analysis in Section 5 focuses on the USFS fire suppression data, which cover 1995 to 2014. The calculation of implicit subsidies in Section 6 uses expenditures from all agencies in the dataset.

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

The parcels dataset we use is a proprietary compilation of county assessor data. It includes location, transaction values, year of construction, and other relevant property characteristics for 18.5 million parcels, or nearly all of the homes in the western United States. We limit this sample to 9.1 million homes in areas with significant wildland vegetation, as defined by Radeloff et al. (2018). For each home, our data includes a measure of its actual location, which is an improvement over previous papers about wildfire risk which rely on publicly available housing counts at the Census block level. In the rural and ex-urban areas that make up the WUI, Census blocks are often very large. Appendix Section B.2.1 includes more detail on these geographic data.

Our final dataset includes 4,581 fires that account for $10.5 billion of suppression costs and links those fires to 9.1 million western US homes in the WUI. Detailed descriptive statistics are included in the online appendix.

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 homes, 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. We recover this difference empirically by estimating the casual impact of home presence and density on firefighting costs.

Our empirical strategy takes 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 II 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 stars and are colored by the distance from the ignition point to the nearest home (top-coded at 30 kilometers).

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

$$ln(\text{Cost}_{ift}) = g(\text{Homes}_{it}) + X_{ift}\rho + \delta_f + \omega_{st} + \eta_{ift} \tag{3}$$

$Cost_{ift}$ is the suppression cost for fire i in national forest f in month-of-sample t. We are primarily interested in how this cost depends on the potential threat posed by the fire to private homes, Homes_{it}. We begin in Section 5.2 by parameterizing

Homes_{it} as the distance from the ignition point of the fire to the nearest home. In Section 5.3, we consider the total number of homes near the ignition point. In either case, our preferred model approximates $g(\cdot)$ with a binned step function to allow a flexible response of costs to threatened homes.

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

We include additional control variables X_{ift} to address the fact that locations of private homes are not randomly assigned. Even within a given national forest, areas near homes may differ systematically from areas far from homes in ways that affect firefighting cost. The control variables X_{ift} include the slope of the terrain at the ignition site, the geographic aspect, the vegetation type (fuel model), and weather conditions at the point of ignition on the ignition day.[14] We also estimate a specification where we limit the sample to fires caused by lightning, which ensures that the location and timing of fires is not driven by the presence of people. The identifying assumption in this analysis is that unobserved determinants of fire cost, η_{ift}, are independent of Homes_{it}, conditional on national forest fixed effects and our other controls.

This empirical strategy based on national forests requires us restrict the analysis to fires managed by USFS, since lands managed by other agencies are not similarly arranged into large contiguous units.[15] Moreover, Forest Service expenditures account for over 80% of expenditures in our dataset, due both to the disproportionate role of USFS in fire management and the longer temporal coverage of the USFS data. The online appendix explores this relationship for other agencies. When adding up historical expenditures associated with each home in Section 6, we use data from all

14. Weather variables vary over time, while elevation, slope, aspect, and fuel model are constant.

15. For example, Cal Fire incidents occur on diffuse private and state lands, while BLM owned lands often consist of smaller patches of land managed by district offices.

agencies.

5.2 Proximity to homes

We begin by considering a version of Equation (3) where the threat to private homes, Homes_{it}, is proxied by the distance from the ignition point to the nearest home that existed at the time of the fire. Figure III shows estimates from three flexible 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 less than five kilometers away from homes. Regardless of the functional form that we choose, there is a clear gradient in firefighting costs with distance from nearest home. The relationship is steep, monotonic and close to linear. Relative to a fire that starts 40+ kilometers from any home, the log cost of a fire less than five kilometers from homes is higher by about 2.25. Taken literally, these estimates imply that a fire that starts less than 5 km from homes would cost about 70% less if there were no homes within 25 km, and 90% less if there were no homes within 40 km.[16]

Table I estimates alternative models using a binned specification. Column (1) follows Figure III. Column (2) adds additional controls for pre-determined fire characteristics. As we show in the appendix, the signs and magnitudes of the included covariates match expectations. Firefighting costs are higher where the terrain slopes more steeply, reflecting difficulty of access. Costs also increase with wind speed on the ignition day, consistent with the importance of wind in fire spread. Vapor pressure differential (VPD) is a measure of atmospheric dryness, where higher values imply drier air; as expected, high VPD increases firefighting costs.[17] Costs are also higher

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

17. VPD is the deficit between the observed vapor pressure and the vapor pressure at the current

for fires on south- or southwest-facing slopes, which receive additional sun exposure and thus tend to have more readily combustible vegetation. While we find that many of these covariates have meaningful effects on firefighting costs, including them in the regression has little effect on our estimated distance gradient.

The remaining columns show three robustness checks. Column (3) replaces the time fixed effects with more granular month-of-sample by state fixed effects, which allow for arbitrary shocks to firefighting costs in each month of the dataset in each state. These temporally more precise controls absorb higher frequency local cost fluctuations that might be caused by weather patterns or other factors. This alternative specification produces a similar distance gradient. Column (4) restricts the sample to fires started by lightning. Some types of human-caused fires are more likely to occur near populated areas, introducing a potential identification concern if fires due to arson or campfires or other causes vary systematically in their difficulty to extinguish. The locations of lightning strikes are plausibly random and thus purged of this potential bias. If anything, the estimated distance gradient is steeper when this restriction is applied, though the estimates are not different in a statistical sense. Column (5) restricts to fires occurring in "timber" vegetation (fuel models), 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. The online appendix shows that these results are robust to further controlling for the distance from the ignition point to the nearest major road. The large effects of threatened homes on firefighting costs are likely explained by the high cost of stopping fires in place by digging firelines, dropping retardant from aircraft, and taking other costly measures. An anecdote in Arno and Allison-Bunnell (2002) helps to contextualize this result: "Consider the campaign against the 217,000-acre Clear Creek Fire on the Salmon-Challis National Forest in central Idaho during the summer of 2000. Although the fire burned mostly in undeveloped mountainous terrain, it was near enough to populated valleys, including the town of Salmon, to inspire frenzied efforts to stop the advancing flames with heavy equipment... [and] the monumental expenditure of $71 million... In contrast, the 182,000-acre Wilderness Complex fire farther west in similar terrain was monitored and allowed to burn with very little suppression effort at a cost of about half a million dollars."

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).

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 (3) that parameterizes Homes_{it} as the total number of homes within that radius. We use a 30 kilometer radius in our baseline specification. The online appendix shows results for alternative radii.

Figure IV shows results from a binned step function specification. The reference bin is fires with zero homes within 30 km, and the other bins evenly divide the remaining fires into deciles. The presence of just one to 31 homes almost doubles expenditures on a fire. Costs are further increasing over the first few deciles, up to about 100–300 homes. Beyond that costs change very little. The regression coefficients imply that a fire threatening 300 homes costs about 5 times as much as a fire with no nearby homes, while a fire threatening over ten thousand homes costs about 6.5 times as much as a fire with no nearby homes.[18] This strongly nonlinear relationship implies that the benefits of wildland firefighting are essentially non-rival, so that marginal protection costs are decreasing in population density.

One way to contextualize these results is to convert the numbers of homes in Figure IV into conventional measures of residential density such as the number of homes per unit area. Land use planners typically work with *net* density, which measures land consumption per housing unit after subtracting out open space, parks, pasture, roads, and other land uses. For comparison to this standard measure, we calculate the average of the reported lot sizes for all homes within 30 km of the fire. The median net density across fires in the fourth non-zero bin, where costs level off, is 0.16 homes per acre.[19] Mann et al. (2014) define 5 tiers of residential density: sparse, low, medium, high, and very high. A value of 0.16 homes per acre is between the cutoffs for “low” and “medium”.

18. Regression details are in the appendix. The relevant coefficients are 1.61 and 1.87, implying approximate cost ratios of $e^{1.61} = 5.00$ and $e^{1.87} = 6.49$.

19. This calculation is meant to provide broad context as opposed to a highly accurate measure of net density. We calculate the mean lot size within 30 km of each fire, and then calculate the median average lot size in each decile bin in the figure. These range from 0.11 homes per acre in the left-most non-zero bin to 0.91 homes per acre in the right-most bin. The average lot size within 30 km of each fire is sensitive to some very large reported parcels. Lot size is also missing for some homes, which we necessarily omit from this calculation.

5.4 Additional Results and Robustness Checks

In addition to the checks described above, we include a more detailed set of additional results and robustness checks in the online appendix, which we describe here in brief. First, we show that the estimated density effects in Figure IV are robust to the same checks shown in Table I, such as limiting to lightning-caused fires or including temporally more precise fixed effects. We also show that using the total transaction value of homes instead of the number of nearby homes yields similar results. Furthermore, we show that the effect of development density on firefighting costs is robust to using different radii around the ignition point.

Our measure of valuable structures threatened by a fire does not include public infrastructure such as school buildings and municipal parks that would also be considered by incident commanders when choosing response levels. This means that our approach assigns the cost of protecting those public goods to nearby homeowners. For local public goods such as schools and parks, this makes intuitive sense, since construction of such local public goods follows as a direct result of housing construction (Brueckner 1997). It should also be noted that built structures in the WUI areas where we are focused are disproportionately residential, with residents who travel by car to more-developed commercial areas for shopping, work, and school.

Since firefighting costs are only consistently reported for incidents larger than 300 acres, a potential concern is bias due to sample selection. Our analysis could be affected if the subset of ignitions that reach this size differs with distance from homes in a way that is correlated with suppression costs. For example, one might worry that concentrated initial attack efforts near homes make ignitions near homes unlikely to grow large unless conditions are difficult (e.g., high winds). This selection would result in an upward bias in a naive regression of firefighting costs on distance to homes. Importantly, we are able to control directly for the most significant potential confounders. Wind, weather conditions, and topography are primary determinants of suppression difficulty and cost (Gebert, Calkin, and Yoder 2007). Table I 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.

We also compare our regression-based method to a different empirical approach. Auditors from the USDA Office of the Inspector General have studied federal firefighting expenditures using interview methods. USFS managers reported that in their experience, 50 to 95% of USFS firefighting expenditures are devoted to protecting private structures (USDA 2006). Appendix Table 4 reports implicit subsidy estimates that ignore the regression results in this section and instead use these interviews to identify the share of firefighting expenditures devoted to protecting homes. Specifically, we assume that protecting homes accounts for 72.5% of each fire's costs (the midpoint of the reported range). The resulting distribution of homeowner-level implicit subsidies is similar to the main estimates that we calculate in Section 6. This similarity across methods is reassuring.

Finally, because our baseline estimates are not suitable to consider the impact of homes on the *frequency* of fires in an area, we conduct a separate analysis to investigate how this might impact our findings. As some wildland fires are ignited by humans, increased human population may lead to 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 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 4.3% increase in the number of large fires each year, or about 0.06 additional large fires per year. The finding that human presence increases fire frequency is consistent with work by ecologists and geographers (Syphard et al. 2007; Massada et al. 2012; Faivre et al. 2014; Balch et al. 2017). This implies that our estimates may slightly undercount the additional firefighting cost created by new homes.

6 The Implicit Subsidy To Homeowners

This section calculates geographically differentiated implicit subsidies due to wildland firefighting. For every individual home in the western United States, we calculate an actuarial ("ex ante") measure of the expected net present value of the cost incurred by the federal and state governments to protect the home during wildfires. Section 6.1

describes the methods that we use to estimate historical ("ex post") and expected ("ex ante") protection costs for each home. Section 6.2 summarizes the estimated costs and demonstrates the relationship between observable risk predictors and historical cost experience. Section 6.3 describes the geographic incidence of these implicit subsidies at regional and local scales, and Section 6.4 describes the incidence according to income.

6.1 Methods for realized and expected protection costs

6.1.1 Calculating Historical Federal Firefighting Expenditures

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

For each fire in the dataset, we use the estimates from Equation (3) to predict the firefighting cost for the incident if there had been no homes within 40 kilometers of the ignition point. The calculation of these counterfactual costs is described in detail in Appendix Section B.3. For each fire i we calculate the difference Δ_i between the observed firefighting cost and the predicted counterfactual cost with no nearby homes. We then allocate the home protection costs Δ_i over potentially threatened homes. We include homes as potentially threatened if they are located within 40 km of the ignition point and are in areas with wildland vegetation following Radeloff et al. (2005) (see Appendix Section B.2 for details). Within potentially threatened homes, we assign a larger share of Δ_i to those located closer to the ignition point using weights derived from the estimated regression coefficients from Equation (3). The incident-specific weight w_{ij} assigned to each threatened home j corresponds to the expected increase in costs if home j were the nearest home to the fire, relative to a fire threatening no homes. Protection cost Δ_i is then allocated proportionally using the normalized weights $\bar{w}_{ij} = w_{ij}/\sum_j w_{ij}$.[20] This exercise divides Δ_i across j potentially threatened

20. Another weighting scheme used in other applications is inverse distance weighting (IDW). Our approach is conservative relative to IDW, in that it allocates costs more evenly over potentially threatened homes. For example, under IDW, a home 1 km from the ignition point would receive 15 times the cost allocation of a home 15 km from the ignition point. Using the regression coefficients

homes, yielding costs δ_{ij} for each home, where $\sum_{j=1}^{J} \delta_{ij} = \Delta_i$.

Finally, the costs allocated to each home from fires during the period of the historical data are summed up to yield total historical expenditures associated with each home. For home j, this is $\rho_j = \sum_{i=1}^{I} \delta_{ij}$. 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.

While the dataset in Section 5 was limited to USFS fires in order to take advantage of variation in ignition locations within national forests, the calculation of historical firefighting costs in this section also includes expenditures by BLM, NPS, and BIA in order to more fully capture federal agency expenditures.[21]

6.1.2 Calculating ex ante Expected Federal Firefighting Expenditures

The estimate of interest in the conceptual model in Section 3 is not realized expenditures, but expected expenditures. The observed history of firefighting costs is 20 years or less, which in many regions may not be a long enough period to fully describe the underlying fire risk. To estimate expected firefighting costs, we group regions with similar ecological and fire risk characteristics together into actuarial groups (as an insurance company might do). We calculate expected cost for homes in each group as $\mathbb{E}_{h,d,s}[\rho_j]$.

This calculation takes expectations over bins of wildfire hazard h, development density d, and geographic region g. Wildfire hazard is defined at the parcel level using the spatially explicit wildfire hazard potential (WHP) scores provided by Dillon (2015), which are a physical measure of wildfire risk taking into account ecological and topographical factors. The WHP score is a categorical variable with six levels. Development density (population per square meter) comes from the Gridded Population of the World (GPW) dataset, which reports population density within 1 km grid cells. We define 5 bins of density based on the quintiles of the distribution of GPW grid cells. We define geographic regions based on the boundaries of the seven Geographic Area Coordinating Centers (GACCs) that coordinate regional firefighting operations

as weights, the 1 km home receives 2 times the cost allocation of the 15 km home.

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

in the West. This binning process results in 210 actuarial groups. 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 to protect each home from fire.

Appendix Section A.2 shows the geographic distribution of the variables used to define actuarial groups. Appendix Section A.2.4 discusses another approach to calculating expected protection costs using machine learning methods. A regression tree can be used to define actuarial groups that minimize the prediction error for historical costs in each group. This approach yields similar results for expected protection costs.

