Environmental Externalities of Urban Growth: Evidence from the California Wildfires

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Abstract

I use geospatial data from California to estimate the environmental externalities of urban development. Housing impacts wildfire probability non-monotonically. In the cross-section, each additional house between 0 and 300 housing units increases wildfire probability by 0.01 (OLS) or 0.24 (IV) percentage points from a baseline of 0.918 percent. Each unit beyond 300 decreases wildfire probability by 0.01 (OLS) or 0.45 (IV) percentage points until the probability reaches zero. Long difference estimates show similar non-linear impacts. Property buyouts combined with building bans are the most effective form of development restriction. Policies that limit maximum density can increase expected wildfire costs.

1 Introduction

Between 1990 and 2020, 16 million houses were built on previously undeveloped land in the United States (Radeloff et al., 2023). Regulations limiting the construction of new housing near city centers and population growth have driven new development to the urban edge, where cities meet farms as well as forests, grassland, shrubs, and wetland (the "wildland")

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(Burchfield et al., 2006). The cost of wildfires also increased during that period. In 2021, total wildfire suppression costs were nearly \$4.2 billion, compared to \$3.2 billion in 2018 and \$788 million in 1990 (measured in 2020 US dollars) (National Interagency Fire Center, 2023). Property losses due to direct wildfire damage also increased during this period, from \$15.5 billion in 1990 to \$21.9 billion in 2020 (measured in 2020 US dollars).

This paper studies the relationship between urban growth and wildfire costs in California. California was the top state in number of wildfires and total acres burned between 2017 and 2021. In 2021, over 15 percent of California's households (approximately 2 million) lived in areas with high-to-extreme wildfire risk (Insurance Information Institute, 2022). The potential reconstruction value for residential structures alone totaled over \$270 billion.[1] Houses in wildfire-prone areas are more affordable than those in lower-risk areas (Ellis, 2020), all else being equal. Notably, many jurisdictions in the state have restricted housing supply, particularly near urban centers (Kahn, 2011; Monkkonen, Lens and Manville, 2020). These restrictions have contributed to land development away from urban cores, thus expanding cities horizontally rather than vertically (Burchfield et al., 2006; Glaeser, Gyourko and Saks, 2006; Saiz, 2010; Gyourko and Molloy, 2015*a*; Molloy, 2020).

Wildfire costs may increase as urban areas expand into previously undeveloped land for several reasons. First, the probability of wildfire incidents may increase with more housing or land development. All else being equal, increased human presence may lead to more ignitions since 90 percent of wildfires are caused by human activity (Radeloff et al., 2018). Housing developers, households, and government officials may not account for the marginal contribution of new development to wildfire probability, leading to over-building at the urban edge (or under-building in low-risk areas) relative to the social optimum. In fact, as Syphard et al. (2017) note, the federal government has a significant financial stake in wildfire losses. However, it does not regulate new construction in fire-prone areas or designate wildfire-prone zones in the way it designates floodplains.

To study the impact of housing development on wildfire costs, I construct a geospatial dataset that covers California and captures land and housing development patterns across the state over time. I compile a panel dataset using land use data from the National Land Cover Database (NLCD) (Dewitz, J., and U.S. Geological Survey, 2021) and housing data from

[1] The Insurance Information Institute calculated potential reconstruction values in 2020, using the cost of materials and labor needed to rebuild after the destruction of the residential structure. Calculations factor in pricing variations due to different geographic locations. In the past two decades, much of the housing stock destroyed by wildfires has been rebuilt (Flavelle, 2018; Ho, 2020).

the 1990, 2000, and 2010 decennial Census (Seirup and Yetman, 2006; Seirup, Yetman and Razafindrazay, 2012; Center For International Earth Science Information Network-CIESIN-Columbia University, 2017). I then map housing development to the point of ignition for all wildfires registered between 2000 and 2018.

The empirical challenge is that housing development is correlated with factors that contribute to wildfire risk. If households prefer lower wildfire risk areas, those areas will be more developed, all else equal. On the other hand, if households want to live on hillsides or near grasslands, then development will be positively correlated with risk. I employ two identification strategies to address potential omitted variable bias and endogeneity. The first approach leverages distance to the 1947 freeway plan as an instrument for development, following Baum-Snow (2007). I also use a long difference specification to measure the effect of changes in development on changes in wildfire probability. These approaches rely on different assumptions and identifying variation, but yield quantitatively similar results. I find that wildfire probability increases as previously undeveloped land develops but decreases at higher levels of development until the probability of wildfire reaches zero. In the cross-section, each additional house between 0 and 300 housing units increases wildfire probability by 0.01 (OLS) or 0.24 (IV) percentage points from a baseline average of 0.918 percent in areas with no housing units. Each additional unit beyond 300 decreases wildfire probability by 0.01 (OLS) or 0.45 (IV) percentage points until the probability of wildfire approaches zero. Long difference estimates show similar non-linear impacts. Adding 50 housing units to undeveloped areas increases average wildfire probability from 1.1 to 6.7 percent, while adding 150 weakly decreases average wildfire probability.

I then show that, as land at the urban edge develops, the need for (and total cost of) fire suppression increases, as does the wildfire damage. Simulation and observational studies suggest that suppression is more costly and losses are larger when homes are built near fire-prone wildlands (Haas, Calkin and Thompson, 2013; Barrett, 2018; Xu, Webb and Evans, 2019; Schoennagel et al., 2017). I show that fires burn more broadly when sparked in undeveloped areas but are more likely suppressed when near urban areas. Using data on suppression costs from Mietkiewicz et al. (2020) and CalFire, I estimate that, on average, development increases suppression costs by \$375-\$730 for every additional housing unit near a fire's point of ignition for a decrease in fire size of 0.0018 square kilometers (0.43 acres).

Lastly, I calculate counterfactual wildfire probabilities and suppression costs under four counterfactual housing distributions. The first set of counterfactuals limits new housing development in wildfire-prone areas. The second considers the effects of property buyouts, where some or all existing housing units in wildfire-prone pixels are relocated. Together, these counterfactual exercises cover current policy discussions regarding construction in wildfire-prone areas (Barrett, 2019; Segerstrom, 2023; Sommer, Hersher and Kellman, 2023). These counterfactuals rely on increased housing supply in areas at low risk for wildfires and therefore go against current land use regulations in California (Ospital, 2022). Restricting or removing *some* housing units away from the urban edge may not impact wildfire probability and may increase the associated costs.

This paper contributes to three literatures. First, it contributes to the growing literature on housing supply and adaptation to climate change. Closest to this paper is Ang (2023). Our papers differ in two crucial ways. First, I estimate the effect of housing and land development on wildfire probability, while Ang's paper studies the relationship between population density and the probability of ignition. The two papers also use different sources of variation to estimate these causal relationships. Both papers find a non-monotonic relationship between wildfire risk and human presence, which suggests that our findings are robust to different measurements and identification strategies. Second, we focus on different costs associated with wildfire exposure. Ang leverages a quantitative spatial model to calculate counterfactual costs due to exposure to smoke. My paper focuses on suppression costs and property damage, capturing a different set of wildfire-related costs. My paper also relates to Ospital (2022), which estimates that land use regulations explain 7 percent of the residents living in fire-prone areas in Southern California. Ospital takes wildfire risk as exogenous to human development, but I show that wildfire probability increases as land becomes more developed. I show that land development impacts wildfire risk non-monotonically, such that the estimated costs in Ospital (2022) are lower bounds at low levels of development but upper bounds at higher levels. Another closely related paper is Baylis and Boomhower (2023). They show that public expenditure on wildfire suppression subsidizes households living in fire-prone areas. I show that development at the urban edge also creates a non-monotonic externality due to a higher probability of wildfires. Omitting the ignition externalities may understate (overstate) the costs associated with the suppression externality if housing or land development is sparse (dense) enough.

My paper complements simulation-based work on the impact of urban growth into the Wildland-Urban Interface on wildfires (Radeloff et al., 2018; Mietkiewicz et al., 2020; Kunreuther et al., 2022), as well as recent work by Taylor and Druckenmiller (2022), which estimates the impact of developing wetlands on flood claims. I also contribute to the broader literature on the costs of housing supply restrictions. Land use regulations cause prices to be higher (Glaeser and Gyourko, 2003; Saiz, 2010; Albouy and Ehrlich, 2018; Gyourko and Krimmel, 2021), and in turn, induce cities to grow horizontally (Burchfield et al., 2006; Monte, Redding and Rossi-Hansberg, 2018). As urban areas expand, there may be environmental externalities for which economists have not yet accounted, mainly where wildland is being developed.[2] Most of the land developed between 2001 and 2019 in the United States was previously wildland.[3]

This paper also builds on the literature on the economics of environmental disasters, particularly the nascent literature in economics studying wildfires. Liao and Kousky (2022) estimate wildfires' impact on California's municipal budgets. There is also a growing literature on wildfire mitigation and suppression (Baylis and Boomhower, 2023, 2021; Kunreuther et al., 2022), the costs of wildfires in mortgage markets (Biswas, Hossain and Zink, 2023), and costs in terms of exposure to pollution (Burke et al., 2021, 2022; Ang, 2023).

Section 2 explains how urban growth can impact the probability and cost of wildfire incidents, and characterizes the wildfire landscape in California. Section 3 describes the construction of my dataset and provides some descriptive statistics. Section 4 estimates the impact of urban growth on wildfire probability. Section 5 estimates the impact of urban growth on wildfire-related costs. Section 6 simulates expected wildfire costs under alternative land use policies. Section 7 concludes.

2 How can urban growth impact wildfires?

Since 1983, the United States has experienced an average of 70,000 wildfires per year (US EPA, 2016). While the number of incidents has stayed roughly constant for the past 40 years, the average area burned, the number of large fires, fire-season length, and wildfire-related costs have increased (Westerling et al., 2006; Jolly et al., 2015; MacDonald et al., 2023).

The aggregate impact of urban growth on wildfire ignitions is ambiguous because the impact of land development on the availability of fuel is ambiguous. A wildfire requires two primary inputs to start and spread: fuel and a source of heat. As a simplification, I can write the fire

[2]Ecologists have estimated that areas where human development and undeveloped wildland meet are most likely to experience wildfires, diseases such as Lyme disease, flooding and mudslides (see Radeloff et al., 2018, for a summary).

[3]Canonical urban models, such as the Alonso-Muth-Mills monocentric city model, often assume that land at the edge of the city is used for agriculture (see Alonso, 1964; Brueckner, 1987; Giuliano and Small, 1991; Anas, Arnott and Small, 1998; Glaeser and Gyourko, 2002; Tsai, 2005; Clifton et al., 2008; Duranton and Puga, 2015, for a review). The growth of cities' spatial footprint has been linked to greater commuting costs (Glaeser and Kahn, 2004), blight in the urban core (Brueckner and Helsley, 2011), and a larger carbon footprint due to automobile emissions (Kahn, 2000; Glaeser and Kahn, 2010; Kahn and Walsh, 2015).

production function in a given location i as

$$P(Ignition)_i = a(Fuel_i, Spark_i) \tag{1}$$

where $P(Ignition)$ is the probability of ignition, $a(\cdot)$ is a function such that $Fuel$ and $Spark$ are complements, and $a(0, Spark) = 0$ and $a(Fuel, 0) \approx 0$.[4] The wildfire "spread" function is more complicated due to variability in fire behavior. Wildfires grow as flames ignite neighboring fuel and as embers and firebrands from existing burns are carried downwind (Scott and Burgan, 2005; Finney et al., 2011; Prestemon et al., 2013; Kearns et al., 2022). Conditional on an ignition, fire size B of an incident that started in i can be written as

$$B_i = b(Fuel_i, Wind_i, Hilliness_i, Suppression_i) \tag{2}$$

where $b(\cdot)$ is a function increasing in fuel, wind, and hilliness, and decreasing in suppression, with $\lim_{Fuel \to 0} b(0, \cdot) = 0$ (Narayanaraj and Wimberly, 2012; Finney et al., 2015; Alexandre et al., 2016; Fernandes et al., 2016; Abatzoglou et al., 2018). Wind and hilliness are complements (Keeley and Syphard, 2019). Not all fuel behaves the same: combustible materials ignite and burn at different temperatures, promote flames of different lengths, and may generate embers light and hot enough to ignite fires downwind (Lippitt et al., 2012; Syphard, Rustigian-Romsos and Keeley, 2021). Much of the debate in environmental science, forestry, and wildfire science has focused on the role of higher fuel availability in explaining the increase in wildfire activity and severity. Rising temperatures, droughts and earlier snowmelt have contributed to the drying out of vegetation in the American West, thus lowering the ignition point of potential wildfire fuel (Westerling et al., 2006; Abatzoglou and Williams, 2016; Schoennagel et al., 2017; Williams et al., 2019; Parks and Abatzoglou, 2020; Turco et al., 2023).

Housing development in wildfire-prone areas can impact *spark* and *fuel*, potentially affecting wildfire probability and size. Development is positively correlated with a higher incidence of sparks. Incidents in California were geographically concentrated: most incidents occurred near urban areas in Southern California and along the central valleys and mountainous regions (Figure 1). Moreover, wildfires in undeveloped areas *near* exurban or suburban settlements were also more likely to have human causes (Appendix Figure B.3).[5] 89 percent of all wildfire incidents in California between 2001 and 2018 were human-caused, either

[4] Spontaneous combustions are possible but rare relative to combustions that have a source of heat (Restuccia, Huang and Rein, 2017). I use the wildfire incident dataset from Short (2022) in my analysis, and this dataset does not distinguish spontaneous combustion wildfires.

[5] One might be concerned that fires in remote or uninhabited areas are less likely to be documented, causing the econometrician to underestimate the number of fires. Small or easily suppressed incidents are less likely to be

directly (e.g., equipment and vehicle use, arson/incendiarism, debris and open burning, recreation/ceremony, misuse of fire by a minor, smoking and fireworks) and indirectly (e.g., power generation/transmission/distribution) (Appendix Figure B.2A).[6]

The impact of land development on the availability of fuel is ambiguous. On one hand, housing and infrastructure development can remove vegetation. Modern building codes limit the addition of new fuel by requiring that homes be built of nonflammable, more resilient materials (Baylis and Boomhower, 2021). Households in fire-prone areas can further reduce fuel availability by thinning nearby vegetation (Bevers, Omi and Hof, 2004), creating fuel breaks or defensible spaces (Reinhardt et al., 2008; Moritz et al., 2014; Syphard et al., 2014). However, land development near undeveloped wildland may increase fuel availability. Mechanisms include increased fire suppression, which can lead to build-up of vegetation (Hessburg and Agee, 2003); removal of fire-resistant native plants; and introduction of invasive species, particularly of brushes and grasses that are flammable when dry (Lippitt et al., 2012; Bar-Massada, Radeloff and Stewart, 2014).