6.1.3 Incorporating Additional Expenditure Categories

Governments incur additional firefighting expenses beyond direct expenditures by federal agencies. To reflect this, we calculate several different measures of protection cost that incorporate successively broader categories of costs. Each of these measures represents a tradeoff between completeness and strength of required assumptions. A "suppression only" measure includes direct firefighting costs by USFS, BLM, NPS, and BIA. This measure requires the fewest assumptions beyond those in Section 5.1, but omits potentially important categories of expenditures. A "suppression plus" measure also accounts for the annual fixed costs of maintaining response capabilities ("preparedness" expenditures), and federal reimbursements to state and firefighting agencies through the Fire Management Assistance Grant (FMAG) program. Finally, our third measure is specific to California, the largest state in the West and a state where we have detailed state-level expenditure data.

The first element that we add to the "suppression plus" measure is federal preparedness spending. Allocating preparedness spending to individual fires involves two challenges, one conceptual and one computational. Conceptually, it is not clear how these annual costs should be attributed to individual incidents. We choose to divide preparedness costs equally across ignitions.[22] After this even division, we then calculate the share of preparedness costs due to homes using the same model as for suppression

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

expenditures.[23] 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 assumption that the geographic distribution of ignitions is similar to the geographic distribution of fires exceeding 300 acres. Under this assumption, we can achieve the same spatial allocation of preparedness costs by allocating preparedness spending across large fires only. This procedure yields an amount of preparedness spending for each fire that can be attributed to homes. Finally, we allocate these per-fire costs across nearby homes using the same distance weights used for suppression spending.

The "suppression plus" measure also includes FEMA reimbursements to states and cities as a proxy for state and local wildland firefighting costs. We take all wildfire-related incidents from FEMA and aggregate them to the state-year level. We then assign state-year FEMA reimbursements to parcels using the same method as for preparedness spending.[24]

6.1.4 A Separate Cost Measure for California

Our final measure focuses on California, the largest and most populous state in the West. For this measure, we exclude FEMA reimbursements and instead include Cal Fire incident costs as a direct measure of state government expenditures. The incident-level Cal Fire data include geographic coordinates as well as costs, so we are able to directly allocate these suppression costs in the same way that we allocated federal direct suppression costs in the "suppression only" scenario.

6.2 Results: Implicit Subsidy Magnitudes

Figure V plots conditional means of historical protection costs. The figure shows average fire protection costs for homes in each of 400 bins, using the "suppression

23. 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.

24. This reflects an additional assumption that the spatial distribution of fires for which FEMA makes reimbursements is similar to the overall distribution of fires in the data.

plus" cost metric. The sample of homes in this figure includes all 8.6 million homes in the western U.S. located near areas of wildland vegetation (about 44% of all western U.S. residential homes, condos, and apartments). The color scale indicates average protection costs for homes in each cell (on a log scale). The range of historical protection costs is large. The average net present value of historical protection costs is a few hundred dollars per home for the lowest-cost cells and almost $100,000 per home in the highest-cost cells.

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

We compute our final measures of expected protection cost using the 210 actuarial groups described in Section 6.1.2. These coarser bins reduce noise relative to Figure V while also allowing for regional variation. Table II describes the distribution of the resulting expected protection costs for the 8.6 million homes in our sampling area in the 11 western states. The first three columns describe the upper half of the distribution of the expected present value of firefighting costs attributable to each home using different cost measures. Using the "suppression only" measure, 50% of WUI homes have expected protection costs under $500, while the highest-risk homes have costs that are much larger. Five percent of homes have expected costs exceeding $3,800. One percent of homes have expected protection costs exceeding $12,700. Using the "suppression plus" measure results in higher costs. The 95th and 99th percentiles of this distribution are about twice as high as for the "suppression only" measure. When we restrict the sample to California homes, where we have higher quality data on state-level expenditures, we find that the 95th and 99th percentile costs are roughly similar to the previous column.

The right-hand column of Table II reports the "suppression plus" measure as a share of the transaction value of the property.[25] These implicit subsidies are large compared to housing values. For the 5% of homes with the highest relative costs, the present value of expected future firefighting costs is more than 7% of property value. For the highest 1% of homes, it exceeds 20%.

The expected costs in Table II are calculated by averaging together the experiences of groups of homes in different locations with similar risk characteristics. This means that the expected cost metrics do not simply reflect an unlucky or exceptional fire history in one small location. Instead, they represent the aggregate cost history of all homes in a given actuarial category. The homes at or above the 95th percentile represent 78 actuarial groups, while homes above the 99th percentile represent 23 actuarial groups.

6.3 Results: Geographic Incidence

Figure VI shows the broad geographic distribution of expected protection costs. This map shows the average expected protection cost for homes in each 15 kilometer hexagonal cell, using the "suppression plus" cost measure (results for the other cost measures are in Appendix Section A.2. The color scale corresponds to increasing costs. The scale is top-coded, so that the darkest red corresponds to homes with expected protection costs of $30,000 or more. Average expected protection costs are highest in Northern California, central Oregon and Washington, and Idaho and western Montana. These are all sparsely populated areas with many areas of high fire risk.

The costs of protecting homes are a surprisingly large part of the bundle of federal benefits provided to households in these areas. To contextualize our findings, the annual implicit subsidies to homeowners in Montana and Idaho via firefighting are larger than federal transfers to those states under the Temporary Assistance to Needy Families (TANF) program.[26] Notably, Southern California, which also features high

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

26. Federal TANF expenditures in FY2016 were $32 million for Montana and $26 million for Idaho.

fire risk and frequent costly fires, has somewhat lower expected protection cost than these other regions. This likely reflects greater development density in fire-prone parts of Southern California, which reduces per-home firefighting costs.

Significant local variation in wildfire risk and development density in the West means that expected protection costs also vary substantially over small distances. Figures VIIa and VIIb illustrate this local variation for two areas in California. These maps show the net present value of per-home expected protection costs averaged within 5 kilometer hexagonal cells. Figure VIIa shows Shasta County in Northern California. Expected protection costs are several hundred dollars per home or less in the more densely developed areas of central Redding and Anderson. Outside of these urban areas, wildfire hazard increases and density decreases rapidly. As a result, expected protection costs are much higher. In some of the more remote Census blocks that border national forest lands or other public wildlands, costs are tens of thousands of dollars per home. These areas have a high underlying physical risk of fire, meaning that homes built here are likely to repeatedly require costly firefighting efforts to avoid destruction. In addition, these areas include fewer total homes, raising the per-home cost of firefighting. Figure VIIb shows San Diego County in Southern California. Again, fire protection costs per home are low in the densely developed areas of San Diego, and increase in the high fire-risk, low-housing-density areas that border federal- and state-owned lands in the eastern part of the County.

6.4 Results: Incidence across Income Groups

Figure VIII explores the distributional effects of firefighting expenditures. A frequently-repeated claim about wildland firefighting in the United States is that it primarily benefits the rich (see, for example, "A Case for Letting Malibu Burn" (Davis 1995)). Our data tell a different story. Panel A shows that on average, homes in low-income areas of the West receive substantially more benefit from government firefighting efforts than homes in high-income areas. This likely reflects the fact that the areas with the highest per-home expected protection costs are low-density rural and semi-rural areas. Panel B considers an alternative measure of wealth, which is the transaction

U.S. Dept. of Health and Human Services, Office of Family Assistance, "TANF Financial Data - FY 2016", published February 2018. See sheet C.1.

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.

7 Discussion

This section discusses the economic implications of the implicit subsidies that we identify. Section 7.1 considers the implications for economic efficiency, including location choice, development density, and private risk-reducing investments. Section 7.2 discusses potential policies to internalize these costs.

7.1 Economic Efficiency

7.1.1 New Development in High-Risk Areas

Under a business-as-usual scenario, the dominant pattern of land use change in California and the rest of the West through 2050 is predicted to be conversion of undeveloped or sparsely developed areas to low-density housing use, with much of this development located in high fire risk areas (Gude, Rasker, and Noort 2008; Mann et al. 2014). The degree to which this pattern of development is influenced by freely provided fire protection depends on the size of the subsidies that we measure and the elasticity of new residential development with respect to those costs.

In the low-density ex-urban and rural areas where we measure large implicit subsidies, existing research suggests that housing supply is quite elastic. Development is generally not limited by land availability or regulation, unlike in coastal cities (Glaeser and Gottlieb 2009). Saiz (2010) reports supply elasticities in the metropolitan statistical areas (MSA) around Denver, Colorado Springs, and Albuquerque of 1.53, 1.67, and 2.27, respectively. This includes urban areas and thus may understate supply elasticities in WUI areas. As further evidence of elastic housing supply, we observe that home prices in our highest-subsidy areas are 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 marginal cost.

The local elasticity of demand depends on long-distance migration, within-city location choice, and household formation. Existing research offers a range of estimates for these various margins.[27] Collectively, these estimates suggest that -1.0 is a conservative estimate of the overall (across- and within-city) elasticity of new housing demand in high fire-risk regions.

Given these elasticities, the protection costs that we measure may imply substantial amounts of excess development. Distortions on the extensive margin – whether or not any development happens in a given area – depend on average protection costs. Our average protection cost estimates can be interpreted as the minimum amount by which average WTP to live in a WUI area must exceed housing and private insurance costs for new development to be efficient. We find that average expected protection costs for homes in the highest category of fire risk and lowest category of density equal about 25% of the transaction price of a home. Thus, new development in such areas is welfare-improving only when residents would derive large value from the location relative to other possible locations with lower fire risk. This condition appears difficult to reconcile with the high reported elasticities of development with respect to price.

7.1.2 Development Density and Lot Size

These results also have implications for areas with existing home development.[28] Figure IV shows that beyond net densities of roughly 0.16 homes per acre, expenditures on firefighting increase little with additional development. The sharp decrease in per capita protection costs with density is a surprising result. This fact suggests that protection from fires is non-rival: at medium and high densities, adding additional homes in the path of a fire does not seem to decrease the protection enjoyed by those already there. Providing fire protection for free removes the incentive to consider these economies, effectively subsidizing low-density development patterns.

27. For cross-city location decisions, Albouy (2009) uses a large price elasticity of -6.0, following Bartik (1991). Kennan and Walker (2011) finds a smaller value of about -0.5. For the within-city decision about whether to locate on the urban periphery or in the city center, Voith, Brueckner, and Holtz-Eakin (2000) use an elasticity of -0.5. Anas and Chu (1984) find a within-city location choice elasticity of between -0.27 and -0.87. Polinsky and Ellwood (1979) and Muth (1971) both find that the price elasticity of demand for new, detached single family housing is about -1.0.

28. In the context of the model in Section 3, this amounts to considering what happens to the housing market during a second period in which the total number of households N increases.

Given the durable nature of housing, our protection costs are not high enough to justify abandonment of already-constructed homes. Thus, if a policy were implemented today that charged all new homes the marginal fire protection cost for their area, we would expect more construction in already-developed areas (relative to a regime with unpriced fire protection). If "densification" is seen as an independently desirable outcome because of other market failures affecting land use, pricing fire protection may have additional benefits. Economists have identified market failures like congestion that contribute to urban sprawl, while also recognizing that sprawl reflects fundamentals like population growth and technology (Brueckner 2001; Glaeser and Kahn 2004).

7.1.3 Private Risk-reducing Investments

Free firefighting may also 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-resistant roofing and other materials. Once the home is built, residents can maintain vegetation to create "defensible space". If these investments reduce the level of firefighting dispatch required to protect the home in the event of a fire, providing firefighting for free may lead to underinvestment in these partial substitutes.

Researchers report that many homeowners in WUI areas fail to create adequate defensible space around their homes, despite widespread outreach efforts by fire officials (Champ, Donovan, and Barth 2013; Dickinson et al. 2015). Underinvestment in self-protection may reflect imperfect information or behavioral failures by homeowners. The substantial externalities that we identify in this paper are another possible explanation. Local governments can mandate self-protection through building codes and vegetation inspections. However, their incentive to implement and enforce such regulations is limited by the large share of firefighting costs shouldered by the federal and state governments. We see further study of private and municipal investments in risk mitigation as an important area for additional research.

7.1.4 Other Market Failures

Subsidized fire protection may interact with other market failures. The favorable tax treatment of mortgage interest represents an important pre-existing subsidy to housing consumption (Poterba 1992). Collecting government revenues to fund firefighting (for example through income taxes) imposes additional efficiency costs. On the other hand, there may be redistributive benefits from transferring wealth to low-income parts of the West via subsidized firefighting. Another group of market failures includes possible inefficiencies in federal wildfire management. If fire managers face inadequate incentives to minimize incident costs, the protection costs that we measure in this study could be reduced through efficiency improvements in firefighting. Arguably, one might expect greater local or individual accountability for firefighting costs to increase pressure to control these costs.

Large wildfires can also impose costs on downwind populations via smoke exposure. If protecting homes also reduces smoke, there are additional external benefits. However, firefighting does not categorically reduce smoke exposure. Firefighting in WUI areas often includes a large component of "point protection" activities that protect valuable assets while having little effect on the size of the overall burned area (National Wildfire Coordinating Group 2014; Wei et al. 2018).

Finally, electric utilities incur large costs to reduce the risk of wildfires from electrical equipment (e.g., trimming vegetation around power lines). Regulated utilities must provide service in high-risk areas, and wildfire prevention costs are recovered from all the utility's ratepayers (unless special tariffs are enacted for WUI customers). Including information on these other expenditures would increase our cost estimates. Similarly, incorporating federal and state government expenditures on vegetation treatments on public land that reduce fuels availability would also increase our estimates.

7.2 Policies to Internalize Protection Costs

These potential distortions could be reduced by policies that internalize protection costs. One possibility is to require home-builders to pay a fee equal to the net present value of expected protection costs when building a new home in an undeveloped or sparsely developed area. The empirical analysis presented in this study provides a road map for calculating this spatially specific corrective tax.

Importantly, the effect of such a policy does not depend on the accuracy of individuals' beliefs about wildfire risk. The tax amount would be computed by the government based on the best available data on protection costs. The full amount would be paid at the time of construction. Under such a policy, the external costs of fire protection would be highly salient for homebuyers.[29]

In 2014, California began requiring all homeowners in the Cal Fire protection area to pay an equal annual fee of about $150 per year. The fee was unpopular among homeowners and was suspended in 2017. This study shows that such a fee would need to be much more geographically differentiated in order to correct incentives (as opposed to simply raising revenue). Another lesson from this study is that exempting owners of existing homes could increase the political acceptability of such a policy without reducing its effectiveness, since the protection costs we estimate are not generally high enough to justify abandonment of existing homes.

An alternative policy is to assign firefighting costs to local governments, which would recover these costs through property taxes or other taxes. This approach would incentivize cities and counties to consider firefighting costs in zoning, land use, and building code decisions. Of course, it would not be efficient for each city or county to self-supply its firefighting needs. Firefighting could continue to be supplied via the current system of west-wide dispatch with local governments reimbursing the federal and state governments for a larger share of costs.

8 Conclusion

Unlike other types of natural disasters, a large share of the total costs of wildfires are incurred through costly efforts to prevent property damage. The federal and state governments spend billions of dollars each year fighting wildfires. We find that efforts to protect private homes account for most of this spending. This means that decisions

29. Pricing the external component of wildfire costs (firefighting costs) in such a visible way might yield ancillary benefits by increasing buyers' overall attentiveness to wildfire risk, including private costs (expected property damage) that are thought to be imperfectly salient.

by homeowners and local governments about siting, construction, and maintenance of homes in high fire-risk areas generate large cost externalities. We also find that beyond relatively low levels of housing development, the marginal effect of additional homes on firefighting expenditures is surprisingly small.

We use our results to calculate spatially differentiated implicit subsidies for homes throughout the western United States. Wildfire spending represents a large transfer of federal and state revenues to a small number of landowners in high-cost places. In our highest-risk groups, the net present value of the government's expected future cost for fire protection is over 10 percent of the transaction value of a home. These results imply that wildland fire protection is a quantitatively important mechanism for redistribution to such areas that has not been fully appreciated by economists.

We discuss three margins along which this implicit subsidy may distort outcomes in the housing market. The first is the location of new residential development. New development appears to be relatively price-elastic in the ex-urban and rural areas where we measure the largest implicit subsidies, implying potentially large amounts of excess development. Second, because per-household suppression expenditures decline sharply in housing density, providing fire protection for free effectively subsidizes low-density development and large lot sizes. Finally, homeowners face reduced incentives to make defensive investments in fire-resistant construction and vegetation management.

Assigning a larger share of wildland firefighting costs to local governments or individual homeowners would change incentives for residential development in high-risk areas. One such policy would be a spatially differentiated "fire protection fee" for new construction that reflects the expected future wildland firefighting costs that would be incurred to protect the home. The empirical analysis in this study provides a road map for calculating such a fee.

More broadly, these results for wildfires underscore the importance of institutions in adapting to climate change. The costs of inefficient policies will continue to increase as the climate warms. For wildfires, as for many other impacts of climate change, the ultimate costs of a warmer planet will be determined not only by the degree of physical change but also by the mediating influence of public policy.

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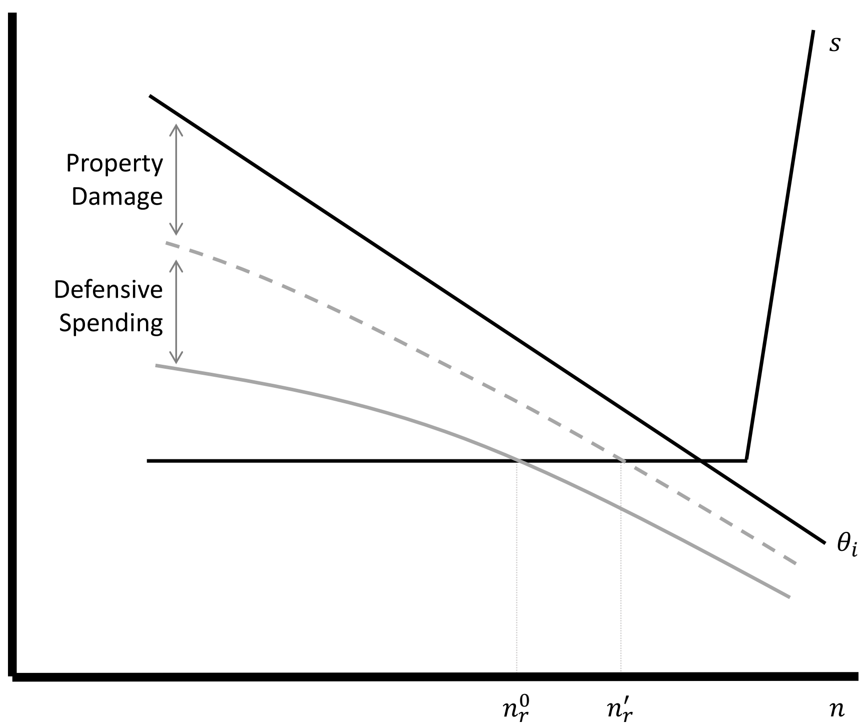
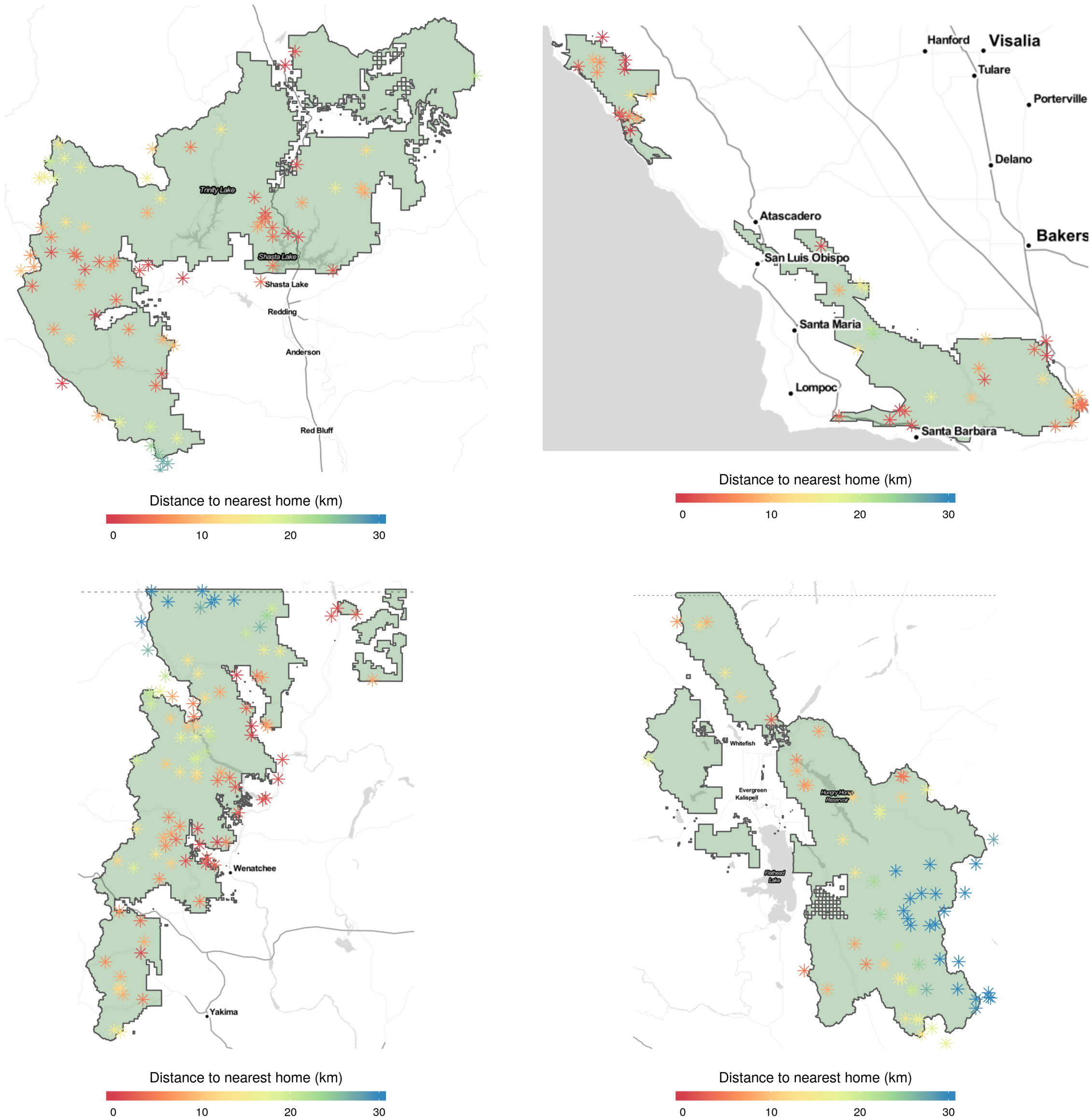
Figure I: The Market for Housing in a Risky Place



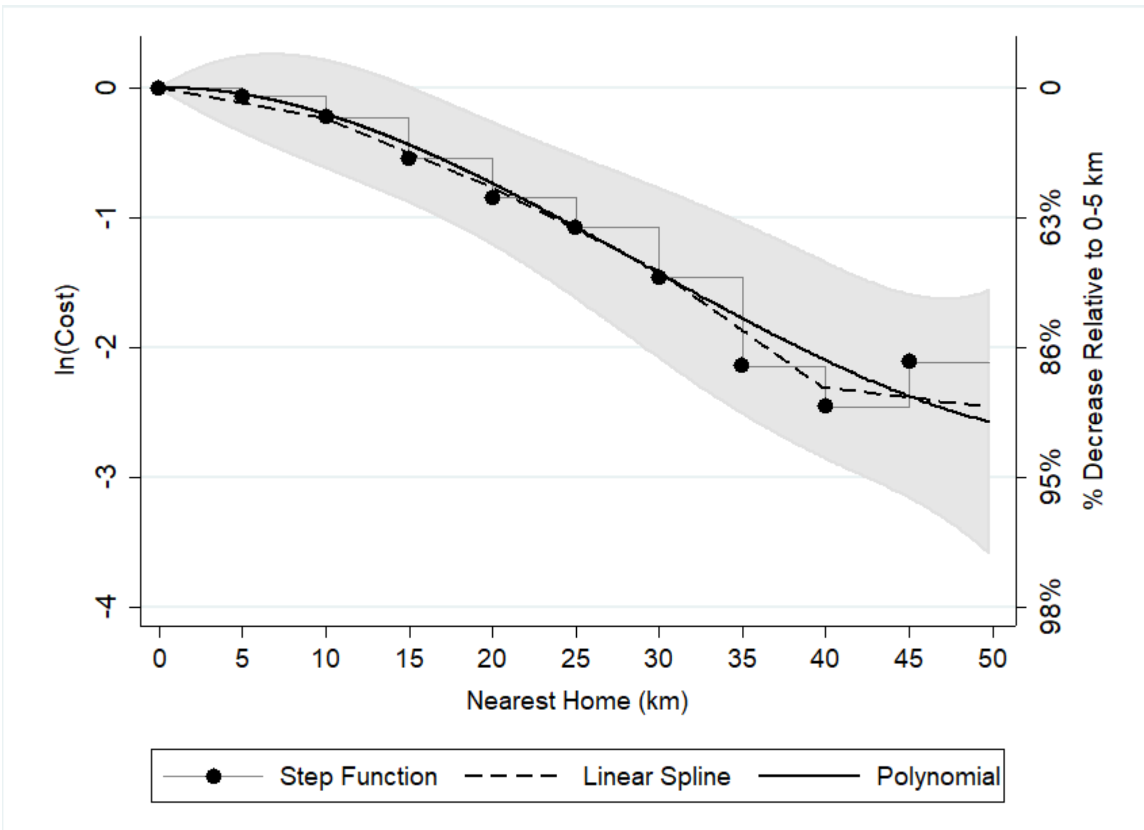
Notes: Illustration of the relationship between demand for housing in the risky place, government provision of defensive expenditures, and housing supply, as described in Section 3.

Figure II: Example National Forest Units



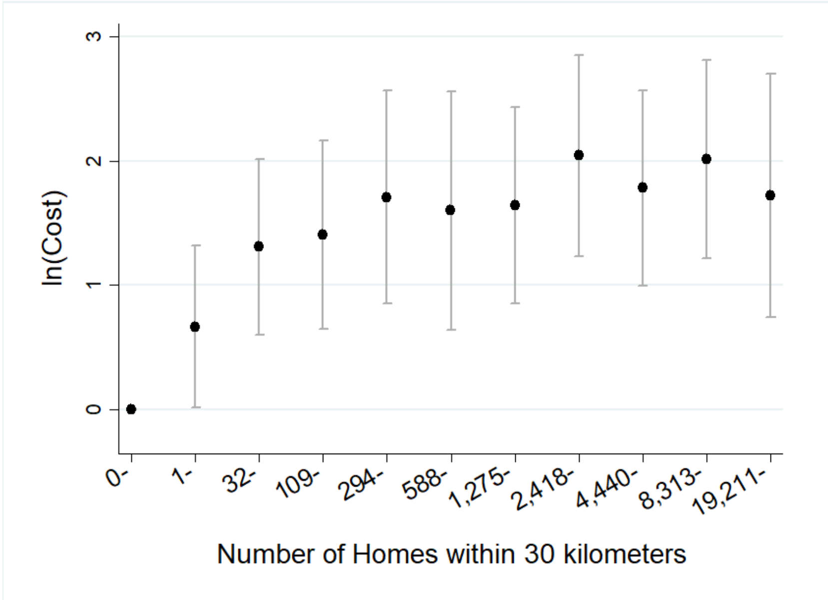
Notes: Each panel shows a single national forest area in light green. The star symbols represent individual wildfires, colored according to the distance to the nearest home. Clockwise from upper left, the forests are Shasta Trinity National Forest (California), Los Padres National Forest (California),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

Figure III: The Effect of Homes on Firefighting Costs



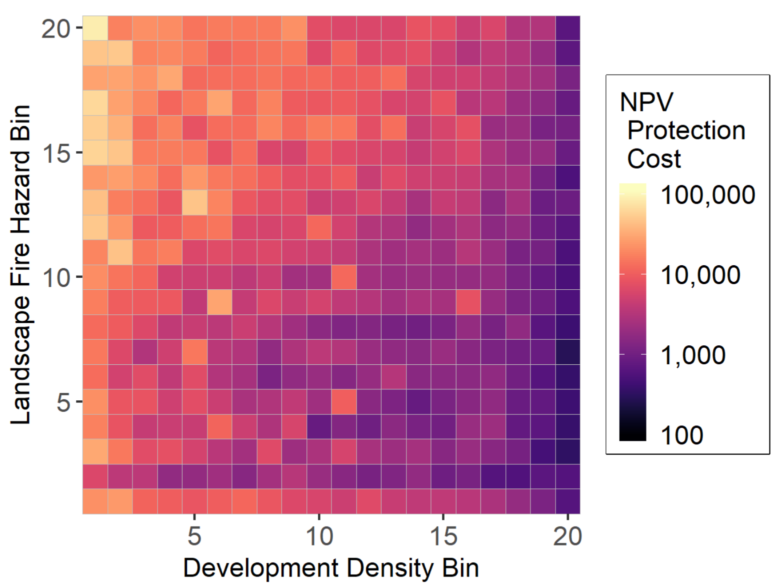
Notes: This figure reports results of three separate regressions of log firefighting cost on distance from the ignition point to the nearest home. The step function plots coefficients from a regression of log costs on indicators for 5 km distance bins. The linear spline is a piecewise linear regression with knots every 10 km. The gray shaded area around the cubic polynomial is the 95% confidence interval for that model. Each regression includes national forest fixed effects, state by month-of-year fixed effects, and state by year fixed effects. Standard errors are clustered by national forest. The right-hand vertical scale shows the approximate percentage decrease in costs relative to a fire less than five kilometers from homes, calculated as $exp(\beta) - 1$ for a coefficient β in the binned regression.