Now consider the impact of increasing human presence in fire-prone areas on wildfire costs. Denote total wildfire costs as C, a function of wildfire probability, and direct and indirect fire costs. N denotes the number of locations i where a wildfire can start. Assuming the cost of incidents that never materialize is 0, we have:

$$C = \sum_{i=1}^{N} P(Ignition)_i \cdot C_i(B_i) \tag{3}$$

where $C_i(B_i)$, the cost of an fire that starts in location i, depends on the size of the fire B_i. C can include suppression costs, uninsured damages to property (Baylis and Boomhower, 2023; Biswas, Hossain and Zink, 2023), loss of life, evacuation costs (Barrett, 2018), human exposure to wildfire smoke (Bowman et al., 2011; Gray, 2020), carbon release due to burning (Mack et al., 2011), and ecosystem loss (Barrett, 2018).

registered. The data may therefore be undercounting incidents in remote areas, and those documented may be larger. On the other hand, fires in developed areas that are small and easier to suppress may also go unreported. In this case, the data may be undercounting incidents in areas with settled areas, and those that are documented may require firefighter's assistance in suppression. Therefore, fires in both developed and undeveloped areas are likely underreported.

[6] Balch et al. (2017) estimate that, across the United States, 84 percent of wildfires and 97 percent of fires that threatened homes between 1992 and 2012 were human-ignited.

Rewriting equations (1), (2) and (3) to reflect the impact of development d:

$$P(Ignition)(d) = a(Fuel(d), Spark(d))$$
$$B(d) = b(Fuel(d), Wind, Hilliness, Suppression(d))$$

then the impact of increasing human settlement in fire-prone areas can be written as

$$\frac{\partial C}{\partial d} = \sum_{i=1}^{N} \left(\underbrace{\frac{\partial P(Ignition)_i}{\partial d} \cdot C(B_i)}_{\text{Ignition effect}} + \underbrace{P(Ignition)_i \cdot \frac{\partial C}{\partial B} \frac{\partial B_i}{\partial d}}_{\text{Exposure effect}} \right) \tag{4}$$

Equation (4) shows that development can impact wildfire costs in two ways. The first mechanism is "ignition," which captures the change in the probability of fires starting. The second channel is "exposure," which captures the impact on size B, the increase in demand for suppression and the greater exposure of property and households to loss. The change in total costs depends on the sum of two products, which are not equivalent to the product of the sums. Thus, heterogeneity in C_i and B_i can magnify or undermine the ignition probability changes from a small increase in development. Prior work has studied the "exposure" effect,[7] so I focus on the "ignition" effect. In the next section, I describe the data used to estimate equation (4).

3 Data

The foundation of my data is a grid of "pixels" measuring 1 kilometer by 1 kilometer. This grid covers all of California, excluding islands. I use pixels as my unit of measurement to hold constant the area and boundaries of each unit of observation. Existing administrative units of measurement either differ widely in area or have boundaries that are endogenous to my explanatory variables of interest.[8] I then map several geospatial datasets to this grid to

[7] Baylis and Boomhower (2023) show that 1-31 housing units within 30km of a fire doubles suppression costs. Ospital (2022) estimates a present-discounted cost of wildfire risk of $14,149 per person in San Diego. Other papers estimate the impacts of exposure to wildfire smoke on health, educational, and labor outcomes (Burke et al., 2021, 2022; Heft-Neal et al., 2022, 2023; Cabral and Dillender, 2024).

[8] For instance, municipal boundaries may shift with land development, so I cannot directly compare growing jurisdictions over time, particularly if new development takes place in unincorporated areas. Similarly, the coverage of Census blocks and ZIP codes changes with development. Census tracts are larger when housing (or population) density is lower. If fires ignite randomly, then incident probability will be mechanically higher in larger (i.e., less developed) pixels. My grid of equally-sized pixels addresses both of the concerns mentioned above while keeping the area of my units of analysis small enough to capture the effect of development on wildfire risk.

measure the following variables:

Development: I employ two measures of development. My first measure is housing development, i.e., the number of housing units in each pixel. I map rasterized data from the 1990, 2000, and 2010 decennial Census (Seirup and Yetman, 2006; Seirup, Yetman and Razafindrazay, 2012; Center For International Earth Science Information Network-CIESIN-Columbia University, 2017) as well as 2016 housing density estimates from Scott et al. (2020). I also measure "land development," which is the share of each pixel with "developed" land cover as classified in the National Land Cover Database (NLCD) (Dewitz, J., and U.S. Geological Survey, 2021). Each pixel in the NLCD 30m-by-30m raster grid indicates a land cover category based on vegetation and surface imperviousness. For each grid pixel, I calculate the share of the pixel covered by each land cover type. I drop all pixels that are one hundred percent covered by water since those pixels correspond to the Pacific Ocean, large bays (e.g., the San Francisco Bay), or large lakes (e.g., Lake Tahoe). Appendix Figure B.6 shows the correlation between these two development measures in 2000/2001 and 2010/2016. I use Zonal Statistics from the QGIS toolbox to map development to each pixel. The rasters are slightly offset from my grid, introducing some classical measurement error to the housing and land development variables.

Wildfires: I use geocoded data from the National Wildfire Coordinating Group (NWCG) to measure the number of wildfire incidents per pixel from 1992 to 2018 (Short, 2022). This incident-level dataset is maintained by the US Forest Service and consolidates information on wildfires from the reporting systems of federal, state, and local fire organizations. Each recorded fire includes the latitude and longitude where it started, as well as the discovery date, which I use to determine when the fire started. I calculate the empirical wildfire probability in each pixel i over any given period as the number of wildfires divided by the number of years in that period.

I also use the reported incident cause and final wildfire area from NWCG in my analysis. Wildfires can have natural or human causes. Naturally occurring wildfires are most often due to lightning. I decompose human-caused incidents into two categories: directly and indirectly human-caused. Directly human-caused wildfires include fires started intentionally (e.g., arson), accidentally (e.g., firearms use), or as a consequence of neglectful use of fire (e.g., debris burning, fireworks, smoking, or misuse of fire by a minor). "Indirect human cause" includes wildfires originated from human infrastructure and equipment and includes fires caused by faulty power lines and by sparks from railroads and lawnmowers. Most fire incidents with a known cause in California between 1992 and 2018 were caused by direct or indirect human activity (Appendix Figure B.2). However, 42.4 percent of incidents have the cause listed as “Missing data/not specified/undetermined”. Wildland fire investigators use factors such as burn patterns and first responder testimony to determine wildfire cause.[9] Distinguishing lightning- and human-caused fires is relatively simple: lightning splinters vegetation, damages the ground and can usually be connected to recent electrical storms. Human-caused fires are more challenging to tell apart, especially when there is limited evidence of the source of the ignition. Appendix Figure B.4 shows that the share of incidents with unknown cause increases over time, suggesting that the investigation has yet to conclude or reach a determination. My results hold when I exclude fires of unknown cause.

Additional data: I map other potential determinants of urban growth and wildfire to my grid. I measure each pixel’s distance to the nearest highway and the 1947 federal highway plan from Brinkman and Lin (2022). I also calculate each pixel’s distance to the nearest interstate and state freeway using a map from the Federal Highway Administration (2020) and Caltrans (2021), respectively. I measure the distance of each pixel to the nearest power transmission line using mapped data from the California Energy Commission (2023). I use digital elevation data from the U.S. Geological Survey (2021) to calculate the average slope for that pixel, and the share of the pixel with slope greater than 15 percent, following Saiz (2010). I also map my grid onto state and national park maps and measure the share of each pixel in a park, and is thus undevelopable (National Park Service, 2019; California State Parks, 2022). I measure land prices using high-resolution data in 2010 from Nolte (2020*a*).[10] I convert Nolte’s data from log dollars per hectare to dollars per hectare, measured at the 480m resolution. I then multiply that value by 4.8^2 to calculate total value in the 480m-by-480m pixel. Finally, I sum values to derive total property value in each pixel in my 1km^2 grid.

Appendix Table C.1 summarizes key variables in my dataset. The average pixel was 6.25 percent developed in 2001, with 93.75 percent of land barren or covered in wildland (forest, shrub, grass, or wetlands), agricultural land (crop, pasture, or hay), or water. Low or medium-intensity development (i.e., impervious land cover constitutes less than 80 percent of total cover) comprise most of the developed land. Unsurprisingly, pixels are very heterogeneous. The median pixel was completely undeveloped in 2001, with nearly 90 percent of all pixels

[9] National Wildfire Coordinating Group (2016) is a guide for determining wildfire causes.

[10] Nolte (2020*b*) describes the construction of the dataset in depth.

being less than 10 percent developed. Forest, shrub/grassland, and wetlands (i.e., wildland) covered close to 100 percent of nearly half of the pixels. Among the pixels with any amount of land development, wildland comprised 65 percent of the pixel's land cover on average. California also became more developed during the sample period. Housing density increased by 2.6 units between 2000 and 2010, over a baseline mean of 21 housing units per square kilometer in 2000. Between 2001 and 2016, 11.2 percent of pixels increased their share of land developed.[11] Appendix Table C.1 also shows wide variation in land development determinants. The median pixel had slopes higher than 15 percent in 28 percent of its area. In other words, for more than 50 percent of pixels, over 25 percent of their land is undevelopable due to hillside steepness (Saiz, 2010). Some pixels are also entirely contained in national or state parks, and as such are legally undevelopable. Finally, pixels vary in their access to transportation and electricity infrastructure. The average pixel is nearly 10 kilometers from the nearest powerline and 60 kilometers from the 1947 freeway plan.

4 Impact on ignition

4.1 Observational evidence

The probability of wildfire incidents varies cross-sectionally with housing density and land development. Figure 2 regresses the average wildfire probability between 2001 and 2003 on a step function of housing density (panel A) and land development (panel B), controlling for county fixed effects to allow for geographic variation in underlying fire risk. I document three empirical facts. First, the probability of wildfires increases initially with development. Pixels with 200 to 400 housing units, i.e., housing density of 200-400 units per square kilometer, had almost five times the wildfire probability of pixels with no housing units (4.16-4.72 vs. 0.84

[11] Appendix Figure B.10 plots the distribution of changes in development. Panel A indicates that some pixels experienced a decrease in number of housing units between 2000 and 2010. Decreases in the number of housing units are possible under conversions and consolidation (e.g., duplex becomes single-family). Some of the decline in housing supply may be due to mismeasurement. Since I construct my dataset using geospatial tools, it is possible that underlying 2000 and 2010 housing rasters are slightly offset or become slightly offset when I reproject the data. Thus, 100 units mapped to pixel i in 2000 might map to pixel j in 2010. Pixels that lost housing units were mainly in Los Angeles County, Orange County, and San Diego County. However, these counties experienced housing growth in my data during this period, which suggests some mismeasurement. Panel B shows that some pixels experienced decreases in development. In this case, negative changes mainly reflect the conversion of recreational open land into agricultural land.

percent). The average probability in undeveloped pixels was 0.76 percent, while the average probability for pixels 15-20 percent developed was 5.13 percent. This initial increase in wildfire probability suggests that human settlement may play a role in increasing wildfire risk. However, the relationship between development and wildfire probabilities is non-monotonic. At higher levels of development (over 800 units per square kilometer or over 80 percent developed), increases in development may correlate with decreases in the probability of wildfires. This second fact suggests that the fuel management and removal mechanism may dominate at higher levels of development. Finally, this figure suggests that wildfire ignition risk is highest in low-to-moderately developed areas. The probability of fires was approximately 4.4 percent where housing density was between 100 and 250 houses per pixel, and 5.5 percent for pixels 30 to 55 percent developed. Ang (2023) documents a similar relationship between wildfire probability and population density.

OLS estimates in the cross-section may not estimate the causal impact of changes in housing or land development on fire probability due to omitted variable bias. We should be concerned that each pixel's development is correlated with an underlying wildfire risk factor that the econometrician cannot observe. If households prefer lower-risk areas, those areas will be more developed, all else equal. OLS will understate the relationship between development and wildfire ignition in this case. Moreover, suppose underlying wildfire risk increases over time in some areas. In that case, these areas may experience slower development than areas with similar wildfire probabilities at baseline, whose risk did not change. In this case, cross-sectional OLS estimates that pool wildfire probabilities over time will overstate the impact of development on fire probability.

To address these identification concerns, I employ two empirical approaches that rely on different assumptions and identifying variation to establish a causal effect. The first uses cross-sectional variation in development and deploys an instrumental variable that exogenously impacts the probability of development without being correlated with underlying wildfire risk (Section 4.2). This approach estimates the impact of small increases in development on wildfire probability in areas with low rates of housing density or land development. In the second approach, I take long differences within geographic units, similar to Taylor and Druckenmiller (2022) (Section 4.3). Unlike the IV approach, which allows me to estimate local linear average treatment effects of development on fire probability for low-to-medium development pixels, the long differences approach yields a distribution of treatment effects, holding geographic conditions constant. I show results for both of my measures of development – the number of housing units and land development share – in each of the empirical strategies.

4.2 Cross-sectional instrumental variable approach

I estimate the exogenous effect of housing development on probability using an instrumental variables approach. I follow the strategy in Baum-Snow (2007) and Baum-Snow et al. (2020) and use log distance to the 1947 freeway plans as an instrumental variable for development and housing density in each pixel i:

$$d_i = g(z_i) + \zeta_i \tag{5}$$

$$P(wildfire)_i = h(d_i) + X_i'\gamma + \eta_i \tag{6}$$

where $P(wildfire)_i$ is the empirical wildfire probability between 2001 and 2003, d_i is the measure of development, X_i are covariates (e.g., share of pixel covered in wildland in 2001), z_i is the pixel's distance to the 1947 plan in kilometers, $h(\cdot)$ is a function of d, and $g(\cdot)$ is a function of z. Baum-Snow (2007) shows a reduced form relationship between the 1947 freeway plan and suburbanization. I argue that distance to the planned freeway is a valid, exogenous instrument for the degree of residential development across California. The identifying assumption is that distance to the proposed network is orthogonal to changes in wildfire risk during the analysis period, i.e., $E[g(z)\eta] = 0$. The 1947 plans were designed to facilitate trade and national defense, not urban growth. Underlying wildfire risk was not taken into consideration in the creation of the 1947 plans, such that this instrument is plausibly exogenous to the unobserved component of fire risk.

Table 1 estimates equations (5) and (6). $h(d)$ is a linear spline function with a knot at $d = 300$ housing units for housing development regressions and $d = 50$ for land development regressions. The coefficients represent the change in slope from the preceding interval. Knots were selected so I can separately identify the relationship between development and wildfire probability for areas where risk increases with development and for areas where it decreases (Figure 2). $g(z)$ is also a linear spline function of pixel distance to the 1947 freeway plan, measured in kilometers, with a knot placed at $z = 20$km. Panel A shows the results when d is measured as the number of housing units in 2000, while panel B uses share of pixel developed in 2001.

Panel A, column 2 estimates that each additional house between 0 and 300 housing units *increases* wildfire probability by 0.238 percentage points from a baseline of 0.918 percent in areas with no housing units. Each additional unit beyond 300 *decreases* wildfire probability by 0.451 percentage points. The IV estimates are much larger, suggesting that OLS provides a lower-bound estimate for complier pixels. Panel B shows similar patterns to panel A for share of pixel developed. A 1 percentage point increase in share of pixel developed increases wildfire probability by 0.551 percentage points at low-to-moderate levels of development. Once a pixel is at least 50% developed, a 1 percentage point increase development decreases wildfire probability by 0.673 percentage points. When housing or land development is sufficiently high, the probability of wildfires is statistically indistinguishable from zero.