Figure IV: Non-linear Effects of the Number of Nearby Homes



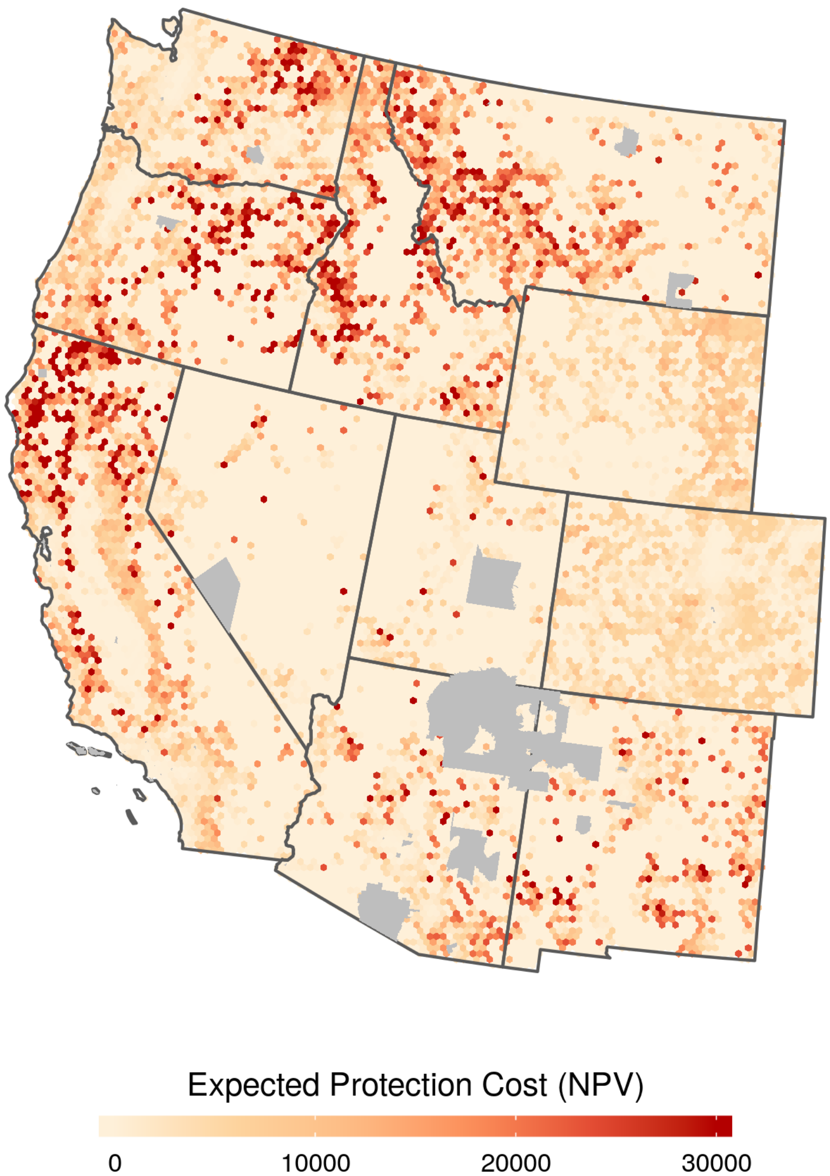
Notes: This figure shows point estimates and 95% confidence intervals from a regression of log fire suppression cost on deciles of home counts within 30 kilometers of the fire's ignition point. The regression includes national forest fixed effects, state by month-of-year fixed effects, and state by year fixed effects. Standard errors are clustered by national forest.

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



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

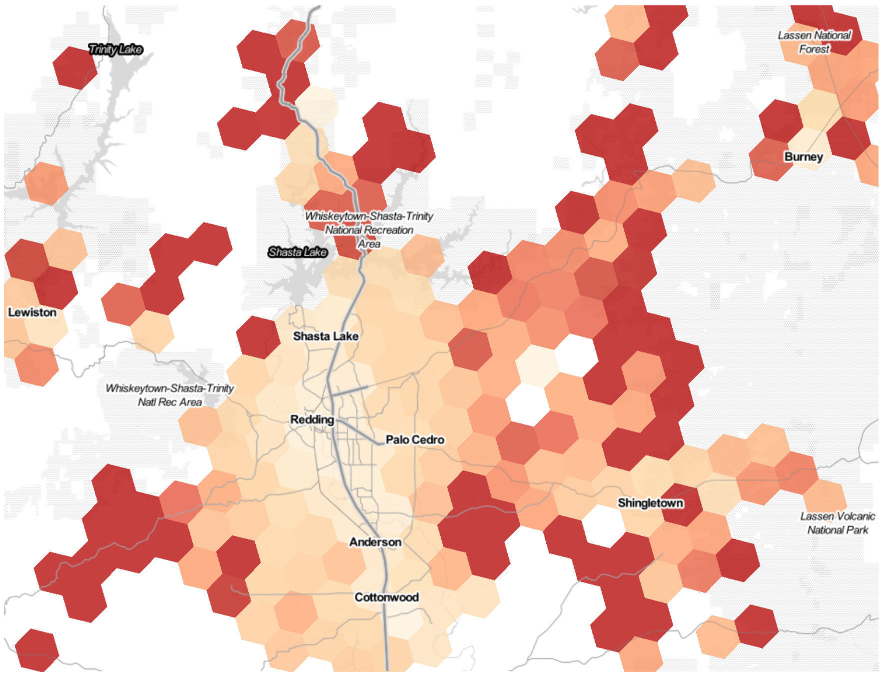
Figure VI: Expected protection costs (west-wide)



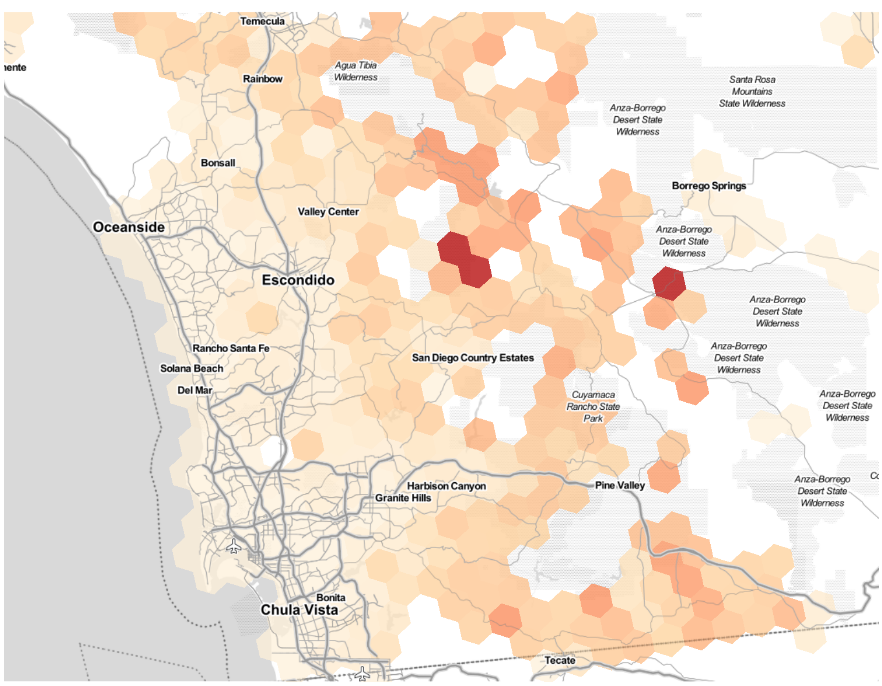
Notes: Net present value of the government's expected cost to protect a home from wildfires, averaged across 15 km hex cells. Map shows expected cost per home in 2017 dollars. Scale is top-coded at $30,000. Sample includes 8.6 million homes near wildland vegetation areas. See Section 6 for details on construction of these costs. Gray areas indicate missing data.

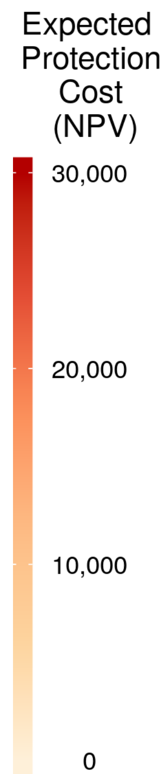
Figure VII: Expected protection costs (local maps)

(a) Shasta County, California



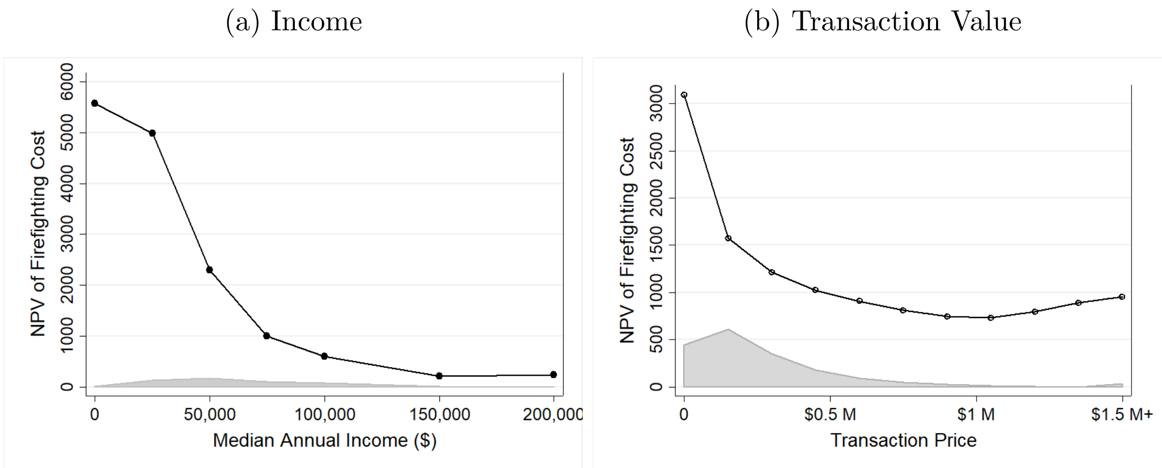
(b) San Diego County, California





Notes: Best viewed in color. Reproduces Figure VI with 5 km cells. White and crosshatched areas are unpopulated or public lands.

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



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

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

	(1)	(2)	(3)	(4)	(5)
Distance to Homes (km)					
10–20	-0.34**	-0.34**	-0.42**	-0.38*	-0.46
	(0.15)	(0.15)	(0.19)	(0.21)	(0.32)
20–30	-0.97***	-0.90***	-1.00***	-0.97***	-1.52***
	(0.28)	(0.27)	(0.37)	(0.34)	(0.57)
30–40	-1.73***	-1.66***	-1.67***	-1.72***	-2.50***
	(0.46)	(0.45)	(0.51)	(0.50)	(0.73)
40+	-2.09***	-2.03***	-1.93***	-2.11***	-2.21**
	(0.41)	(0.38)	(0.46)	(0.45)	(0.91)
Controls for Weather, Topography, and Vegetation		X	X	X	X
National Forest FE	X	X	X	X	X
Year by State FE	X	X		X	X
Month-of-Year by State FE	X	X		X	X
Month-of-Sample by State FE			X		
Lightning fires only				X	
Timber Fuels only					X
Fires	2,089	2,089	2,089	1,470	772
R^2	0.42	0.43	0.54	0.45	0.58

Notes: This table reports the results of five separate OLS regressions. The sample includes western U.S. fires managed by the Forest Service during 1995–2014. In each regression the dependent variable is the natural log of suppression cost. The table rows report coefficients and standard errors on dummy variables corresponding to distance to the nearest home. The omitted category is 0–10 kilometers. Controls for weather, topography, and vegetation include wind speed, wind speed squared, terrain slope, slope squared, vapor pressure differential (VPD), VPD squared, precipitation, precipitation squared, an indicator for south/southwest facing, and indicators for fuel models (vegetation types) from LANDFIRE. Weather variables are measured on the day of ignition and topographic variables are measured at the ignition site. See online appendix for regression coefficients for these controls. National forest fixed effects include 86 national forests in the western U.S. Standard errors are clustered at the national forest level.

Table II: Expected Protection Costs for 8.6 Million Western Homes

	(1) **Federal Suppression Only ($)**	(2) **Suppression Plus ($)**	(3) **California Only ($)**	(4) **Share of Property Value (%)**
Mean	1,077	2,408	2,720	1.8
p50	500	1,200	1,300	0.7
p90	2,100	5,200	6,600	4.0
p95	3,800	8,400	9,100	7.0
p99	12,700	22,700	18,200	22.5
N	8,633,554	8,633,554	3,483,715	8,633,554.0

Notes: This table describes the distribution of expected firefighting costs for homes in the western United States states in our sample. These costs represent the additional costs incurred by the federal government to protect each home, and are calculated using 210 actuarial groups based on six categories of landscape fire risk, five categories of housing density, and seven wildland firefighting dispatch regions (GACC regions). Costs are present values using a 5% discount rate. The first three columns report expected costs using three different metrics defined in the text. The final column reports the "suppression plus" cost measure divided by the transaction value of the property. Values are in 2017 dollars. Percentile cutoffs are rounded to the nearest $100. See text for details.

A Additional Results and Robustness Checks

A.1 Effect of Homes on Fire Costs

A.1.1 More Results & Robustness Checks

Appendix Table 1 shows the results from Table I in the main text, including coefficients on the control variables as well as an additional "no controls" specification. It also shows an additional specification that includes controls for the distance from the ignition point to the nearest primary road.[30]

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 I 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 Appendix Table I, as expected. Column (6) shows an additional specification that measures the stock of nearby homes by total transaction value, instead of number of homes. Results are similar.

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

Appendix Figure 2 plots covariate overlap for the covariates included in the regressions.

30. Road data come from the US Census TIGER/Line shapefile for primary roads for 2016. Primary roads roughly correspond to interstate highways.

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

	(1)	(2)	(3)
10–20 km	-0.5232***	-0.3436**	-0.4099**
	(0.1709)	(0.1491)	(0.1586)
20–30 km	-1.1075***	-0.9018***	-0.9957***
	(0.3261)	(0.2676)	(0.2861)
30–40 km	-2.4784***	-1.6605***	-1.7601***
	(0.3796)	(0.4528)	(0.5275)
40+ km	-2.7290***	-2.0257***	-2.1063***
	(0.3631)	(0.3774)	(0.4511)
WindSpeed		0.0642*	0.0691**
		(0.0347)	(0.0347)
WindSpeed^2		-0.0017	-0.0019
		(0.0013)	(0.0013)
TerrainSlope		0.0413**	0.0420**
		(0.0181)	(0.0185)
TerrainSlope^2		-0.0007*	-0.0007*
		(0.0004)	(0.0004)
VaporPressureDifferential		0.0681*	0.0661*
		(0.0371)	(0.0351)
$\text{VaporPressureDifferential}^2$		-0.0015**	-0.0014**
		(0.0007)	(0.0007)
Precipitation		-0.0513	-0.0446
		(0.0440)	(0.0432)
Precipitation^2		0.0010	0.0010
		(0.0010)	(0.0010)
South/SW Aspect		0.2361*	0.2322*
		(0.1356)	(0.1362)
Shrub Fuel Model		-0.1266	-0.1482
		(0.1926)	(0.1921)
Timber Fuel Model		-0.0829	-0.0900
		(0.1545)	(0.1527)
Slash Fuel Model		0.5048	0.4466
		(0.3638)	(0.3730)
Urban/Barren Fuel Model		-0.1804	-0.1837
		(0.2460)	(0.2476)
Distance to Primary Road			0.0109*
			(0.0064)
$(\text{Distance to Primary Road})^2$			-0.0000
			(0.0000)
Constant	13.5168***	10.8345***	10.1655***
	(0.1873)	(1.6243)	(1.6171)
National Forest FE		X	X
Year by State FE		X	X
Month-of-Year by State FE		X	X
Fires	2,089	2,089	2,089
R^2	0.09	0.43	0.43

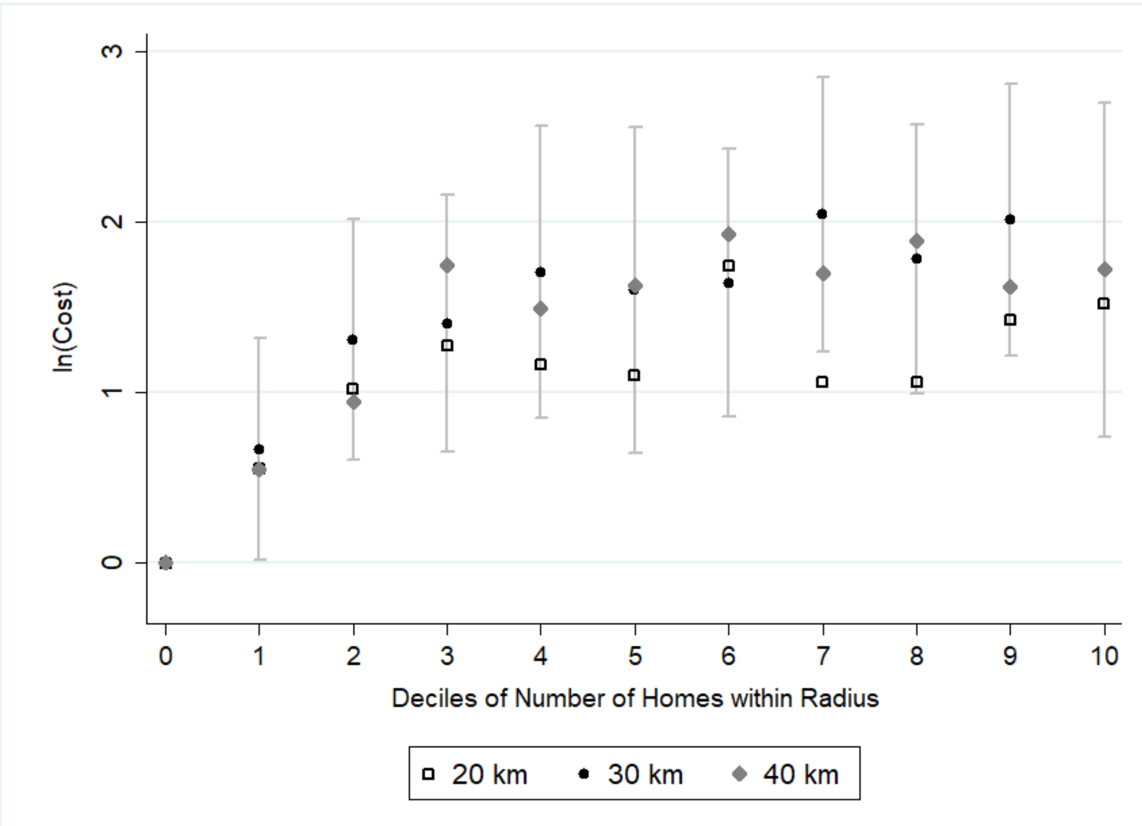
Notes: Column (2) reproduces Column (2) of Table I, showing coefficients for the controls. Column (1) shows a no-controls specification for comparison. Terrain slope is the linear slope of the ground surface. Wind speed is average speed on the day of ignition at the reference weather station listed in FAMWEB (in miles per hour). Vapor pressure deficit is for the ignition location and day, from PRISM, and measured in hectopascals (millibars). Precipitation is the amount of precipitation on the ignition day in mm, from PRISM. Fuel model fixed effects include four categories corresponding to LANDFIRE fuel models for brush, grass, timber, and barren/urban/other. The omitted fuel model category is grass. Forest unit fixed effects include 86 national forests in the western U.S. Standard errors are clustered at the national forest level.