Appendix Figure B.8 plots the first stage relationships and shows that pixels further away from the 1947 plan had fewer housing units in 2000 and were less developed in 2001. Appendix Tables C.3, C.4, and C.5 show that pixels with some development and some wildland comprise the "compliers." Complier pixels are more developable (less steep, not in state or national parks), closer to power lines, closer to state and federal highways, and less likely to be in desert or agricultural areas. Complier pixels also vary in their wildland share of land cover, with wildland comprising from 0 to 75 percent of pixel area.

One could argue against the exogeneity of this instrument. For instance, if power lines were laid next to planned highways instead of actual ones, then my instrument would capture the distance to one potential cause of wildfires. Appendix Figure B.7 maps the location of power lines against actual state and federal freeways (panel A) and the 1947 freeway plan (panel B) and shows that there is no clear pattern of overlap. The results discussed in this section are robust to controlling for hilliness and distance to power lines (Appendix Table C.7).

Figure 3 plots the spline coefficients from Table 1 by incident cause. Each panel plots the OLS and IV coefficient for each segment of the spline function. As the number of housing units increases from 0 to 300, human-caused fires become more likely, including those due to arson/incendiarism, debris and open burning, equipment/vehicle use, misuse of fire by a minor, and smoking. This empirical fact is in line with findings from simulation studies by forestry, ecology, and wildfire experts, which have shown that human presence near wildland increases the probability of wildfires (see Radeloff et al., 2018, for a review). Lightning-caused wildfires do not show statistically significant responses to development. As pixels become moderately developed, the probability of lightning-caused fires decreases. Lightning grounding infrastructure and fewer trees may explain this slightly negative relationship.

Increasing development not only affects own-pixel wildfire probability but also spills over into neighboring pixels. Undeveloped pixels are more likely to experience wildfire ignitions when their neighbors are developed, as shown in Table 2. Panel A restricts the sample to pixels with 0 housing units, and panel B restricts to zero percent developed pixels. I then estimate equation (6) using average development within 5 kilometers. My preferred specification controls for wildland share in each pixel and its neighbors. An undeveloped pixel with no vegetation will never have a wildfire, so controlling for wildland share allows me to compare pixels with similar vegetation coverage but different neighboring development. An additional housing unit within 5 kilometers of an undeveloped pixel j increases the probability of wildfire in j by 0.0353 percentage points over a baseline of 0.578 percent. The non-monotonic relationship between development and wildfire probability also holds here. If neighboring pixels have at least 300 housing units, an additional unit decreases wildfire probability. One possible explanation for this finding is that at higher levels of density, the "fuel break" spillover far outweighs the "ignition" spillover (Bevers, Omi and Hof, 2004; Reinhardt et al., 2008; Moritz et al., 2014; Syphard et al., 2014). Another explanation may be that development is spatially correlated; the subset of pixels with more than 300 units near undeveloped pixels may be highly selected. Panel B's effects are qualitatively similar but statistically indistinguishable from zero. Appendix Table C.8 replicates Table 2 but uses a 1-kilometer ring around each undeveloped pixel instead of 5 kilometers. These results indicate that development increases wildfire probability where land is developing. Moreover, development also increases the likelihood of wildfire ignition in nearby wildland for low-to-moderate levels of development.

4.3 Long difference approach

I now consider the effect of increasing development within a given pixel rather than in the cross-section. Consider the estimating equation below:

$$\Delta P(incident)_i = f(\Delta d_i) + \nu_i \tag{7}$$

where $\Delta P(incident)_i$ is the change in wildfire probability, Δd_i is the change in development, $f(\cdot)$ is a function of change in development and ν_i is an unobservable determinant of changes in wildfire probability. The identifying assumption is that changes in land development are exogenous to *changes* in unobserved determinants of wildfire risk. I estimate $f(\cdot)$ in equation (7) using a linear spline for change in development interacted with initial development levels. Coefficients thus correspond to the slopes for change in wildfire probability, given change in development and initial housing or land development. I control for county fixed effects to allow for county-specific trends in wildfire risk. Appendix Figure B.9 shows that land became more developed, and wildfires became more likely near urban areas in Southern California and in the Sacramento and San Joaquin valleys. Appendix Figure B.10 describes the distribution of changes in development for both of my metrics (pixel development share and number of housing units).

Figure 4 plots the estimated coefficients for equation (7). Panel A measures changes in development using the difference in number of housing units in 2010 and 200. I top code changes in development greater than 400 units (0.05% of pixels) or 80 percentage points (0.02% of pixels) for readability. Additionally, I restrict the analysis to pixels where the number of housing units did not decrease.[12] Increasing development can increase the probability of wildfires, but the impact depends on the initial level of development. In pixels with less than 10 housing units in 2000, 50 additional housing units corresponded to an average increase of $50 \cdot 0.112 = 5.6$ percentage points over a baseline probability of 1.12 percent.

Similarly, adding 50 units to a pixel with 10-150 units in 2000 increased the probability of wildfires by 3.02 percentage points on average, over a baseline probability of 5.4 percent. Larger increases, on the other hand, can reduce the probability of wildfire relative to the baseline. If a pixel with 150 units per square kilometer increases density by 100, then the average decrease in wildfire probability is 4.3 percentage points. For pixels with more than 150 units, the effect of additional housing units on wildfire probability is not statistically different from zero. Panel B replicates panel A using the change in land development share as a proxy for development. As in panel A, a slight increase in land development increases wildfire probability, while larger increases can reduce it, although the estimates are less precise. These estimates provide further evidence that, as pixels develop, they move along the development-wildfire probability curve depicted in Figure 2. This figure illustrates an important issue surrounding land use policy in fire-prone areas: some low-density development increases wildfire risk more than high-density development.

5 Impact on costs

In this section, I estimate the relationship between developing previously undeveloped land and wildfire costs, even if the probability of wildfires did not change. I focus on the costs associated with wildfire suppression. However, there are also costs associated with the loss of human life and property, evacuation of entire communities (Barrett, 2018), human exposure to wildfire smoke (Bowman et al., 2011; Gray, 2020), mortgage markets (Ouazad and Kahn, 2019; Biswas, Hossain and Zink, 2023), carbon release due to burning (Mack et al., 2011), and ecosystem loss (Barrett, 2018).

Suppression includes all actions taken to contain and extinguish a fire. My data do not include information on suppression efforts at the incident level, so instead I study the relationship between sprawl and wildfire size. Appendix Figure B.13 describes the size of wildfire incidents in my data. Panel A shows that the vast majority of fires in California between 2001

[12] Appendix Figure B.12 replicates Figure 4A and includes pixels where the number of housing units decreased.

and 2018 were smaller than 0.25 acres, or roughly 1012 square meters. For reference, square pixels with edges measuring 1000m are approximately 247 acres. Still, 1700 incidents were larger than 300 acres. Panel B shows that a larger share of lightning-caused fires grow larger than 10 acres (9.1 percent versus 6 percent for fires with human or unknown cause) and are more likely to grow larger than 300 acres. Panel C shows how fire size evolves. The average incident size fluctuated year-on-year but trended up.

I estimate the impact of development on suppression costs as follows. First, I calculate aggregate development and land value within some distance of each incident's point of origin. Table 3 estimates the relationship between fire size and development within some radius r. Increasing development by 1 percentage point within 250 meters of a fire is associated with an average decrease in fire size of 0.0085 log points (Panel A). Development within 1 kilometer has a larger impact on fire size than development within 250 meters. The impact of an additional housing unit is smaller, but qualitatively similar. An additional housing unit within 1 kilometer of a fire's point of origin is associated with an average decrease in fire size of 0.0018 log points. This coefficient translates into a decrease in fire size from 0.446 to 0.445 acres when an additional housing unit is nearby.

One could argue that fires are mechanically smaller near developed areas since humans can suppress the fires they started. Appendix Table C.9 suggests that this relationship is not mechanical since lightning-caused fires are also smaller when there is housing nearby. Moreover, the cost of suppression per fire has increased faster than the probability of incidents, suggesting that humans who start fires cannot suppress them costlessly (The Pew Charitable Trusts, 2022).[13]

I can nevertheless place bounds on the change in suppression costs. The cost of suppressing one square kilometer of fire in areas with at least some very low-density housing ranges from \$220 thousand to 360 thousand dollars (Mietkiewicz et al., 2020). An additional housing unit within 250 meters implies fires that are 0.436 percent smaller, which corresponds to an additional \$384-\$747 suppression dollars per fire. Similarly, if development is 1 percentage point higher within 250 meters of the average wildfire incident, the 0.85 percent reduction in fire size would cost \$375-\$730 per incident. Notably, higher density corresponds to smaller impacts on fire size, aligning with Baylis and Boomhower (2023)'s findings.

[13] Appendix Figure B.15 shows how suppression costs per fire have gone up. CalFIRE reported 7,939 fires statewide in 1992 and total suppression costs of \$155.78 million (in 2019 dollars). In 2018, there were 3,504 incidents under CalFIRE's jurisdictions but suppression costs were \$907.80 million.

6 Discussion

In this section, I calculate counterfactual wildfire costs in 2016-2018, given alternative housing development patterns. Consider equation (3), reproduced below, which captures the aggregate cost of wildfires as a function of ignition probability, fire size, and damages:

$$C = \sum_{i=1}^{N} P(Ignition)_i \cdot C_i(B_i)$$

where $P(Ignition)$ is the probability of ignition, B denotes fire size, and $C(B)$ captures the damages and costs associated with suppressing a fire of that size. Section 4 estimated the impact of cross-sectional and longitudinal changes in development on wildfire probability across the distribution of housing and land development. I combine the results from Sections 4 and 5, and calculate wildfire probability and suppression costs under counterfactual housing development patterns. I focus on pixels in the bottom 99th percentile of housing density (i.e., below 1200 units per km^2). The analysis is in partial equilibrium and does not account for changes in prices or amenities. These counterfactuals rely on increased housing supply in areas at low risk for wildfires, but supply in low-risk areas is strictly regulated (Ospital, 2022). I use land value per unit as a proxy for stringency of supply regulation (Gyourko and Molloy, 2015*b*; Nolte, 2020*a*).

First, I estimate the predicted wildfire probability in each pixel using the IV results from Table 1, panel A. I then add the no-development predicted change in wildfire probability to the 2001-2003 estimated probability, thus getting the predicted 2016-2018 wildfire probability. On average, my model overestimates wildfire probability relative to the truth. I predict a continuum of probability values, but the empirical probability distribution bunches at 0 and 33.3 percent (Appendix Figure B.16). I use lower bound estimates of suppression costs and wildfire size to balance out the differences in average wildfire probability.

I consider four counterfactual housing distributions. The first counterfactual bans new housing development in wildfire-prone areas (*Ban new housing in fire-prone areas*). I deem a pixel "wildfire-prone" if the 2001-2003 predicted wildfire probability is larger than 4.7 percent (95th percentile of the predicted probability distribution). For this counterfactual, I assume that the number of housing units stayed constant between 2000 and 2010 in wildfire-prone pixels. I then assume that all units built between 2000 and 2010 in wildfire-prone pixels were instead built in low-risk, limited-supply pixels. These pixels are in the bottom 90th percentile of predicted risk, have land value per unit above \$446,960, and have at least 45 housing units (top 10th percentile of density among pixels with above-median value per unit). I then predict counterfactual wildfire probabilities using the coefficients from Figure 4. These counterfactuals rely on increased housing supply in areas at low risk for wildfires, but supply in low-risk areas is strictly regulated (Ospital, 2022).

The second counterfactual is similar to the first but allows some new housing in wildfire-prone areas (*Restrict density in fire-prone areas*). Here I impose a maximum housing density of 250 housing units to simulate the effects of regulating new supply once wildfire-prone pixels have already been developed. I set the maximum density to 250 units since many California jurisdictions impose a minimum lot size requirement of 1 acre (0.004km^2), corresponding to a maximum housing density of 250 units per pixel (Gyourko, Saiz and Summers, 2008; Acosta-Galvan, 2023). If the number of housing units in 2010 was less than 250, I maintain the number of housing units in 2010. If the pixel already had over 250 units in 2000, I also maintain the 2010 level of housing supply. For pixels that added housing units between 2000 and 2010 and surpassed 250 units during that period, I set housing in 2010 to 250 units. I allocate the excess development evenly across all pixels with at least 200 housing units in 2000 and the bottom 95th percentile of predicted wildfire probability in 2001-2003.

This first set of counterfactuals corresponds to land use policy proposals that partially or wholly limit development in wildfire-prone areas. Much of the policy debate around development and wildfire focuses on new development. In 2020, California's legislature approved a policy proposal that would limit housing construction in areas at risk for wildfire ignition. Governor Gavin Newsom vetoed the law, claiming it would create a loophole to avoid compliance with statewide housing supply requirements (Dooley, 2020). Similar supply restrictions have been discussed in the media (Segerstrom, 2023; Sommer, Hersher and Kellman, 2023) and in academic work by land use and forestry experts (Barrett, 2019).

I additionally consider a set of buyout counterfactuals, where policymakers relocate some or all housing units in wildfire-prone pixels to lower-risk areas. *100% buyout with building ban* removes 100 percent of housing units from wildfire-prone pixels. These units are evenly redistributed to pixels with at least 200 housing units in 2010 and predicted wildfire probability in the bottom 95th percentile. *50% buyout with building ban* only relocates 50 percent of housing units to simulate the effect of relocation policies with partial take-up.

Figure 5A summarizes average counterfactual wildfire probabilities across all pixels. As mentioned earlier, my model slightly overestimates average wildfire probability relative to the empirical probability for 2016-2018. Banning new development in wildfire-prone pixels does not significantly reduce average wildfire probability. The reason is that wildfire-prone pixels (i.e., in the top 95th percentile of predicted risk) gained at most 8 units between 2000 and

2010. The effect of restricting new supply is thus minimal, given the estimates from Figure 4. Property buyouts coupled with building bans can have a larger impact on reducing wildfire probability than building bans alone, at least within one to two decades. However, the efficacy of these types of policies depends on take-up. Under full take-up, the average probability of wildfire would have been 1.20 percent between 2016-2018, 0.5 and 1 percentage point lower than the empirical and predicted averages. This estimate's driving force is the complete relocation of 4.6 million housing units out of fire-prone, low-to-moderate density pixels. In relocating these housing units, these fire-prone areas move out of the "peak" of the inverted U curve from Figure 2 and down to the intercept. Partial take-up affects where each pixel lands along that curve. In some cases, partial property buyouts can increase wildfire risk by moving a pixel towards the peak of the curve in Figure 2A. Together, these estimates show the importance of policy targeting in settings with non-monotonic externalities.

The remainder of Figure 5 calculates the expected cost of wildfire suppression under each counterfactual. I conservatively assume that the suppression cost per squared kilometer is \$220 thousand (Mietkiewicz et al., 2020).[14] Panel B assumes that the average wildfire size is 0.17 km^2, even as housing development and wildfire probabilities change. The underlying assumption here is that suppression efforts do not change with changes in housing development. Panel C allows wildfire size to vary with housing, in line with Baylis and Boomhower (2023). I use the coefficients estimated in column 2 of Table 3A to predict fire size, given housing in each pixel and each counterfactual. I assume that reductions in fire size correspond to increased suppression costs.

Assuming fixed suppression efforts, panel B estimates \$680.4 million in yearly suppression costs between 2016 and 2018. If suppression costs increase with housing, then the predicted estimates from panel A predict \$854 million in yearly suppression costs (panel C). The difference between those estimates is due to the assumption that changes in wildfire size are due to suppression only, and that the cost of suppression is the same for small and large incidents. Nevertheless, both numbers underestimate the actual suppression spending in California. For instance, CalFire's operating budget was about \$3 billion (Brannon, 2021). CalFire's emergency fund, which supports unplanned large fire costs, spent an average of \$677.3 million annually between 2016 and 2018 (CalFire, 2022).

[14] The estimates in Mietkiewicz et al. (2020) range from \$220-360 thousand dollars. CalFire data suggest that the average suppression cost per squared kilometer between 2016-2018 was approximately \$442,565 (measured in 2019 dollars). See Appendix Figure B.15 for further details on suppression costs. Appendix Figure B.18 replicates panels B and C for suppression cost of \$442,565 per kilometer squared.

Panels B and C also calculate expected suppression costs under the four counterfactuals. Buyouts coupled with building bans yield the largest reduction in costs. 100% relocation with building ban halves expected suppression costs relative to the predicted baseline ($356M versus $680M in panel B; $415 vs. $854M). 50% buyout and complete building bans can also decrease suppression spending but to a smaller degree. The impact of restricting density in wildfire-prone areas on expected costs is ambiguous. As shown in panel A, the average wildfire probability can decrease when housing supply in fire-prone areas is limited. However, if the demand for suppression is large enough, even if fires are less frequent, their aggregate cost may be higher than in the status quo.

This section has shown that housing development along the urban edge constitutes an externality. An additional housing unit in downtown San Diego does not change the wildfire probability in those pixels or the neighboring developed pixels. However, additional development in low (moderately) developed areas along the urban edge might increase (decrease) the probability of wildfires. Housing supply regulations in low-risk areas do not account for the additional probability of ignition in higher-risk, less-regulated areas. Moreover, density limitations likely prevent areas from densifying and facing lower wildfire risk.

7 Conclusion

I provided evidence that wildfires become more likely when undeveloped and low-density areas initially develop, but that higher density can reduce wildfire probability. Land and housing development at the urban edge also impose spillovers on undeveloped areas outside the urban edge. I extrapolate the suppression cost associated with an additional house near the fire's point of ignition, showing that additional development increases the need for suppression spending at lower levels of development. Finally, I calculate counterfactual wildfire probability and costs under alternative housing allocations. Restricting or removing *some* housing units away from the urban edge may not impact wildfire probability, and may increase the associated costs. Wildfire costs initially increase with development but then rapidly decrease for higher levels of housing density as the probability of ignition falls to zero.

The results in this paper are at odds with current land use patterns and regulations in California. Development imposes a non-monotonic externality with regards to wildfires, meaning that the marginal social costs (benefits) of one fewer (additional) housing unit are minimized (maximized) when development is close to zero (in the top 1 percent of pixel housing density, i.e., 1200 units per square kilometer). Housing supply regulations that limit density in already developed places distort development 1) in areas where an additional unit brings efficiency gains, and 2) in undeveloped or low-development areas where an additional unit imposes a social cost.

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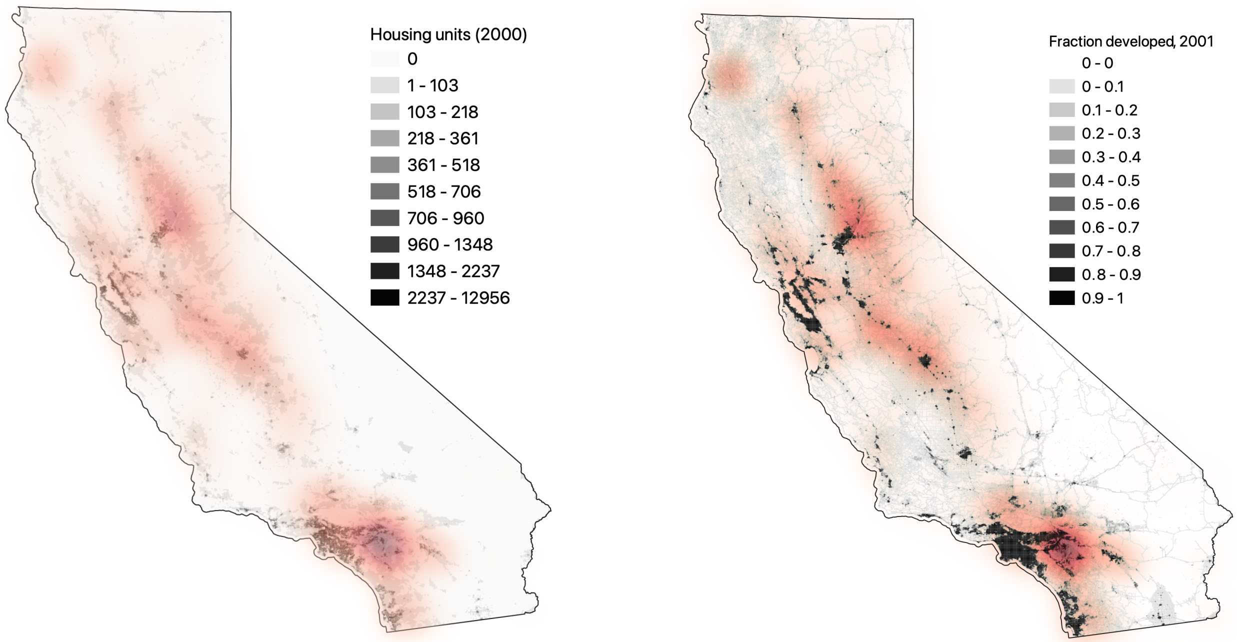
Figure 1: Most wildfire incidents between 2001 and 2018 started near developed areas

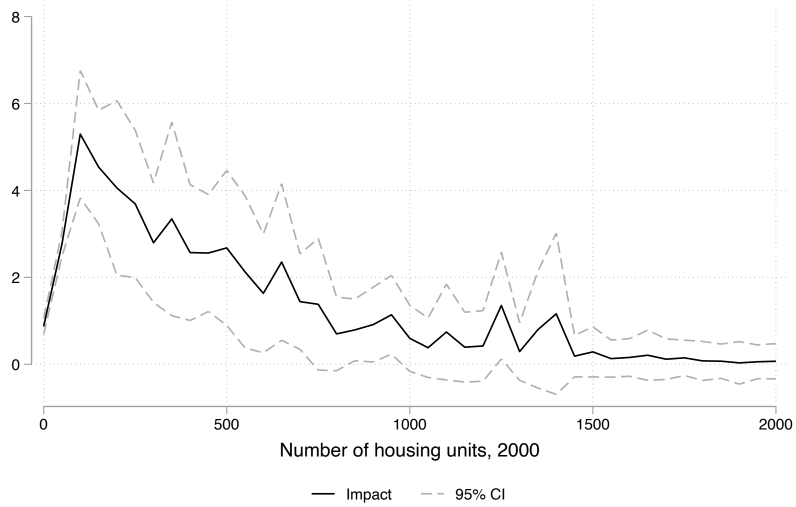
A. Number of housing units (2000) B. Share of pixel developed (2001)



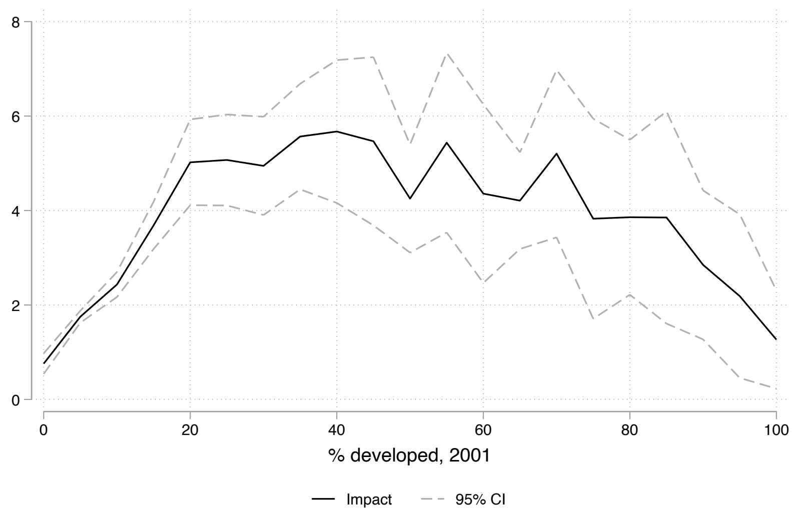
Notes: This figure overlays a heatmap of fire incidents from 2001 to 2018 onto number of housing units in 2000 (panel A) and developed land cover in 2001 (panel B). Darker colors indicate higher density of incidents. Section 3 and Appendix A describe the data in more detail. Appendix Figure B.1 replicates this map, weighing incidents by their size.

Figure 2: Cross-sectional relationship between development and wildfire probability, 2001-2003

A. Number of housing units (2000)



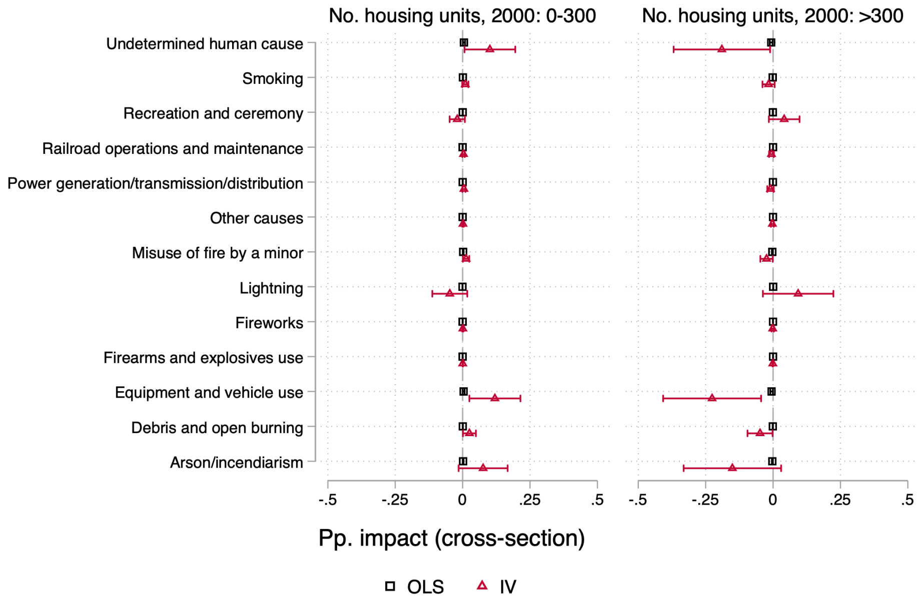
B. Share of pixel developed (2001)



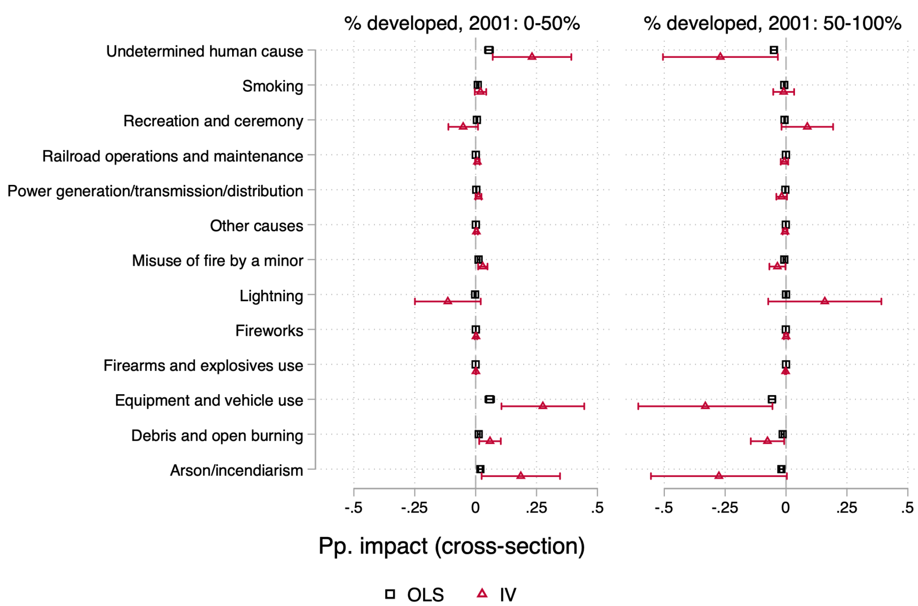
Notes: This figure plots the results of OLS regressions of fire probability in 2001-2003 on a step function of development. Panel A measures development as number of housing units in 2000. Bins in panel A are 50 housing units wide. I top code housing density above 2000 for readability. Only 171 pixels have number of housing units above 2000, and their average incident probability is 3.6 percent between 2001 and 2018. Panel B replicates A using share of the pixel developed in 2001. Bins are 5 percentage points wide. Section 3 and Appendix A describe the data in more detail.