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

	Number					Value
	(1)	(2)	(3)	(4)	(5)	(6)
Quintile Bins						
1	0.97***	0.94***	0.91**	1.00***	1.15	0.90***
	(0.31)	(0.31)	(0.36)	(0.34)	(0.69)	(0.32)
2	1.52***	1.46***	1.38***	1.46***	1.41**	1.42***
	(0.38)	(0.37)	(0.40)	(0.39)	(0.54)	(0.39)
3	1.61***	1.57***	1.37***	1.45***	1.91***	1.67***
	(0.45)	(0.43)	(0.48)	(0.45)	(0.66)	(0.39)
4	1.85***	1.78***	1.75***	1.71***	2.31***	1.65***
	(0.39)	(0.37)	(0.44)	(0.43)	(0.65)	(0.36)
5	1.87***	1.81***	1.54***	1.75***	1.98***	1.92***
	(0.43)	(0.41)	(0.47)	(0.49)	(0.70)	(0.40)
Controls for Weather, Topography, and Vegetation		X	X	X	X	X
National Forest FE	X	X	X	X	X	X
Month-of-Year by State FE	X	X		X	X	X
Year by State FE	X	X		X	X	X
Month-of-Sample by State FE			X			
Lightning fires only				X		
Timber Fuels only					X	
N	2,089	2,089	2,089	1,470	772	2,089
R^2	0.42	0.43	0.54	0.45	0.57	0.43

Notes: Columns (1) through (5) reproduce estimates from Figure IV in the main text, using bins of the number of homes within 30 kilometers as the variables of interest. The bins are equal observation bins for fires with at least one nearby home (see Figure IV 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 one nearby home, and the excluded category is fires with zero nearby homes. See Table I for details on controls for weather, topography, and vegetation. Standard errors are clustered by national forest.

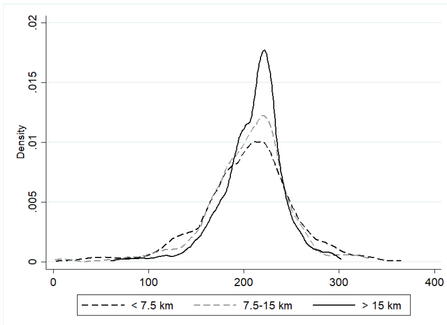
Appendix Figure 1: Costs by Number of Homes: Alternative Radii



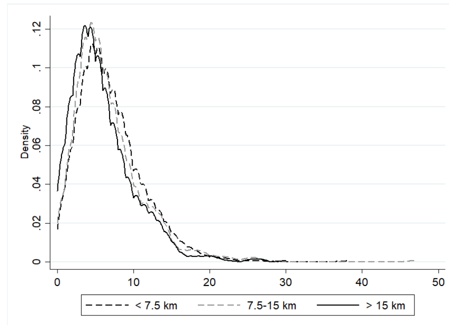
Notes: This figure reproduces Figure IV from the main text using alternative radii. Each set of markers shows coefficients from a single regression using a different radius around the ignition point of the fire. The bins correspond to deciles of the distribution of number of homes within the radius, conditional on any homes within the radius. The omitted category in each regression is fires with zero homes within the radius. For all three radii, there is a clear pattern of quick increases across the first three to four bins, and then roughly constant costs at higher numbers of homes.

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

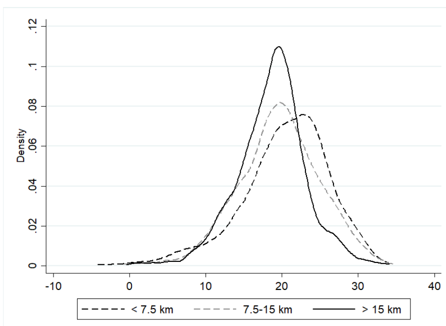
(a) Day of Year (Ignition)



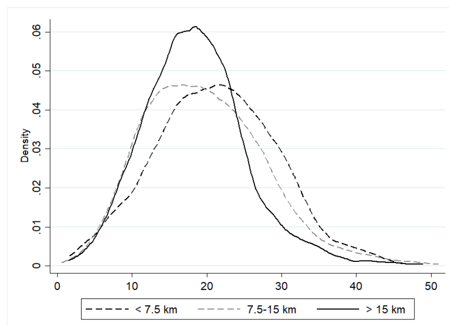
(b) Wind Speed (mph)



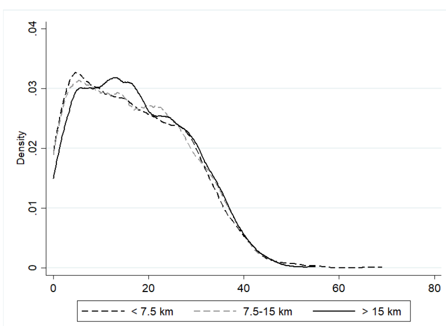
(c) Temperature (F)



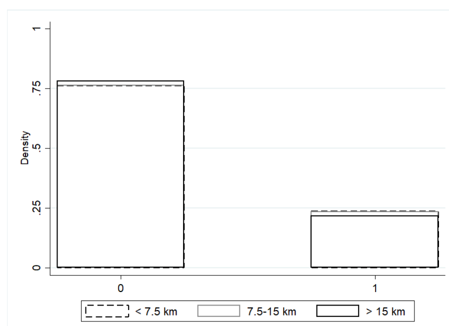
(d) Vapor Pressure Differential



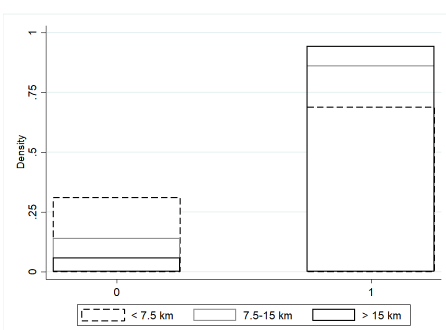
(e) Terrain Slope



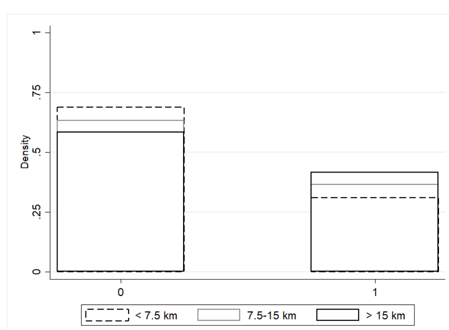
(f) South/southwest-facing



(g) Lightning-caused



(h) "Timber" fuel model



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

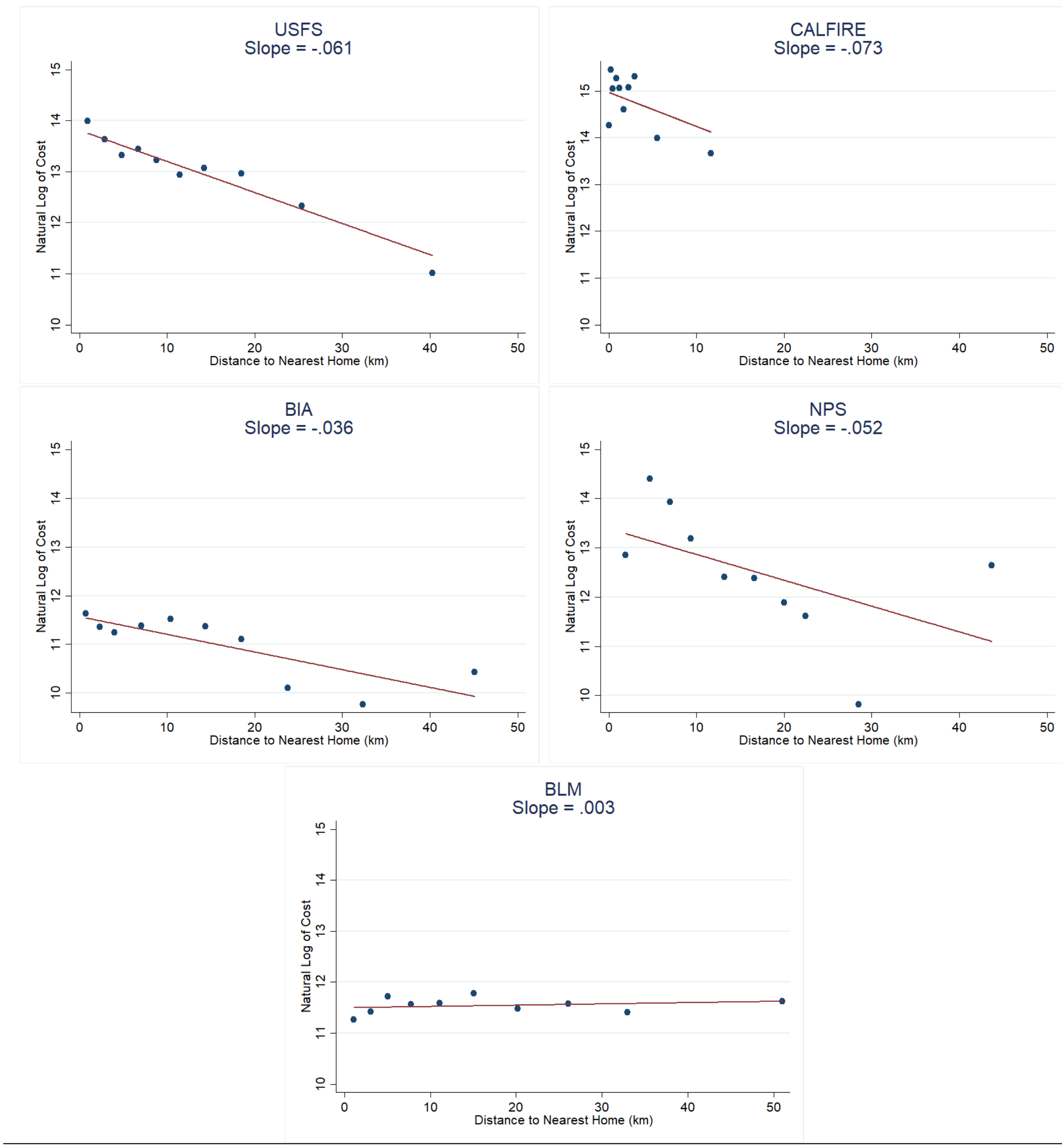
A.1.2 Non-USFS Agencies

The analysis of the effect of home construction on firefighting costs in Section 5 focuses on fires managed by the US Forest Service. Forest Service fires represent the largest group of expenditures and longest time series in our dataset. The national forests also provide a useful source of identifying variation, in that each national forest represents a mostly-contiguous area of public land with broadly similar landscapes and vegetation. This contiguity allows us to take advantage of variation in ignition locations within each of these 86 units using a fixed effects strategy. In comparison, Bureau of Land Management lands are less likely to consist of large contiguous units of land (instead, patches of BLM land in each state are managed by a system of district offices). Similarly, Cal Fire incidents take place on diffuse private and state lands throughout California.

For completeness, this section shows the relationship between homes and ignition costs for each of the agencies from which we were able to obtain data. Given that the empirical design used in the main text is not available for these other agencies, we focus on raw correlations. Appendix Figure 3 plots log firefighting costs against the distance from the ignition point to the nearest home. Across agencies, costs decline for fires located further from homes. Given that the data represent independent administrative databases compiled separately by each agency, the broad similarities across agencies are notable. For the US Forest Service, Cal Fire, the Bureau of Indian Affairs, and the National Park Service, there is a clear downward relationship with a linear slope between -0.036 and -0.073. Bureau of Land Management incidents show a different relationship, with a slope near zero and a lower intercept. One possible explanation for this difference is that it may reflect the characteristics of fires managed by BLM. Compared to USFS fires, the fires managed by BLM are more likely to occur in easier-to-manage grass areas, and less likely to occur in timber fuels. Notwithstanding this pattern for BLM, the broad agreement across the other four agencies is reassuring. This is particularly true given the relatively small size of BLM expenditures relative to USFS and Cal Fire, both overall and in per-incident terms (see Appendix Table 6).