Figure 3: Impact of development on wildfire probability by cause

A. Number of housing units, 2000



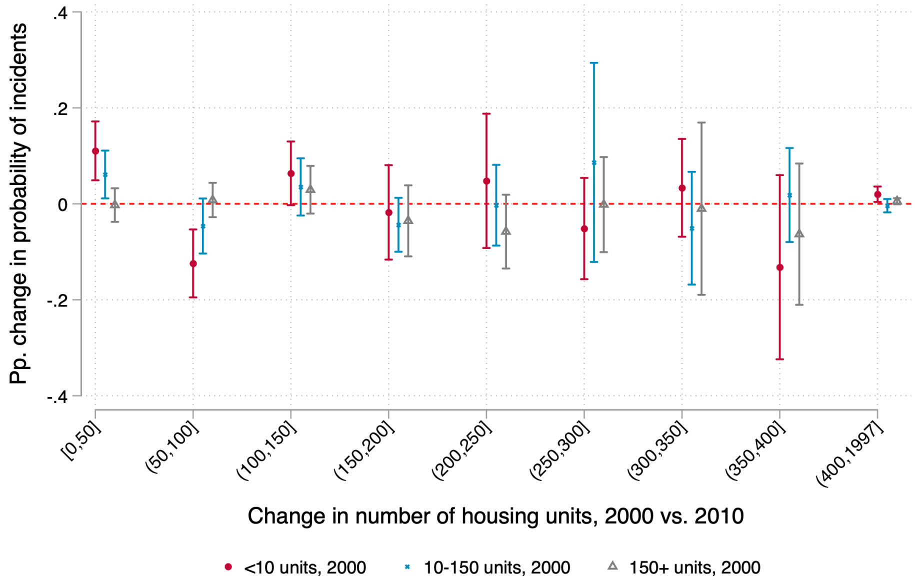
B. Share developed, 2001



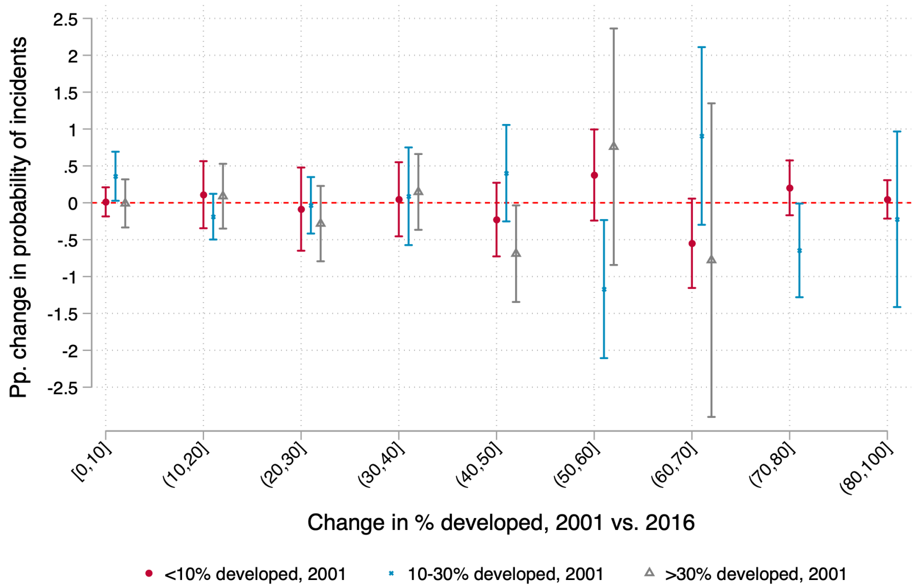
Notes: This figure plots the cross-sectional impact of increasing number of housing units in 2000 and development in 2001 on the probability of wildfires, by wildfire cause. The coefficients represent the change in slope from the preceding interval. Standard errors are conservatively clustered at the county level and estimated via two-step GMM. All regressions include county fixed effect to control for underlying differences in wildfire probability. Appendix Table C.1 shows summary statistics for the analysis sample. Standard errors are conservatively clustered at the county level. All regressions include county fixed effect to control for underlying differences in wildfire probability. Table 1 estimates these regressions for all incidents.

Figure 4: Change in probability of ignition due to increased development

A. Increase in number of housing units, 2000-2010



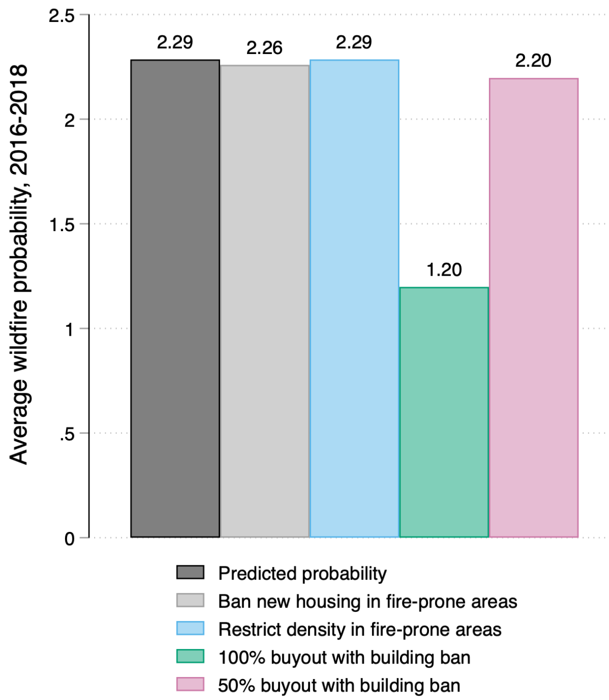
B. Increase in share of pixel developed, 2001-2016



Notes: This figure regresses change in fire probability overtime on a linear spline of change in pixel development interacted with indicators for initial level of development. The change in probability of ignition is measured using 2001-2003 and 2016-2018. Panel A measures change in development as the change in the number of housing units between 2000 and 2010. Panel B replicates panel A using the difference between land development share in 2016 and 2001. Panel A limits the sample to pixels with non-negative change in housing units and top codes increases over 650 units (0.01% of pixels) for readability. Similarly, panel B top codes increases over 80 percent (0.02% of pixels). Appendix Figure B.10 summarizes the average change in development, given initial levels of land development and number of housing units. Appendix Figure B.11 replicates this figure using 5-year averages rather than 3-year. The results using 5-year averages are qualitatively similar, yet smaller due to the higher number of wildfire incidents in 2005-2007 (Appendix Figure B.5). Appendix Figure B.12 includes pixels where the number of housing units decreased, allowing decreases in supply to have their own effect on wildfire probability.

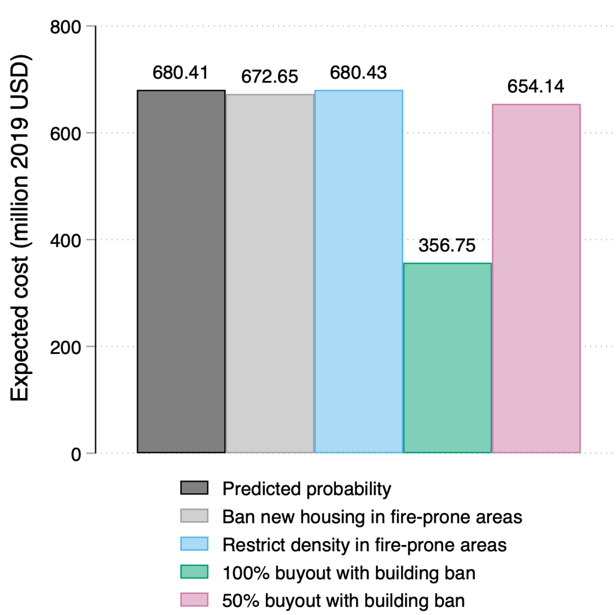
Figure 5: Counterfactual wildfire probability and costs

A. Wildfire probability

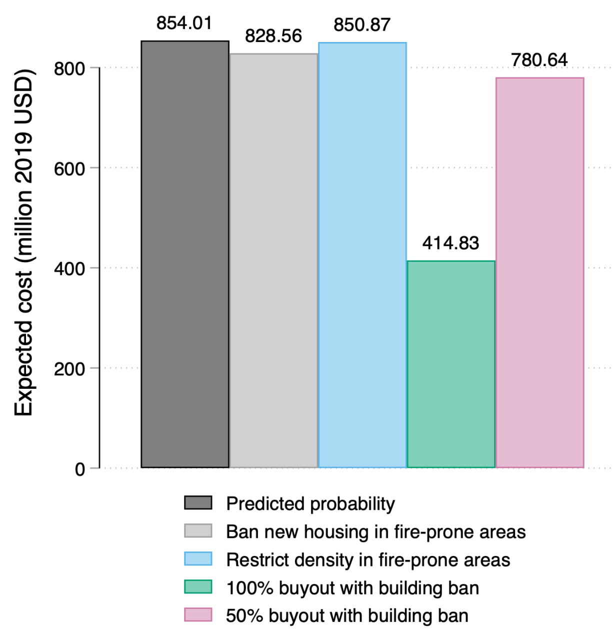


Expected suppression spending (million USD)

B. Fixed suppression costs



C. Flexible suppression costs



Notes: This figure calculates counterfactual wildfire probabilities (panel A) and suppression costs (panels B and C) for four counterfactuals. Section 6 describes the counterfactuals in greater detail. Counterfactuals that hold suppression efforts fixed assume that the distribution of fire sizes remains constant between 2001-2003 and 2016-2018, such that the average incident burns 0.17 km^2. I assume suppression costs are \$220,000 per square kilometer (Mietkiewicz et al., 2020). Expected suppression costs are the sum of suppression cost per kilometer times average incident size, weighted by the wildfire probability calculated in panel A. Appendix Figure B.17 replicates panels B and C, assuming that the average incident size is 0.0008 km^2, which was the median size between 2001 and 2018. Appendix Figure B.18 replicates panels B and C, assuming that suppression cost is \$442,565 per square kilometer.

Table 1: Cross-section impact of development on fire probability

Panel A. Number of housing units		
	100 · P(wildfire)	
	(1) OLS	(2) IV
No. housing units (0,300]	0.00932	0.238
	(0.00431)	(0.110)
No. housing units (300, .)	-0.0139	-0.451
	(0.00566)	(0.212)
Observations	407,960	407,960
$Prob(d < 1)$	0.918	0.918
F-stat	12.302	2.349
Kleibergen-Paap Wald F-stat		1.447
Cragg-Donald Wald F-stat		25.013

Panel B. Share of pixel developed		
	100 · P(wildfire)	
	(1) OLS	(2) IV
% developed, (0, 50]	0.137	0.551
	(0.0186)	(0.197)
% developed, (50,100]	-0.139	-0.673
	(0.0144)	(0.312)
Observations	407,960	407,960
$Prob(d = 0)$	0.756	0.756
F-stat	47.484	5.796
Kleibergen-Paap Wald F-stat		2.291
Cragg-Donald Wald F-stat		242.947

Notes: This table estimates the cross-sectional impact of increasing number of housing units in 2000 and development in 2001 on the probability of wildfires. The coefficients represent the change in slope from the preceding interval. Standard errors are conservatively clustered at the county level and estimated via two-step GMM. All regressions include county fixed effect to control for underlying differences in wildfire probability. Appendix Table C.1 shows summary statistics for the analysis sample. Figure 3 plots the coefficients by incident cause. Appendix Table C.6 replicates this table without controlling for county fixed effects. Appendix Table C.7 additionally controls for hilliness and distance to power lines.

Table 2: Cross-section impact of development within 5km on fire probability in undeveloped pixels

Panel A. Number of housing units

	100 · P(wildfire)			
	(1) OLS	(2) IV	(3) OLS	(4) IV
No. housing units within 5km (0,300]	0.00558	0.0324	0.00584	0.0449
	(0.000819)	(0.0193)	(0.000781)	(0.0212)
No. housing units within 5km (300, .)	-0.00576	-0.0380	-0.00599	-0.0514
	(0.000891)	(0.0280)	(0.000863)	(0.0294)
% wildland			-0.311	-0.842
			(0.151)	(0.907)
% wildland within 5km			0.00687	0.0266
			(0.00276)	(0.0188)
Observations	303,120	303,120	303,120	303,120
$Prob(d = 0)$	0.568	0.568	0.568	0.568
F-stat	23.362	4.696	20.358	1.912
Kleibergen-Paap Wald F-stat		1.606		1.585
Cragg-Donald Wald F-stat		124.968		133.169

Panel B. Share developed

	100 · P(wildfire)			
	(1) OLS	(2) IV	(3) OLS	(4) IV
% developed within 5km, (0, 50]	0.0873	0.290	0.0867	0.00944
	(0.0201)	(0.224)	(0.0196)	(1.629)
% developed within 5km, (50,100]	-0.296	10.78	-0.294	202.8
	(0.0680)	(52.30)	(0.0680)	(881.4)
% wildland			0.355	-5.429
			(0.147)	(20.90)
% wildland within 5km			-0.00245	0.117
			(0.00258)	(0.445)
Observations	224,686	224,686	224,686	224,686
$Prob(d = 0)$	0.330	0.330	0.330	0.330
F-stat	10.005	6.615	6.930	0.173
Kleibergen-Paap Wald F-stat		0.806		0.029
Cragg-Donald Wald F-stat		0.732		0.036

Notes: This table estimates the cross-sectional impact of increasing development within 5 kilometers of undeveloped pixels on own-probability of wildfires. Panel A restricts the sample to pixels with 0 housing units, and panel B restricts the sample to zero percent developed pixels. I then estimate equation (6) using development in pixels within 1 kilometer instead of own-pixel development share. The coefficients represent the change in slope from the preceding interval. Standard errors are conservatively clustered at the county level and estimated via two-step GMM. All regressions include county fixed effect to control for underlying differences in wildfire probability. Appendix Table C.1 shows summary statistics for the analysis sample. Appendix Table C.8 replicates this table using development in pixels within 1 kilometer.

Table 3: Impact of development on log wildfire size

Panel A. Number of housing units	(1)	(2)	(3)	(4)
Housing units within 250m	-0.00436 (0.000639)			
Housing units within 500m		-0.000960 (0.000141)		
Housing units within 1km			-0.000325 (0.0000569)	
Housing units within 2.5km				-0.0000629 (0.0000124)
Constant	-6.364 (0.000000704)	-6.364 (0.000000725)	-6.364 (0.000000977)	-6.364 (0.00000117)
Observations	23,174	23,174	23,174	23,174
R-squared	0.078	0.079	0.078	0.078
Indep. var. mean	8.608	40.071	133.215	731.541
Fire size (sq-km)	0.002	0.002	0.002	0.002

Panel B. Share of pixel developed	(1)	(2)	(3)	(4)
% developed within 250m	-0.00847 (0.000796)			
% developed within 500m		-0.00953 (0.000939)		
% developed within 1km			-0.0108 (0.00120)	
% developed within 2.5km				-0.0112 (0.00159)
Constant	-6.364 (0.00000151)	-6.364 (0.00000153)	-6.364 (0.00000188)	-6.364 (0.00000212)
Observations	23,174	23,174	23,174	23,174
R-squared	0.084	0.084	0.084	0.081
Indep. var. mean	14.930	14.121	13.643	11.578
Fire size (sq-km)	0.002	0.002	0.002	0.002

Notes: This table regresses log wildfire size on development within some distance r of the incident's point of origin. Each observation is a fire incident between 2001 and 2003 in California. All independent variables have been demeaned for more straightforward interpretation. Regressions control for county, year, and incident cause fixed effects. Appendix Figure B.14 plots the average land development and total housing units within 250m and 1km of wildfire incidents.

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A Data appendix

A.1 Measurement of distance variables

All layers are reprojected as EPSG:3310 (NAD83 California Teale Albers south of 36.5). Distances are of interest, not area, so I use a projection that maintains distance and is centered around the area of study. I do not account for elevation when measuring distance between two points, using surface distance instead.

A.2 Land cover from the National Land Cover Database (NLCD)

The National Land Cover Database (NLCD) provides nationwide data on land cover and land cover change for years 1992, 2001, 2004, 2006, 2008, 2011, 2013, 2016, and 2019. The NLCD data comprises of raster datasets at a 30m resolution with Albers Conical Equal Area projections. Each pixel corresponds to one of 16 land use categories based on a modified Anderson Level II classification system. Each surface pixel in the grid is assigned a land cover number, based on vegetation and percent developed impervious surface. The categories from the NLCD and corresponding identifiers are listed below:

- Open water: areas of open water, generally with less than 25% cover of vegetation or soil.
- Developed, open space: areas with a mixture of some constructed materials, but mostly vegetation in the form of lawn grasses. Impervious surfaces account for less than 20% of total cover. These areas most commonly include large-lot single-family housing units, parks, golf courses, and vegetation planted in developed settings for recreation, erosion control, or aesthetic purposes.
- Developed, low density: areas with a mixture of constructed materials and vegetation. Impervious surfaces account for 20% to 49% percent of total cover. These areas most commonly include single-family housing units.
- Developed, high density: Impervious surfaces account for more than 50% of the total cover. It includes both highly developed areas where people reside or work in high numbers. Examples include denser single family subdivisions, apartment com-

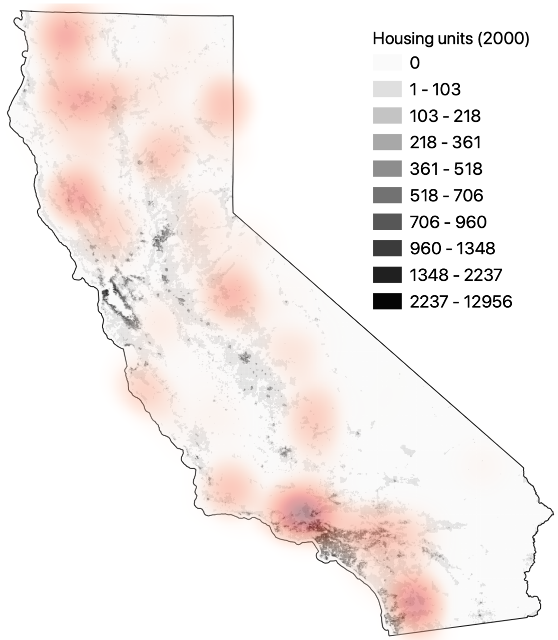
plexes, row houses and commercial/industrial areas. Impervious surfaces account for 50% to 100% of the total cover. NLCD decomposes this category into medium and high intensity, but I group the two groups together to allow for comparisons between the 1992 and 2001 datasets.

- Shrub: shrub canopy greater than 20% of total vegetation
- Forest: trees (evergreen, deciduous or mixed) greater than 20% of total vegetation cover
- Grass: areas dominated by gramanoid or herbaceous vegetation, generally greater than 80% of total vegetation.
- Barren Land (Rock/Sand/Clay): areas of bedrock, desert pavement, scarps, talus, slides, volcanic material, glacial debris, sand dunes, strip mines, gravel pits and other accumulations of earthen material. Generally, vegetation accounts for less than 15% of total cover.
- Planted/cultivated: Pasture/hay or crop vegetation accounts for greater than 20% of total vegetation.

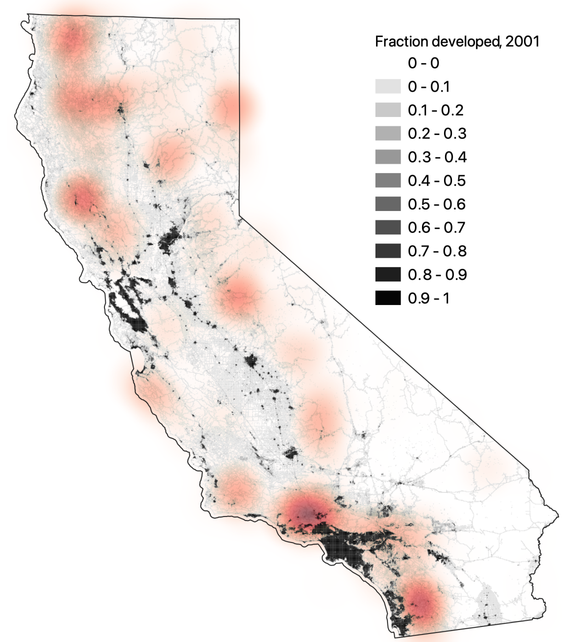
B Appendix Figures

Figure B.1: Wildfires further away from urban areas grew larger

A. Number of housing units, 2000

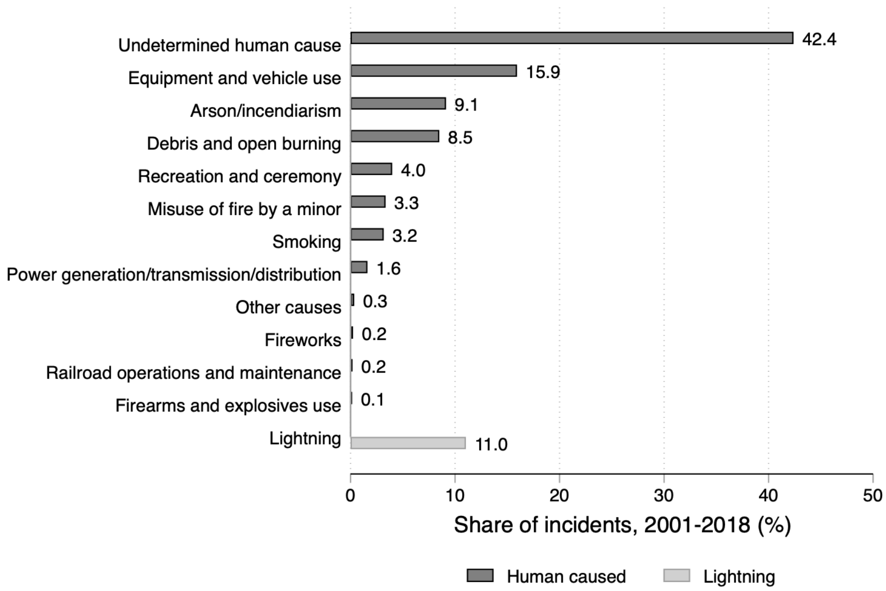


B. Share of pixel developed (2001)



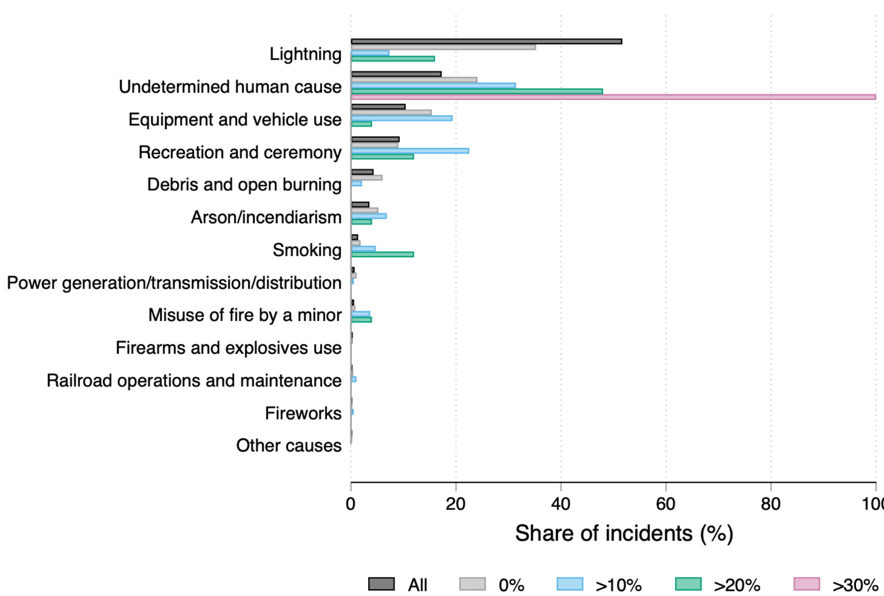
Notes: This figure replicates Figure 1, with incidents weighed by their size. Panel A overlays a heatmap of fire incidents from 2001 to 2018 onto number of housing units in 2000. Panel B maps fire incidents onto developed landcover in 2001. Darker colors indicate greater density of incidents. Section 3 and Appendix A describe the data in more detail.

Figure B.2: Cause of fire incidents in California, 2001-2018



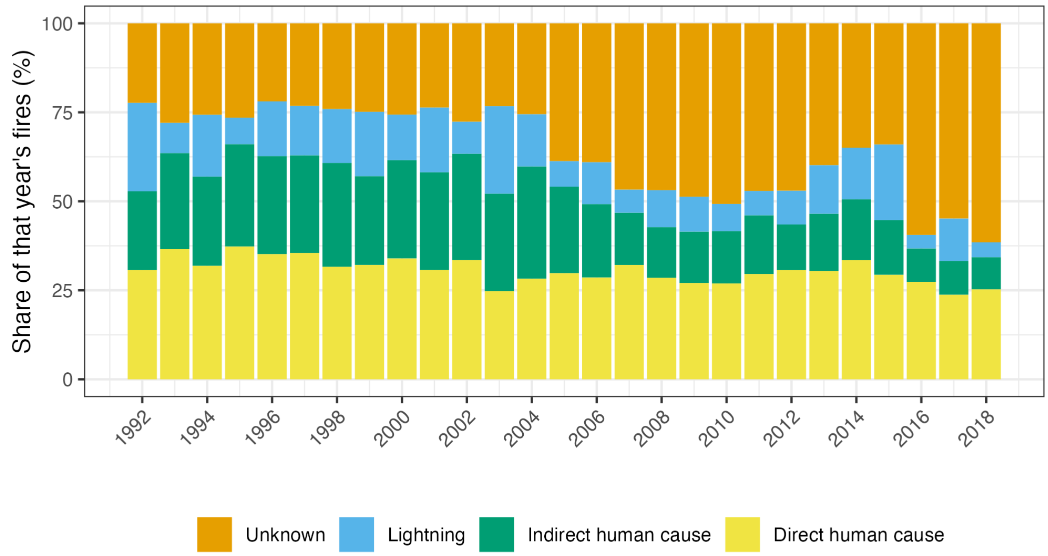
Notes: This figure shows the share of wildfire incidents reported in California between 2001 and 2018, by cause. Section 3 and Appendix A describe the data in more detail. Appendix Figure B.13 shows the distribution of wildfire incidents by size.

Figure B.3: Cause of fire incidents in undeveloped areas, given nearby development, 2001-2018



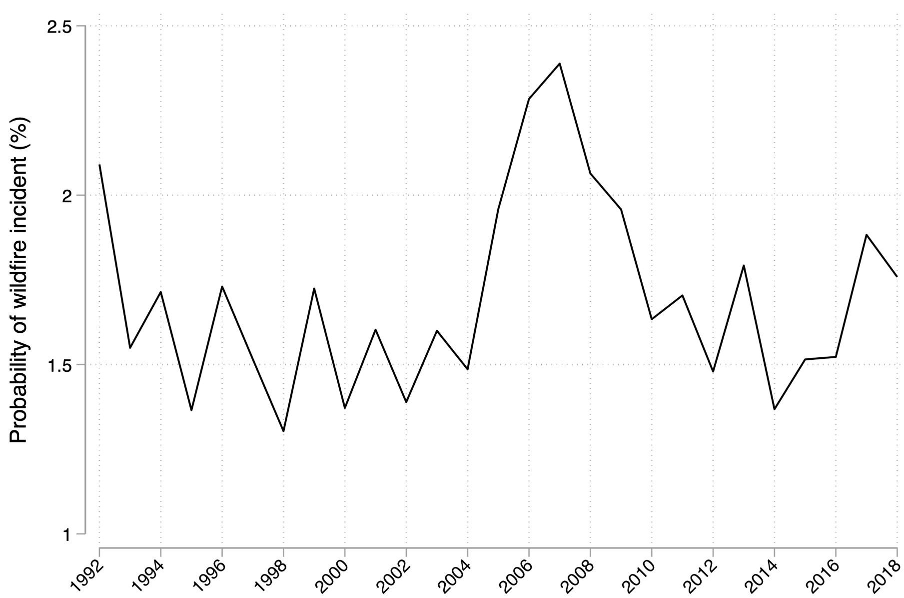
Notes: This figure describes the causes of fire incidents that started in completely undeveloped areas of California. "All" denotes all incidents in undeveloped areas. The other categories restrict to undeveloped areas with $p\%$ developed within 1 kilometer, where $p \in \{0, > 10, > 20, > 30\}$. Section 3 and Appendix A describe the data in more detail, including the construction of the rate of land development.

Figure B.4: Cause of fire incidents in California by year, 2001-2018



Notes: This figure shows the number of fire incidents reported in California between 2001 and 2018, distinguished by cause. Panel A groups incidents into four cause groups: direct human cause, indirect human cause, lightning/natural cause and unknown. Panel B breaks these broad groups down into individual causes. Cause groups are based on definitions from the National Wildfire Coordinating Group (NWCG). Section 3 and Appendix A describe the data in more detail.

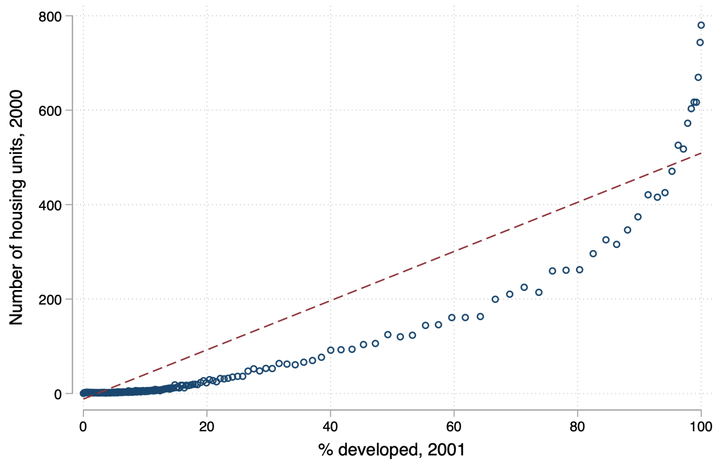
Figure B.5: Empirical wildfire probability by year, 1992-2018



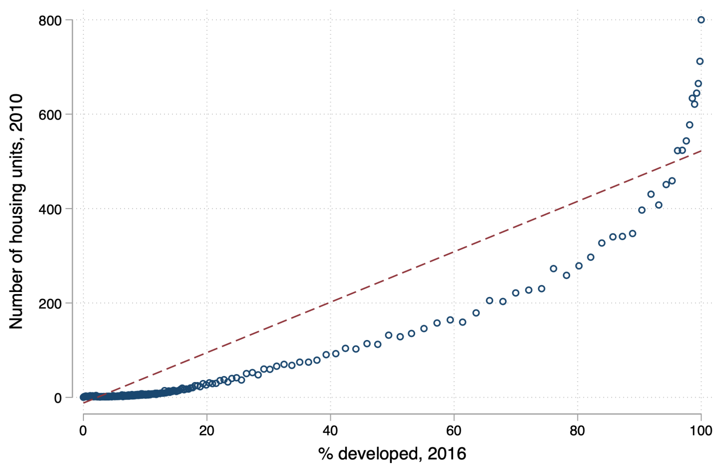
Notes: This figure shows the number of fire incidents reported in California between 1992 and 2018, by year. Section 3 and Appendix A describe the data in more detail.