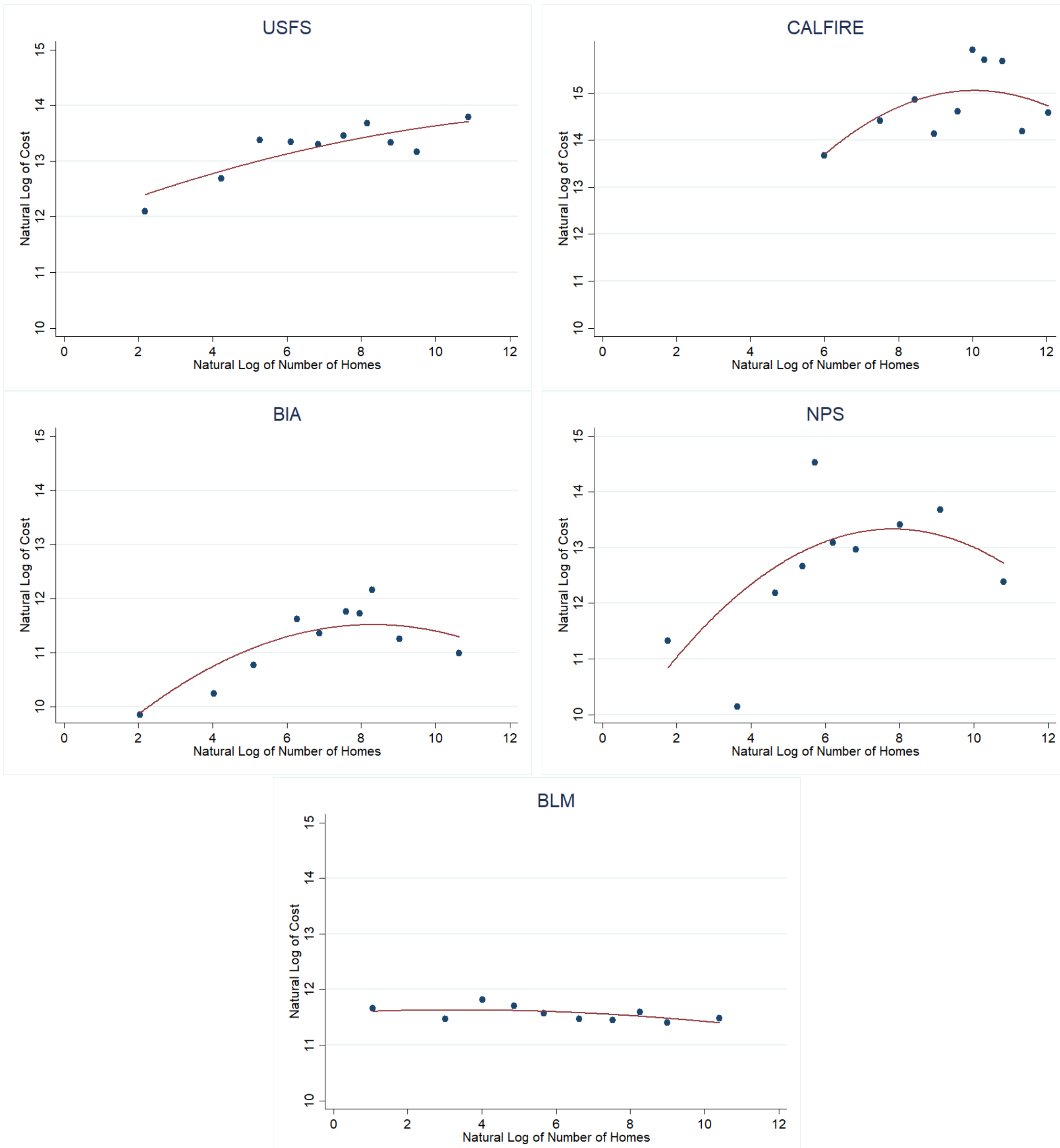
Appendix Figure 4 plots log firefighting costs against the total number of nearby homes. Across agencies, these ln-ln plots imply small or near-zero increases in firefighting costs as the number of nearby homes grows large.

Appendix Figure 3: Cost vs. Distance to Nearest Home, by Agency



Notes: This figure shows binned scatterplots for each agency from which we obtained incident expenditure data. The dots show average log incident costs for each decile of distance to nearest home. The red lines show a linear fit. Cal Fire is the California Department of Forestry and Fire Protection; BIA is the Bureau of Indian Affairs; BLM is the Bureau of Land Management; and NPS is the National Park Service.

Appendix Figure 4: Cost vs. Number of Nearby Homes, by Agency



Notes: This figure shows binned scatterplots for each agency from which we obtained incident expenditure data. The dots show average log incident costs for each decile of log number of nearby homes (fires with zero nearby homes are not plotted). The red lines show a quadratic fit. Cal Fire is the California Department of Forestry and Fire Protection; BIA is the Bureau of Indian Affairs; BLM is the Bureau of Land Management; and NPS is the National Park Service.

A.1.3 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 76 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 existing development, we exclude national forests that had more than 100,000 homes within 30 kilometers of the national forest boundary in 1995 (this excludes the 20% of national forest areas with the highest 1995 populations).

We implement a range of panel regression specifications. The outcome variable is the number of fires larger than 300 acres in each national forest and year. Our preferred statistical approach is a Poisson regression, since the number of large fires in each national forest-year is a count variable.[31] 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 fires 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 assumption that, conditional on these controls, the trend in new home construction near each national forest is uncorrelated with other trends in fire occurrence.

Appendix Table 3 shows the results. All of these regressions include national forest fixed effects to account for time-invariant determinants of fire risk, such as local topography. Across specifications, new home development has a small positive effect on the number of large fires each year. In Column (1), the estimated coefficient in the Poisson regression is 0.042. This implies that adding 1,000 new homes increases the annual number of fires in this national forest by about 4.3%. The mean number of large fires in each national forest-year is 1.48, so this implies that an additional 1,000 homes lead to 0.06 additional large 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.

31. 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.

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

	(1) Poisson	(2) Poisson	(3) Poisson	(4) Poisson	(5) Poisson	(6) Poisson	(7) OLS
Thousands of Homes	0.042***	0.050***	0.040***	0.051***	0.043***	0.040***	0.033*
	(0.008)	(0.011)	(0.013)	(0.011)	(0.012)	(0.013)	(0.018)
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	1,180	1,180	1,180	1,180	1,180	1,180	1,180

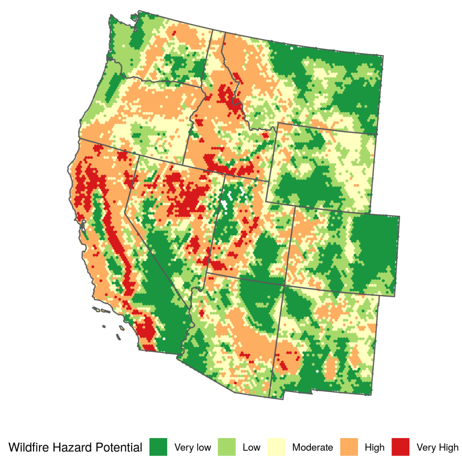
Notes: This table reports the results of seven separate regressions. In each regression the dependent variable is the number of fires larger than 300 acres in each national forest-year. Columns (1)-(6) show results for several Poisson regression specifications, and Column (7) shows an OLS specification for comparison. The variable of interest is the number homes within 30 kilometers of the national forest boundary, in thousands. The table reports regression coefficients and standard errors, which are calculated using a cluster robust variance estimator at the national forest level. For the Poisson specifications, the coefficients can be converted to expected percentage changes in the number of large fires using calculation $e^{\beta} - 1$. See text for details. The mean number of fires in each national forest-year is 1.5. "Regional Linear Trends" and "Regional Quadratic Trends" indicate that the regression includes separate polynomial time trends for each of the five forest service regions included in the sample area.

A.2 Expected Protection Costs

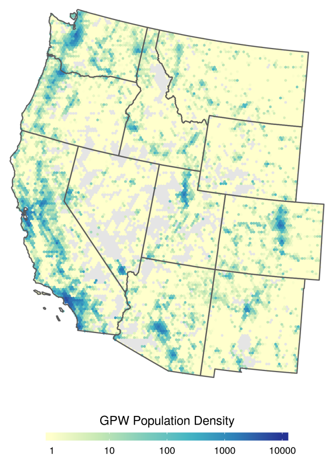
A.2.1 Variables Used to Define Actuarial Groups

Appendix Figure 5: Variables Used to Define Actuarial Groups

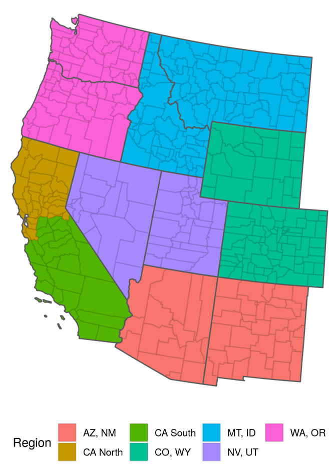
(a) Wildfire Hazard Potential



(b) Population Density



(c) Region



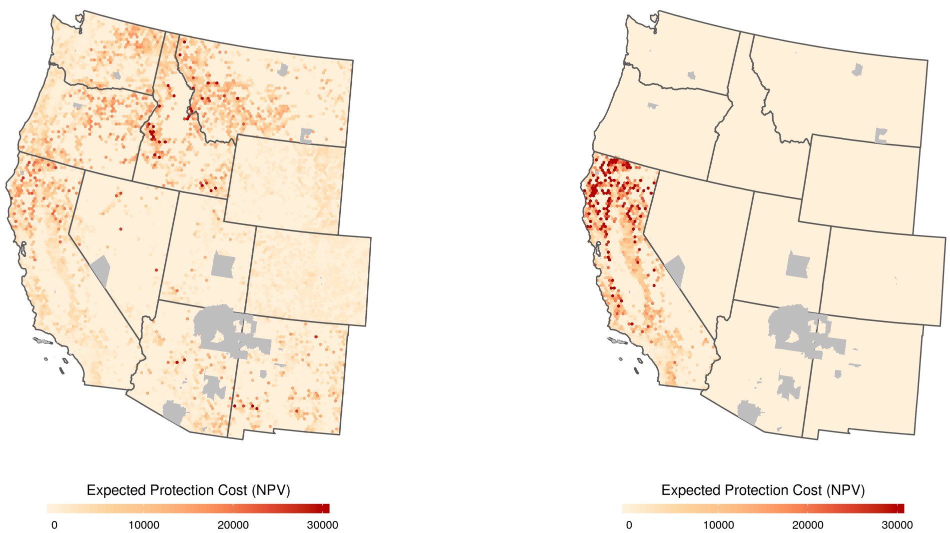
Notes: Wildfire hazard potential: Dillon (2015). Population density: CIESIN (2017).

A.2.2 Maps of Suppression-Only and California-Specific Measures

Appendix Figure 6 reproduces the map in Figure VI using the alternative measures of expected protection cost described in Section 6.1 of the main text. Panel A uses the Suppression Only cost measure described in Section 6.1.2. Panel B uses the

Appendix Figure 6: Expected Protection Cost by Region, Alternative Measures

(a) "Suppression Only" (b) California-specific



Notes: This figure reproduces Figure VI showing alternative measures of expected protection cost. See Section 6 for a detailed description of the construction of these measures. Units for the color scale are 2017 dollars per home. The California-specific measure in Panel (b) is displayed as zero for areas outside California.

California-only cost measure described in Section 6.1.4. The California-specific measure is displayed as zero for all areas outside California.

A.2.3 Alternative Measures Based on Interview Evidence

Table 4 compares implicit subsidy estimates using different methods to measure the share of expenditures devoted to protecting homes. Columns 1A, 2A, and 3A show the main estimates from Table II. Spending on home protection for each incident is the difference between observed costs and predicted costs for that fire in the absence of nearby homes, using the regression model in Section 5. Columns 1B, 2B, and 3B compute analogous subsidy estimates under the alternative assumption that 72.5% of all fire costs are attributable to protecting homes, based on USDA (2006). Comparing 1A to 1B, 2A to 2B, and 3A to 3B shows relatively small differences.

Appendix Table 4: Expected Parcel Protection Costs, Alternative Estimates

	Federal Suppression Only ($)		**Suppression Plus ($)**		**California Only ($)**	
	(1A)	(1B)	(2A)	(2B)	(3A)	(3B)
Mean	1,077	932	2,408	2,128	2,720	2,322
p50	500	400	1,200	1,100	1,300	1,100
p90	2,100	1,800	5,200	4,500	6,600	5,500
p95	3,800	3,400	8,400	7,300	9,100	7,900
p99	12,700	11,100	22,700	20,900	18,200	15,700
N	8,633,554	8,633,554	8,633,554	8,633,554	3,483,715	3,483,715

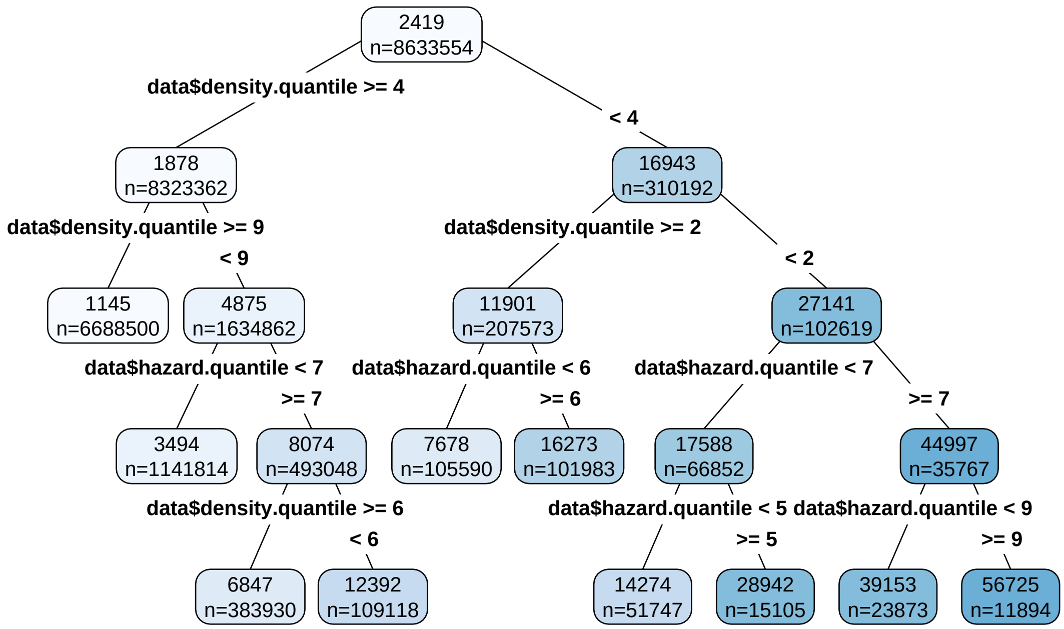
Notes: Columns 1A, 2A, and 3A are identical to Table II. Columns 1B, 2B, and 3B assume that 72.5% of all fire costs are attributable to homes. The method used to divide protection expenditures across individual homes is the same as in the main analysis.

A.2.4 Machine Learning to Define Actuarial Groups

The main analysis assigns homes to actuarial groups and then averages historical costs for homes in each group to yield expected protection costs. Instead of having the researcher define these actuarial groups, it is possible to use a machine learning technique to define groups. To evaluate the robustness of the actuarial groups used in the main text, we implemented such an approach using a regression tree. Using right-hand-side variables supplied by the researcher, the regression tree algorithm groups homes in order to minimize the prediction error for historical firefighting costs in each group. The number of groups is governed by a complexity parameter that specifies the minimum required improvement in prediction accuracy to justify additional splits. Appendix Figure 7 illustrates the approach. For this figure, we use a high value for the complexity parameter so that there are relatively few splits in the tree. The right-hand-side variables are 10 bins of wildfire hazard potential (WHP) and 10 bins of development density as predictors.

To compare results using this approach to those displayed in Table II in the main text, Appendix Table 5 shows the distribution of expected protection costs with a more complex tree using 10 bins of WHP, 10 bins of development density, and the 7 firefighting dispatch regions. This tree generates 79 actuarial groups. The overall distribution of expected protection costs with the regression tree (column 2) is similar

Appendix Figure 7: Illustrative Regression Tree for Defining Actuarial Groups



Notes: This figure illustrates the regression tree approach to defining actuarial groups using a restricted set of predictors and a limited complexity parameter. The top number in each node is the predicted protection cost. The number of homes in each group is given as "n".

to the distribution of expected protection costs in the main analysis (column 1), and the correlation of individual protection costs between the two approaches is 0.8.

Appendix Table 5: Expected Protection Costs using Regression Trees

	(1)	(2)
Mean	2,408	2,416
p50	1,200	1,300
p90	5,200	4,700
p95	8,400	8,000
p99	22,700	22,400
N	8,633,554	8,633,554

Notes: This table shows expected protection costs for the Suppression Plus cost metric. Column 1 is identical to Table II. Column 2 shows the distribution of costs when actuarial groups are selected using a regression tree algorithm. Percentile cutoffs are rounded to the nearest $100.