Figure B.6: Correlation between development and housing units

A. Share of pixel developed (2001) vs. housing units (2000)



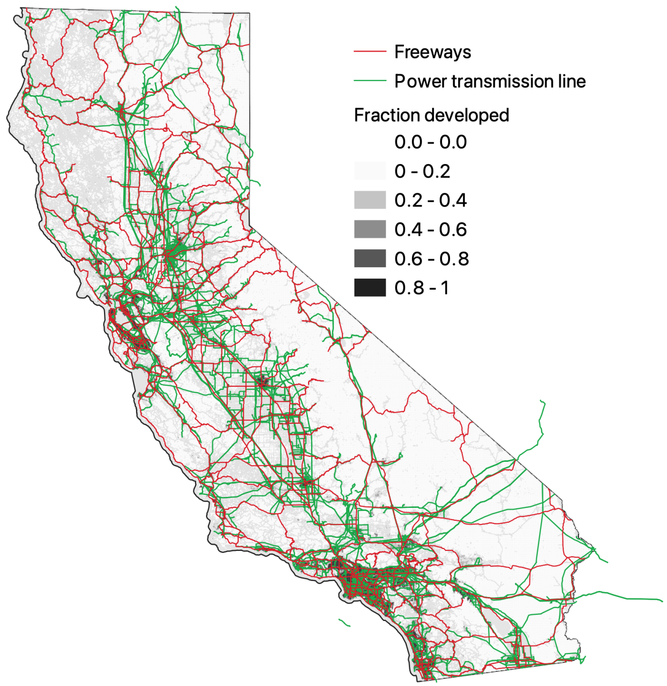
B. Share of pixel developed (2016) vs. housing units (2010)



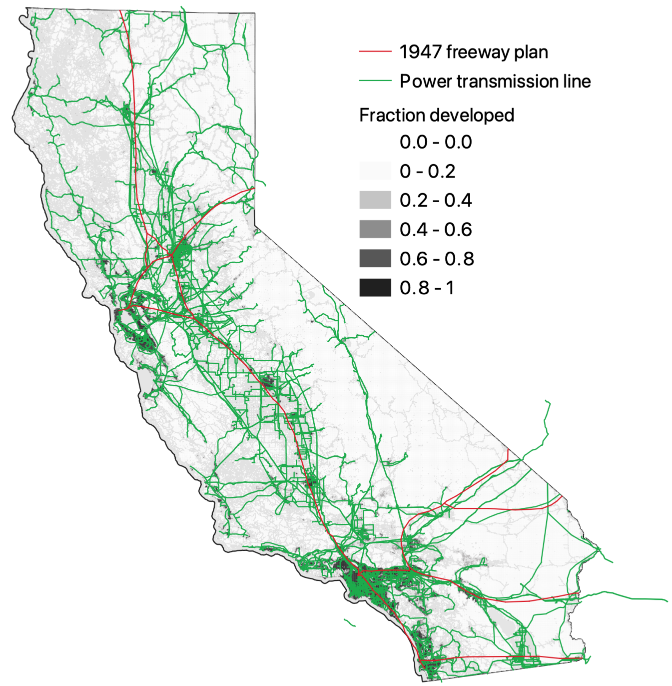
Notes: This figure plots the cross-sectional relationship between this paper's measures of development: share of land developed and number of housing units. Panel A plots land development data for 2001 and housing data for 2000, while panel B compares data for 2016 and 2010 respectively. Section 3 and Appendix A describe the data in more detail.

Figure B.7: Spatial relationship between transmission lines, highways and developed land

A. 2021 freeway map



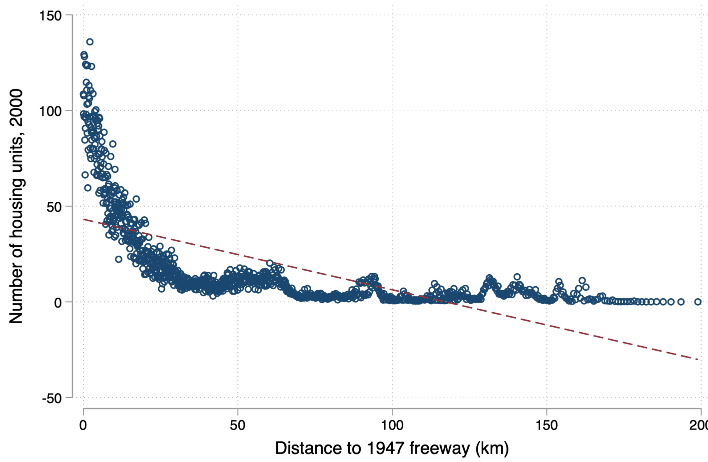
B. 1947 freeway plan



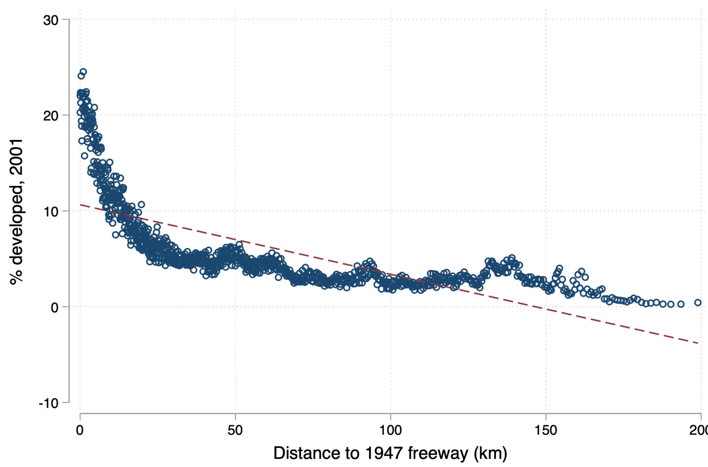
Notes: This figure maps California's power transmission lines and freeways against the rate of land development. Panel A maps 2021 state and federal freeways from Caltrans (2021). Panel B maps the 1947 freeway plan from Brinkman and Lin (2022). Section 3 and Appendix A describe the data in more detail.

Figure B.8: Correlation between development and distance to 1947 freeway plan

A. Number of housing units, 2000



B. Share of pixel developed, 2001

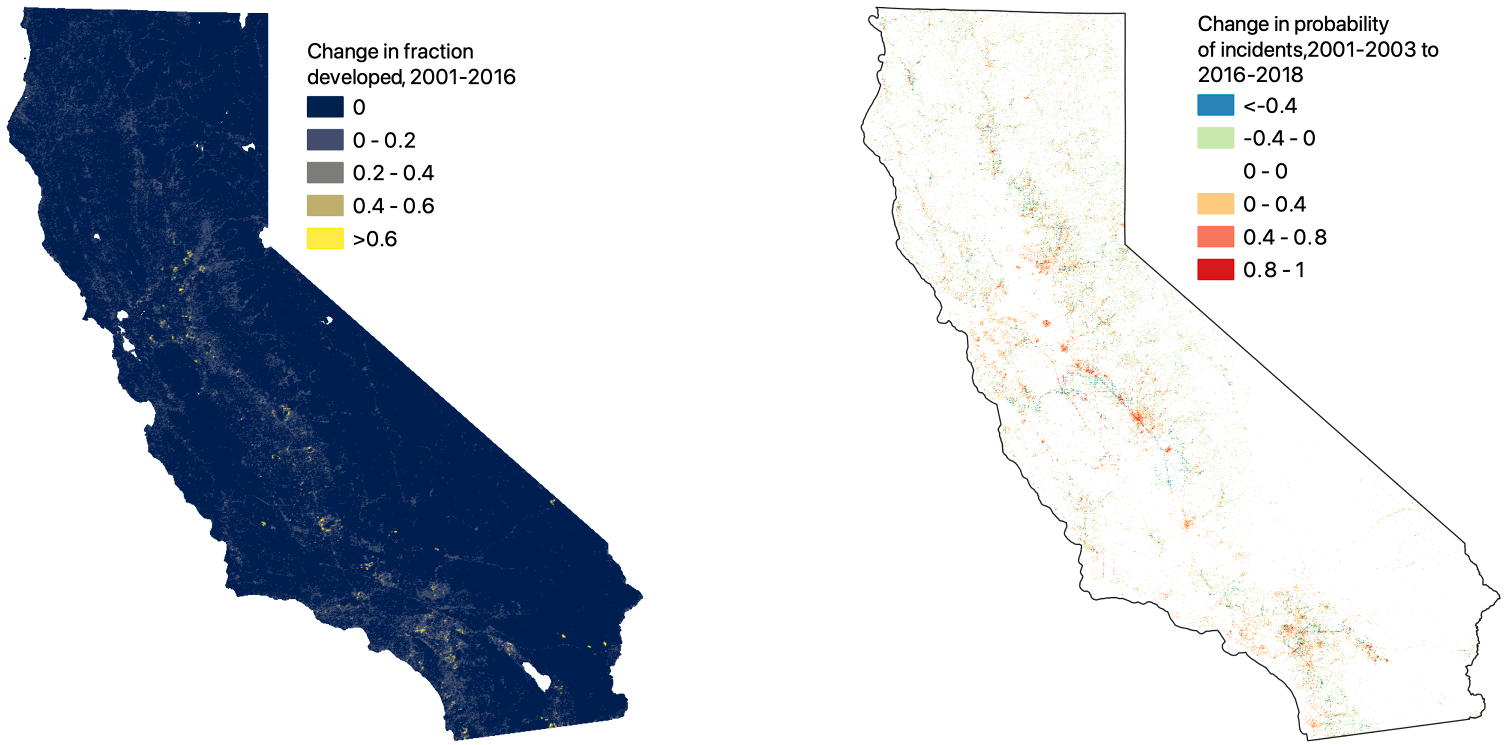


Notes: This figure plots the first stage relationship between distance to the 1947 freeway plan (measured in kilometers), and number of housing units in 2000 (panel A) and share of pixel developed in 2001 (panel B). Section 3 and Appendix A describe the data in more detail.

Figure B.9: Correlation between change in landcover and fire probability

A. Change in share developed, 2001-2016

B. Change in probability of incidents, 2001-2018

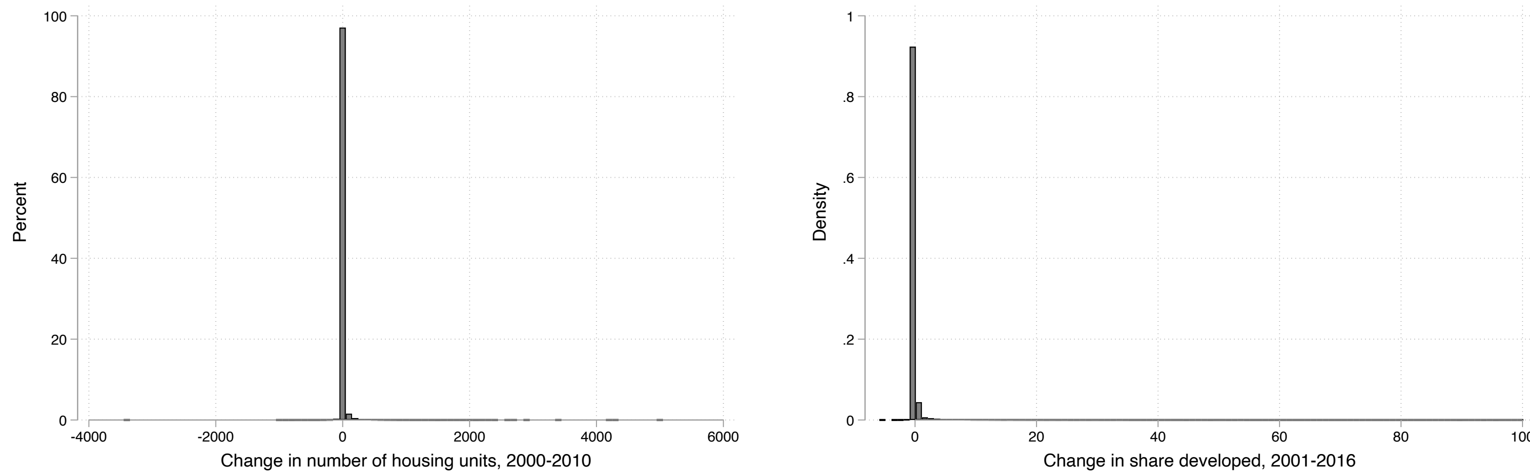


Notes: Panel A maps the change in fraction of pixel land developed for each pixel in my 1km-by-1km grid of California. Panel B maps the change in incident probability from 2001-2003 to 2016-2018 each pixel in my 1km-by-1km grid of California. Appendix Figure B.10 plots the distribution of changes in land development between 2001 and 2016. Section 3 and Appendix A describe the data in more detail.

Figure B.10: Change in development

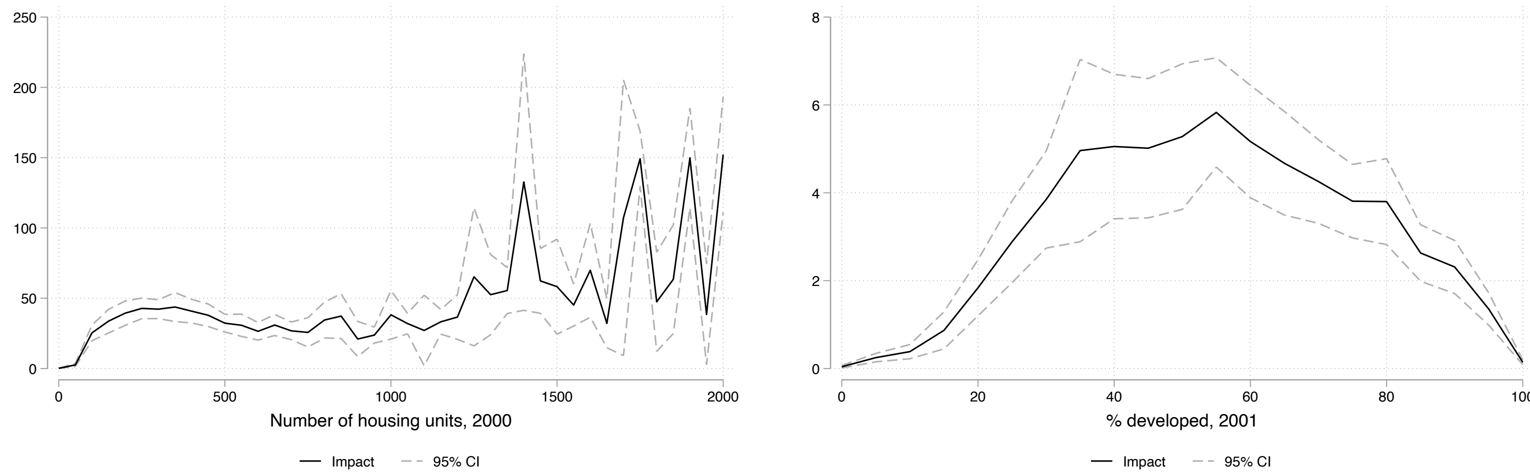
A. Distribution of change in development