B Construction of the dataset

Our data combine administrative data on firefighting expenditures from multiple agencies, parcel-level assessor data for the universe of western U.S. homes, topographical information, risk assessments, and weather conditions data. This section provides a complete account of the dataset construction; readers should refer to section Section 4 in the main paper for a high-level summary. Table 6 gives descriptive statistics for the dataset and Figure 8 maps all of the large fires in the sample, colored by agency.

B.1 Wildland Firefighting Expenditures

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

B.1.1 US Forest Service

The U.S. Department of Agriculture, Forest Service (USFS) accounts for the largest share of fire suppression expenditures of any federal agency and is primarily responsible for fires that ignite in or near the boundaries of National Forest areas. We obtain historical by-incident suppression costs (primarily wage and equipment costs incurred by USFS) for fires managed by the USDA Forest Service from 1995 to 2014 from the National Fire and Aviation Management Web (FAMWEB) Database. Some institutional detail is helpful in understanding the process by which the data are compiled: the FAMWEB database represents a compilation of individual reports on fire occurrence, the conditions in which the fire ignited, and the suppression efforts undertaken by USFS. These reports are entered into the Fire Statistics System (FIRESTAT) application, which is run by the USFS. FAMWEB is the database which contains this information.[32]

Gebert, Calkin, and Yoder (2007) argue that fire suppression costs are captured more accurately by USFS accounting data than in the FAMWEB database. We therefore also obtain separate USFS accounting data on incident level expenditures through a separate Freedom of Information Act request. However, USFS was only able to provide these records for the period 2004–2012. Moreover, because of inconsistencies between agency reporting of incident PCodes, it is not possible to identify the fire characteristics for many fires in the accounting data. In Appendix Section C, we conduct our empirical analysis using both the accounting data and a subset of the FAMWEB data limited to 2004–2012 and find both qualitatively and quantitatively similar results. We conclude that inaccuracies in the FAMWEB database are sufficiently limited within our sampling frame to have limited impact on our empirical questions of interest and therefore conduct the bulk of our analysis with the FAMWEB data because of its greater temporal coverage.[33]

Over the course of our sampling frame, more than 150,000 wildfire incidents are logged in this database. However, since the Forest Service only reports per-fire cost data for fires above 300 acres, we limit this sample to the 2,419 fires in the 11 western states with a size of 300 acres or larger (the smallest size for which suppression expenditures are separately reported) for which the Forest Service was the jurisdictional owner. We also require that each fire have suppression cost, ignition date, and location data available.

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

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

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

spending allocated towards "Fire Preparedness." In total we obtain more than $6.8 billion of preparedness spending for our sampling frame.[34] These preparedness costs represent the cost of maintaining initial attack readiness and other fixed costs of the wildland firefighting system. Section 6 describes how we allocate these costs over ignitions.

B.1.2 Department of Interior Agencies

Four separate agencies within the Department of Interior (DOI) engage in significant fire management. They are the Bureau of Land Management (BLM), the Bureau of Indian Affairs (BIA), the National Park Service (NPS), and the U.S. Fish and Wildlife Service (FWS). We successfully obtained firefighting cost data for BLM, BIA, and NPS through FOIA requests. BLM is responsible for fires that ignite on the 248 million acres of public lands they manage. BIA is responsible for fires starting on the 55 million acres of Indian trust lands, and NPS is responsible for fires igniting within its 417 park units across 84 million acres of land. Each agency provided incident-level data from 2003-2016 from its own accounting databases for fires larger than 100–300 acres. To match the data available from the Forest Service, we limit this sample to include only fires that were the jurisdictional responsibility of the given agency and that affect more than 300 acres and apply similar data quality restrictions as those described for the USFS data. Our final DOI suppression dataset includes 1,617 BLM fires, 315 BIA fires, and 126 NPS fires.

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

B.1.3 California Department of Forestry and Fire Protection

We also collect fire suppression cost data for California, which includes over 50% of the population in our sample area and some of the most frequent and costly wildfires. Suppression cost data for California come from a public records request to the California Department of Forestry and Fire Protection (Cal Fire). Cal Fire is responsible

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

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.[35] The third dataset is an administrative record of firefighting expenditures at the incident level for 788 incidents during 2011–2016. According to Cal Fire, these expenditure data are carefully tracked because they are the basis of cross-agency reimbursements for mutual aid expenditures – for example, reimbursements to California by the federal government under the FEMA Fire Management Assistance Grant (FMAG) program, or by local governments to Cal Fire for firefighting assistance in incorporated areas.

Beginning with the list of significant fires, we drop those that are not the jurisdictional responsibility of Cal Fire. Limiting our sample to fires for which we are able to obtain precise location and suppression cost data results in 104 large fires (and 318 fires of any size) from 2011–2016.

B.1.4 Federal Emergency Management Agency

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

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

B.1.5 Harmonization of Fire Suppression Cost Data

To ensure consistent data quality, we harmonize the data across all agencies from which we source suppression expenditures. Specifically, we ensure that ignition date, ignition location, responsible agency, cause of fire, area burned, and suppression cost data are present for all incidents and that the costs reflect values in 2017 dollars. Federal, state, and local firefighting agencies provide assistance to one another through coordinated dispatch systems and mutual aid agreements. We carefully considered the implications of this aid for our analysis. We confirmed with each agency that its reported costs represent only that agency's costs for a given incident (except for FEMA reimbursements). Thus, we avoid double counting when adding up historical costs across agencies in Section 6. When investigating the effect of homes on costs in Section 5.1, we use only USFS cost data and further limit the sample to incidents where USFS was the primary responsible agency. This restriction is used by Gebert, Calkin, and Yoder (2007), who argue that USFS bears at least 90% of the costs of these fires.[36]

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

Finally, we compute the spatial relationship between each fire and potentially valuable resources nearby. Specifically, we measure the distance from the ignition point of each fire to the nearest parcel in the parcels dataset described in Section B.2, the nearest state or federal highway, and the count of homes and their value within x km of the ignition point, where $x \in \{5, 10, \ldots, 50\}$.

B.1.6 Ignition Point Characteristics and Weather Data

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

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

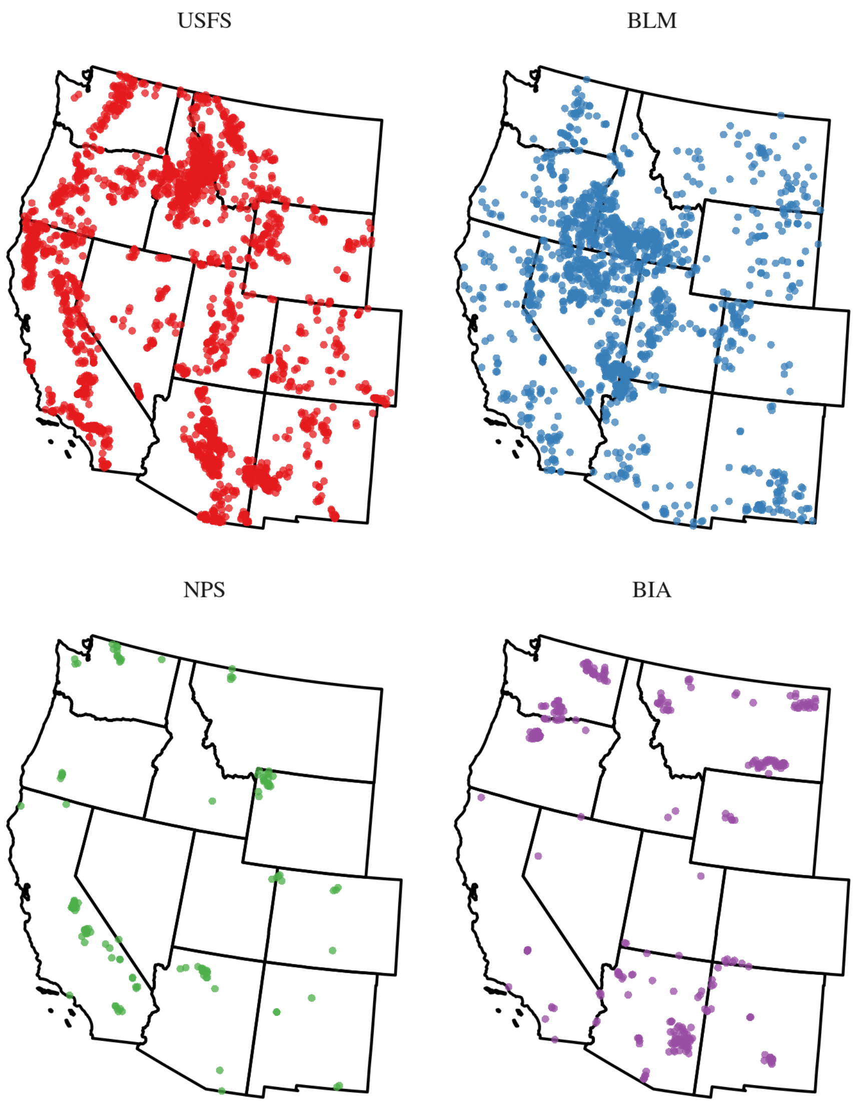
Appendix Table 6: Descriptive statistics

Panel A: Pooled fire characteristics					
	Mean	P10	P50	P90	
Area burned	7,873	383	1,433	16,034	
Fire cost	2,350,820	9,066	227,461	5,233,689	
Elevation	1,554	707	1,559	2,353	
Slope	12	1	10	29	
Temperature	20	13	21	27	
Precipitation	0	0	0	1	
Vapor Pressure Deficit	21	11	21	32	
Nearest home distance	14	1	10	33	
Parcels in 5km	160	0	0	109	
Parcels in 10km	757	0	0	1,011	
Parcels in 20km	3,345	0	90	7,093	
Value in 5km	45,633	0	0	18,536	
Value in 10km	210,261	0	0	182,871	
Value in 20km	936,119	0	13,094	1,450,741	
Panel B: Fire characteristics by agency					
	USFS	BLM	BIA	NPS	Cal Fire
Number of fires	2,419	1,617	315	126	104
Acres burned (1000s)	19,442	13,435	1,814	685	690
Suppression cost (m)	8,799	507	257	94	854

Notes: This table reports descriptive statistics for fires with area greater or equal to 300 acres in our sample. P10, P50, and P90 indicate the 10th, 50th (median), and 90th percentile of values. Aspect is given in degrees, elevation is in meters above sea level, fire cost is in 2017 US $, nearest home distance is in kilometers, parcels is the number of parcels within the given distance, precipitation is in mm, slope is in degrees, temperatures is in Celsius, and Vapor Pressure Deficit is in millibars.

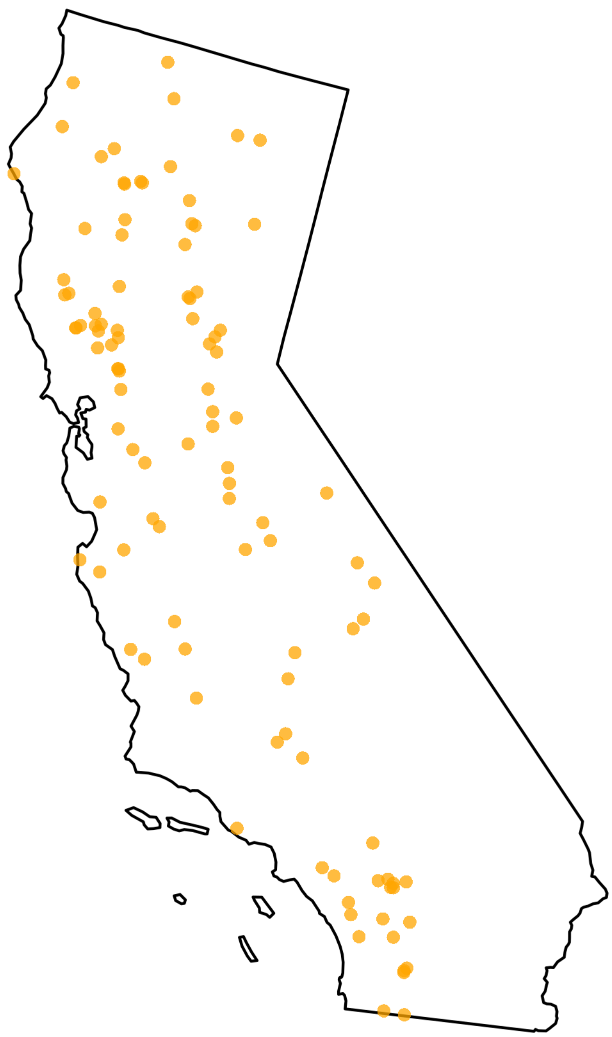
angle of the land and is given in degrees, and aspect represents the direction of the slope and is given in degrees as well. The fuel model data are the 13 Anderson Fire Behavior Fuel Models and describe the fire potential of surface fuel components (e.g., the type of foliage in the area). We also obtain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

Appendix Figure 8: Federal Wildfires



Notes: Map of federally managed fires between 1995 and 2016 larger than 300 acres.

Appendix Figure 9: Cal Fire Wildfires



Notes: Map of Cal Fire-managed fires between 2011 and 2016 larger than 300 acres.

B.2 Parcel Data

The homes data include information on home locations, values, year built, and other property characteristics for 18.5 million parcels, or nearly all of the homes in the western United States. We also include parcels within 50 km of these states to accurately capture the nearness and number of parcels for wildfires that occur near the eastern borders of our sample. These data represent a compilation of tax assessor data from individual counties.[37] A primary advantage of these data is the inclusion of detailed locational information; specifically the data include both latitude and longitude as well as street address for each parcel. While previous studies in this area rely on publicly available data on the number and value of homes in a Census block (Gebert, Calkin, and Yoder 2007; Gude et al. 2013), this confidential dataset enables us to precisely locate homes relative to wildfire ignition points. Because Census blocks can be large in rural areas and particularly when located near national forests, the standard approach using Census block centroids introduces substantial noise into the estimate of distance-to-nearest parcel for each fire. In Section B.2.1 we document the improved locational precision and the data quality benefits produced by this approach.

We limit the sample to include only homes in partially vegetated areas that would be threatened by wildland fires, based on wildland-urban interface (WUI) categories identified in Radeloff et al. (2005). Specifically, we include homes located in the following vegetation categories: high density interface, high density intermix, medium density interface, medium density intermix, low density interface, low density intermix, very low density vegetated, and uninhabited vegetated.[38] We exclude homes in areas without wildland vegetation, and specifically in areas with the following categories: high density no vegetation, medium density no vegetation, low density no vegetation, very low density no vegetation, and uninhabited no vegetation. Because the federal government controls so much land in the West, and so much residential development is in wildland areas, these sample exclusions are not particularly restrictive. Our analysis dataset includes 9,148,972 homes (about 44% of all residential parcels including homes, condos, and apartments in the West).[39] We also link the parcels to the USFS Wildfire Hazard Potential (WHP) ratings to assess physical fire risk (Dillon 2015). These risk scores are designed to "depict the relative potential for wildfire that would be difficult for suppression resources to contain," and combine

37. This proprietary compilation was provided by CoreLogic© through a data agreement with Stanford University.

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

39. This sample of 9.1 million homes used to estimate Equation (3) also includes homes near the sampling area but lying in bordering states in order to appropriately account for all nearby homes. In our main results, we report the expected protection cost only for homes in the 11 western states.

data from a large-scale fire simulator with spatial fuels and vegetation data to produce indicators of WHP. For each parcel, we assign a categorical and a continuous measure of WHP for that location as a measure of the risk faced by that parcel. We also add a measure of population density (population per square meter) from the Gridded Population of the World dataset, which reports density within roughly one km square grid cells.

B.2.1 Comparison to Census Aggregate Data

Our study uses parcel-level data to assess the locations of homes threatened by wildfire. Previous studies rely on counts of housing units at the Census block scale (Gebert, Calkin, and Yoder 2007; Gude et al. 2013). Appendix Table 7 demonstrates that high-risk regions are systematically likely to have large Census block sizes. The average Census block size for homes in the highest decile of firefighting cost is 7.0 square km, and the 95th percentile is 29.7 square kilometers. This large grid size introduces substantial noise into geographic analyses of aggregate home counts. Our study instead uses parcel-level data to assess home locations. This represents a substantial increase in granularity over existing studies.[40] The degree of this advantage over aggregate block-level data depends on the accuracy with which parcel locations are reported in the real estate data. The underlying records in this dataset are collected by county tax assessors, and the quality of the data varies across counties. In the following section, we describe the process by which we obtain highly accurate parcel locations for the dataset and the advantages this provides relative to using Census block centroids.

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

The housing data used in this project come from a compilation of tax assessor data. This dataset includes a field identifying the latitude and longitude of each home in the dataset. Overall, careful investigation of subsamples of the data imply that these coordinates are quite accurate. However, these default locations often locate multiple homes in precisely the same geographic location. To improve the accuracy of parcel locations, we implemented a secure, locally-hosted geocoding algorithm on a local server to calculate coordinates for each home. We used a locally hosted instance of

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

the Nominatim geocoder[41] to geocode homes in our dataset based on the address field, while maintaining data confidentiality and security.

Overall, the geographic coordinates generated by Nominatim align closely with the default locations in the homes data. The median distance between reported locations is 41 meters. For most homes, we believe that the Nominatim locations represent small shifts that slightly improve location accuracy. The exception is for addresses that include typographical errors. In this case, Nominatim may return locations that are not meaningful – for example, that may be hundreds of kilometers outside of the county containing the home.[42] To eliminate these errors, we backstop the Nominatim locations with the default locations in the original dataset (which tend to be more accurate but less precise) using the following rule: if the Nominatim location is A) more than one km outside of the county given in the tax assessor data, B) differs from the tax assessor location by more than 5 km, or C) was not obtained using the street address (e.g., was geolocated by the Nominatim algorithm based only on city and state), we use the tax assessor location instead. Using this backstop method, we re-code 89% of the addresses in our full dataset using Nominatim, and the remainder with the default locations in the original dataset.

Previous studies of wildland-urban interface issues have used publicly-available Census data to identify approximate home locations. The decennial Census includes counts of population and housing units at the Census block level. Forestry studies frequently use these block-level aggregate data to locate homes (e.g., by average population over the area of the Census block, or assigning population to the centroid).[43] One challenge with using aggregate Census data is that Census blocks in areas with high fire risk tend to be many square kilometers or more, reducing the accuracy of the approach. Appendix Table 7 shows this. On the other hand, Census block-based approaches do not rely on the accuracy of address-based geocoding.

The figures and tables in this section explore the robustness of our results to three possible methods to locating homes: our geolocation method, a method that follows previous work in using Census block centroids for homes' locations, and a method using the Census-based list of places (which include both incorporated and unincorporated communities). Appendix Figure 10 reproduces the regression from Figure III in the main text. The results are not qualitatively sensitive to the choice of location method. However, both of the Census-based approaches identify few fires with homes more than 40 km away and the corresponding standard errors for the estimate of the effect of home nearness on fire suppression cost are noisier. In our view, both

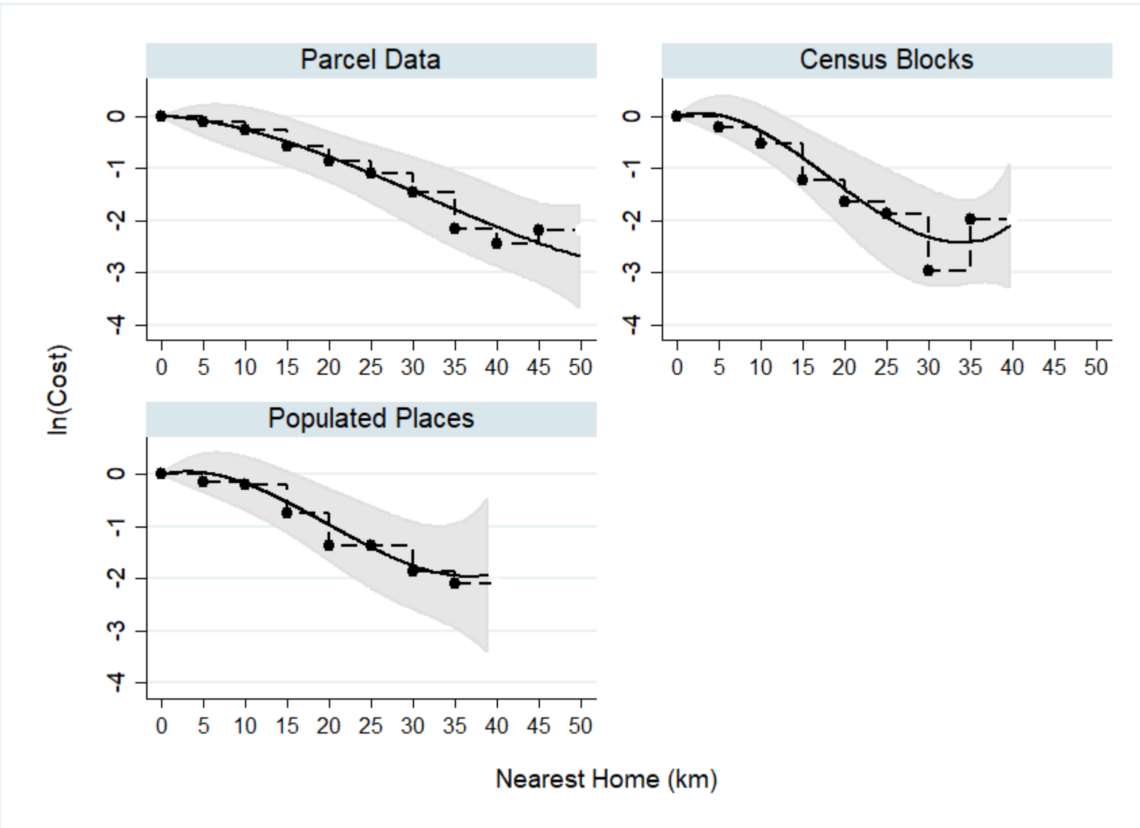
41. Nominatim uses Open Street Map data to conduct forward and reverse geocoding and is available at https://github.com/openstreetmap/Nominatim.

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

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

of these facts reflect that the Census-based approaches systematically underestimate (on average) the distance to nearest home for fires in remote areas for the reasons we describe above.

Appendix Figure 10: Cost by distance to nearest home



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

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

	Area in km^2	
	All Populated Census Blocks	Highest Decile of Firefighting Cost
Mean	1.2	7.0
p90	0.9	14.7
p95	3.0	29.7
p99	22.8	101.7
N	416,983.0	41,835.0

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

B.3 Calculating Counterfactual Costs With No Nearby Homes

For each fire i, we use the regression results from Section 5 to calculate Δ_i, the increase in firefighting costs relative to what would have been spent on the incident if there were no nearby homes. This section describes that calculation and compares it to an alternative calculation based on a generalized linear model (GLM) approach.

B.3.1 Main Approach

Our main approach computes Δ_i using the binned model in Section 5.1. Consider a specification with 5 bins, corresponding to 0, 10, 20, 30, and 40+ kilometers distance to nearest home, where the omitted category is the 40+ kilometer bin. Let β_d represent the regression coefficient on the dummy variable for bin d. These coefficients give the increase in log firefighting costs when the nearest home is located d km away, relative to 40+ km. The percentage increase in firefighting costs in raw dollars can be calculated as $e^{\beta_d - 0.5s} - 1$, where s is the sample analog of the variance of β_d (Halvorsen and Palmquist 1980; Kennedy 1981). In other words, the regression provides an estimate of the average effect of distance to nearest home on firefighting costs. We use these average effect estimates to calculate counterfactual costs in the absence of any homes within 40 km. For homes in bin d, letting c_i be the observed cost and $\tilde{c_i}$ the counterfactual cost, we calculate $\tilde{c_i} = \frac{c_i}{e^{\beta_d - 0.5s}}$. Then Δ_i is $c_i - \tilde{c}_i$.

B.3.2 Alternative Approaches: GLM and Retransformation

These counterfactual costs could be computed in other ways. A similar approach with the same OLS semi-log regression is to use the regression coefficients to generate predicted log costs under the counterfactual, and then "re-transform" these predicted values to predictions in dollar units (Duan 1983; Manning et al. 1987; Manning 1998). These counterfactual predicted costs can then be subtracted from predicted costs given the observed distance to home, $\hat{c}_i$. In practice, the various retransformation estimators are vulnerable to specification error, especially in the presence of heteroskedasticity (Manning and Mullahy 2001).

A potentially more attractive approach is to use a statistical model that does not require retransformation. Instead of semilog OLS, Manning and Mullahy (2001) recommends the use of a generalized linear model (GLM) with a log link function. Among other advantages, the GLM model generates predicted values in raw dollar units. We implement the GLM approach as a check on the robustness of our main estimates. Following the results of the selection algorithm in Manning and Mullahy (2001), we use a GLM model with a gamma distribution and a log link.[44] With the

44. See page 471 in Manning and Mullahy (2001). The resulting value of λ is about 2.3.

GLM approach, Δ_i can be calculated either by using the implied average change in costs in each distance bin (as we did for the OLS estimates), or by directly generating predicted costs given the observed and counterfactual x's. We show results for both approaches. Table 8 shows that the average predicted cost differences are similar across approaches. The approach using OLS generates slightly smaller predicted cost differences, implying that the cost differences we use in the main text are conservative.

Appendix Table 8: Counterfactual cost differences

Observed distance	(1) OLS	(2) GLM	(3) GLM
Panel A. Average Percentage Change in Costs			
0-10	86	88	88
10-20	80	86	86
20-30	66	77	77
30-40	30	45	45
40+	0	0	0
Panel B. Average Dollar Difference (thousands)			
0-10	4,113	4,207	4,662
10-20	2,874	3,070	3,170
20-30	1,351	1,573	1,669
30-40	397	599	299
40+	0	0	0

Notes: Panel A shows the average percentage decrease in cost for an otherwise-identical fire with no homes within 40 km. Panel B shows the average difference in expenditures for an otherwise-identical fire with no homes within 40 km (in thousands of dollars). Column (1) uses the percentage changes implied by the semilog OLS regression coefficients to scale the observed costs. Column (2) uses the percentage changes implied by the GLM regression coefficients to scale the observed costs. Column (3) also uses GLM, but reports the difference in predicted costs using the observed values of the covariates and predicted costs with no homes within 40 km.

C Comparison to Forest Service Accounting Data

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

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

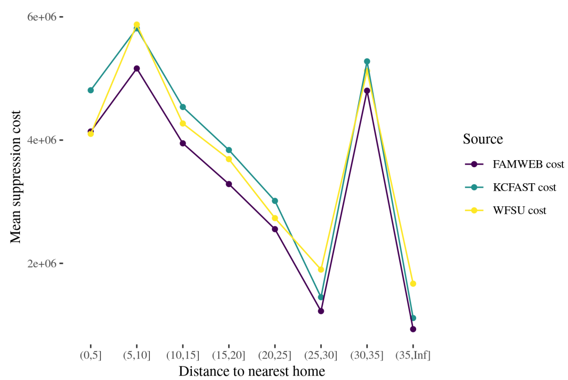
Appendix Table 9: Annual costs by suppression cost dataset

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

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

Next, we match the costs in the accounting dataset to the FAMWEB data using the P-code to identify whether the relationship between suppression costs and distance from homes is stable across the use of either source of cost data. We match from the P-code and year to the suppression expenditure data from FAMWEB. This match is not

Appendix Figure 11: Comparison of FAMWEB and accounting data: mean suppression costs and distance to nearest home

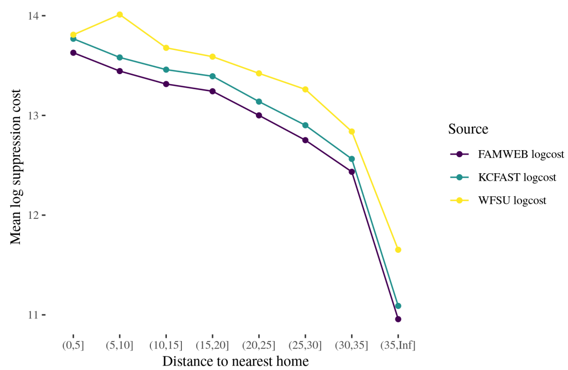


entirely straightforward: the guidelines over the issuance of P-codes and the proper accounting procedures have changed over the years, and many fires are submitted under the same P-code. In particular, large complex fires are often accounted for using the same P-code.[45] For the 997 fires in our FAMWEB dataset from 2004-2012, we are able to match 799 of these to the accounting dataset.

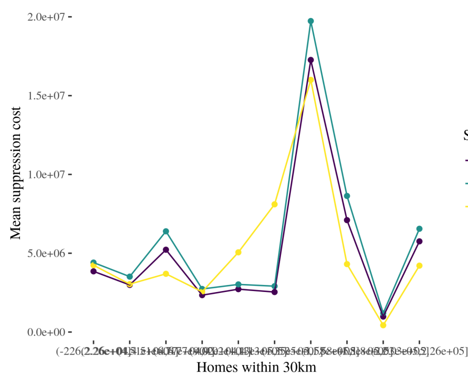
We estimate the relationship between fire cost and nearby homes for four sets of costs: A) FAMWEB costs for all fires in FAMWEB, B) FAMWEB costs for all 2004-2012 fires in FAMWEB, C) FAMWEB costs for fires that match to the accounting data, and D) accounting data costs for all fires that match to FAMWEB data. Figures 11 to 14 plot binned averages and sums of costs for each dataset on distance from nearest home and on number of homes within 30km. Although the sums differ due to the difference in the number of fires included for each set of data, the means have similar patterns. Our conclusions about the usefulness of the FAMWEB data are similar to those of Schuster, Cleaves, and Bell (1997), who wrote at the time that, "One of the purposes for our analysis of per-acre fire expenditures was to assess the quality of suppression expenditure estimates contained in the NIFMID database. These estimates are widely regarded as unreliable. However, the correlation between uncorrected, NIFMID-based expenditures and those from the accounting system is 0.85, a surprisingly high level."

45. 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.

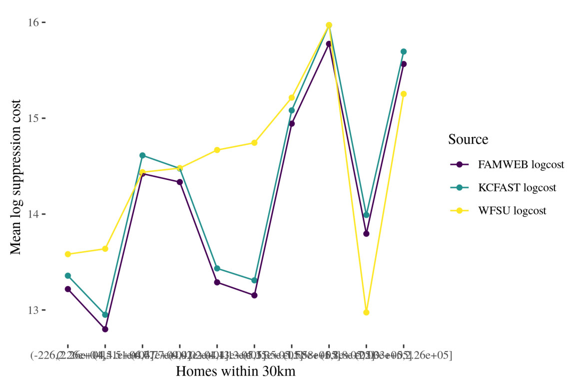
Appendix Figure 12: Comparison of FAMWEB and accounting data: mean log suppression costs and distance to nearest home



Appendix Figure 13: Comparison of FAMWEB and accounting data: mean suppression costs and number of homes in 30km



Appendix Figure 14: Comparison of FAMWEB and accounting data: mean log suppression costs and number of homes in 30km



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