(i) Number of housing units, 2000-2010 (ii) Share of pixel developed, 2001-2016



B. Change in development given initial conditions

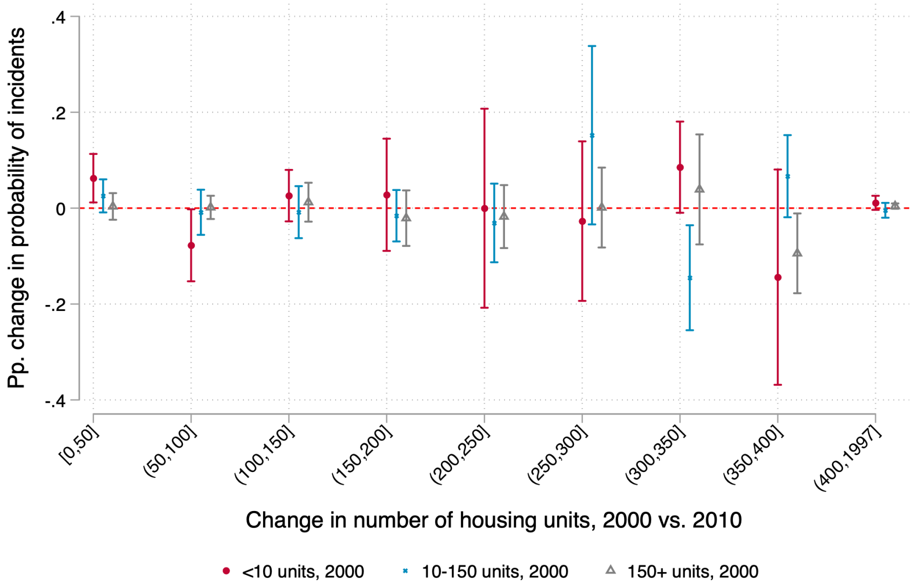
(i) Number of housing units, 2000-2010 (ii) Share of pixel developed, 2001-2016 (pp)



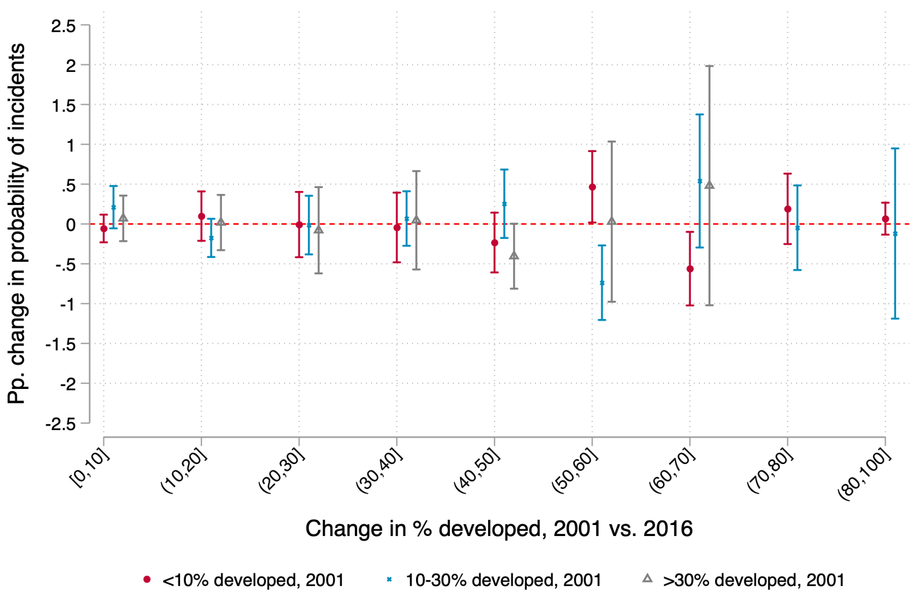
Notes: This figure describes change in development on a step function of development bins in the beginning of my analysis period. Panel A shows a histogram of change in number of housing units (i) and share of pixel developed (ii). Change in housing units is the difference between the number of housing units in 2010, and the number of housing units in 2000. Change in land development units is the difference between the share of pixel developed in 2016 and 2001. Panel B calculates the average change in development across initial development levels. Section 3 and Appendix A describe the data in more detail.

Figure B.11: Impact of change in development on change in wildfire probability, 2001-2005 vs. 2014-2018

A. Change in number of housing units

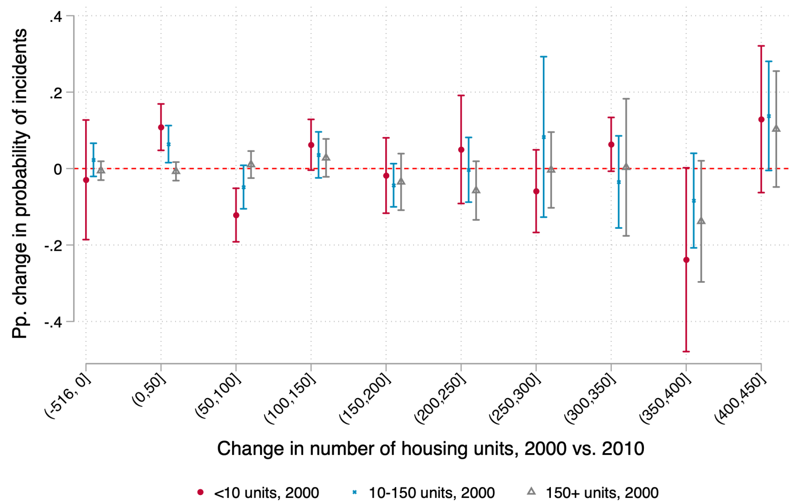


B. Change in share of pixel developed



Notes: This figure replicates Figure 4 for the change in incident probability between 2001-2005 and 2014-2018. Panel A measures change in development as the change in the number of housing units between 2000 and 2010. Panel B replicates Panel A using the difference between share of pixel developed in 2016, and share developed in 2001, to measure change in development. Panel A limits the sample to pixels with non-negative change in housing units and bins increases in housing density greater than 650 units (.11% of pixels) to handle outliers and for readability. Appendix Figure B.10 summarizes the average change in development, given initial levels of land development and number of housing units. Section 3 and Appendix A describe the data in more detail.

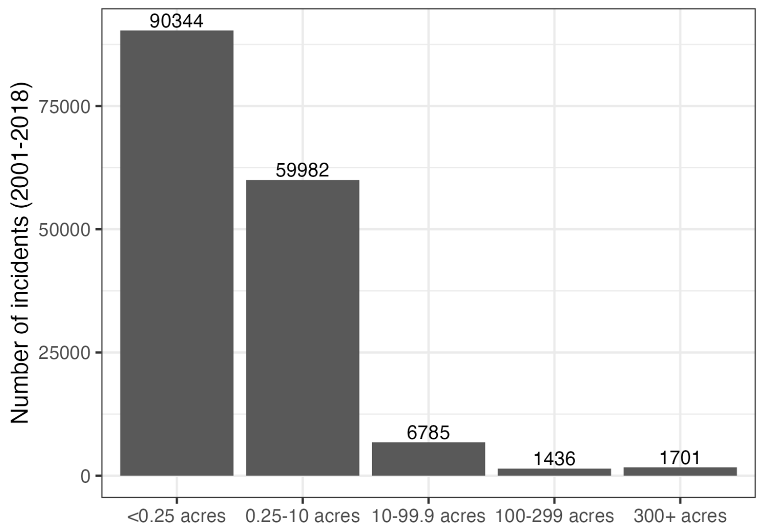
Figure B.12: Long difference estimates, including decreases in number of housing uits



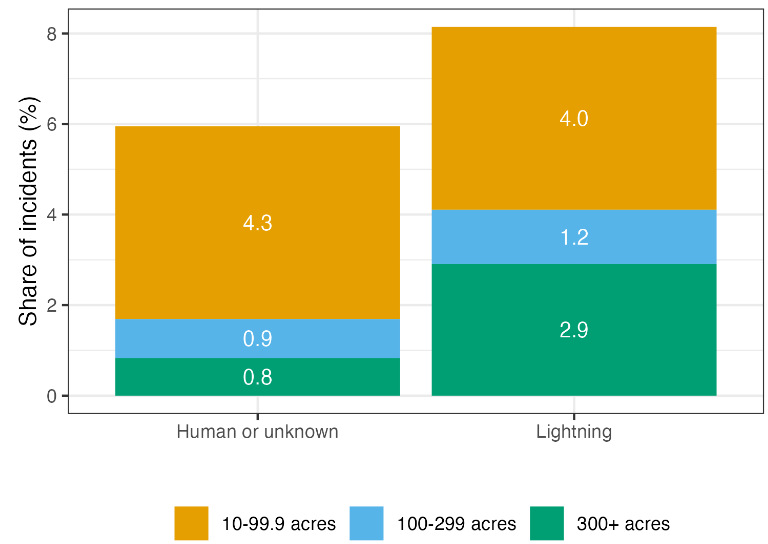
Notes: This figure replicates panel A of Figure 4 but includes pixels where the number of housing units decreased between 2001 and 2010. This figure regresses change in fire probability over time on a linear spline of change in pixel development interacted with indicators for initial level of development. The change in probability of ignition is measured using 2001-2003 and 2016-2018. Changes in development are changes in the number of housing units between 2000 and 2010. I top code increases over 650 units (.01% of pixels) for readability. Decreases range between -50 and 0. Small decreases in the number of housing units may be due to mismeasurement. Since I construct my dataset using geospatial tools, it is possible that underlying 2000 and 2010 housing rasters are slightly offset, or become slightly offset when I reproject the data. Thus, 100 units that were mapped to pixel i in 2000 might be mapped to pixel j in 2010. Pixels that lost housing units were mainly located in Los Angeles County, Orange County and San Diego County. However, these were the counties that experienced housing growth in my data during this time period, which suggests some degree of mismeasurement. In the paper, I restrict the analysis to pixels where the number of housing units did not decrease. Section 3 and Appendix A describe the data in more detail.

Figure B.13: Average fire size

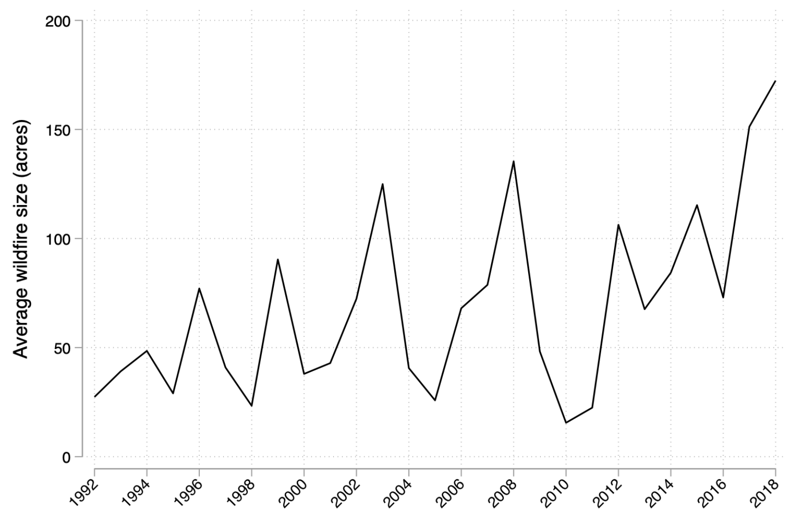
A. Number of incidents by size



B. Share of incidents by cause and size



C. Average wildfire size by year

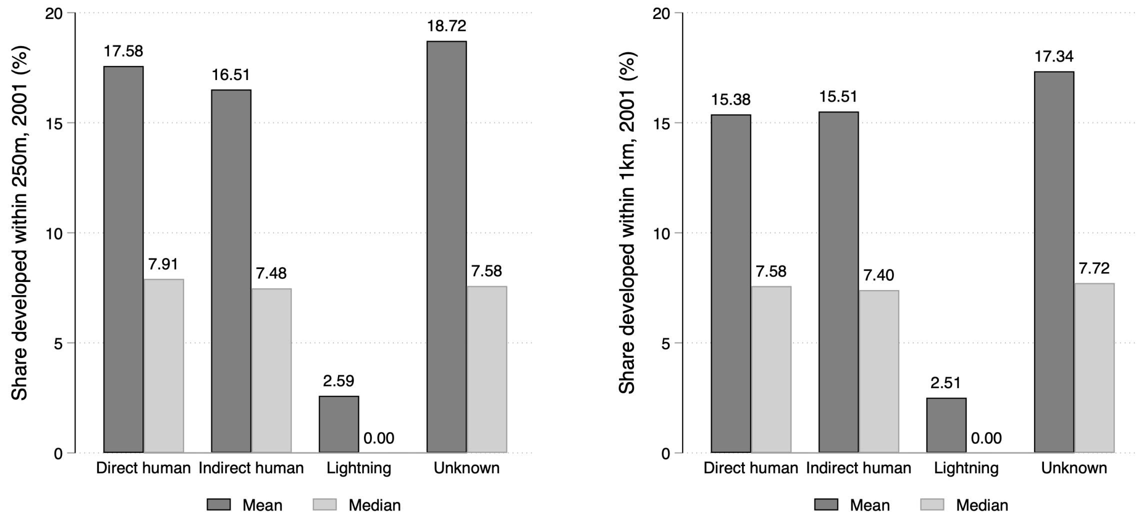


Notes: This figure describes the size of wildfire incidents that were registered in California between 2001 and 2018 (Short, 2022). Section 3 and Appendix A describe the data in more detail.

Figure B.14: Development near fire origination spots

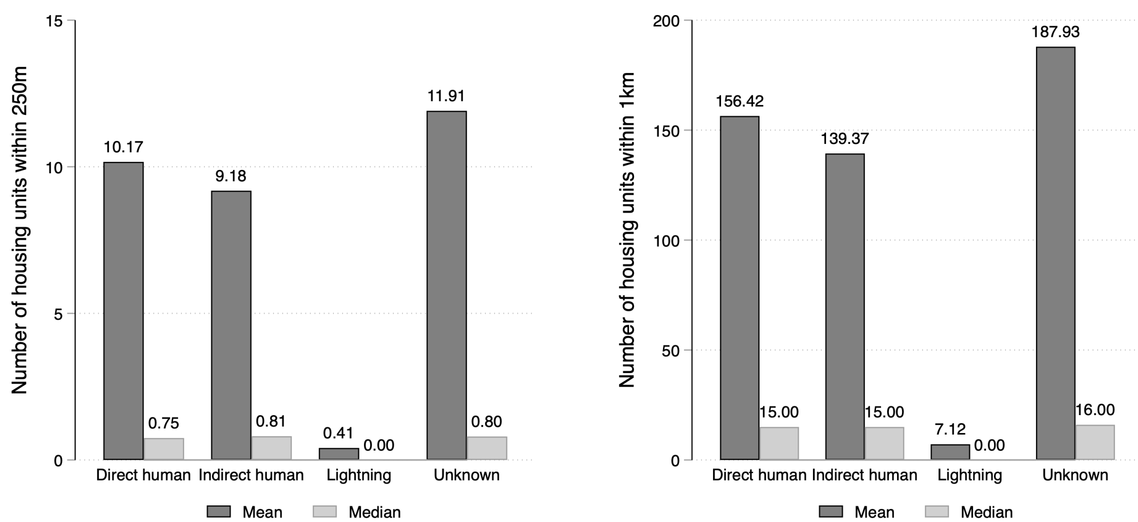
A. Share of land developed developed within

250m 1km



B. Number of housing units within

250m 1km

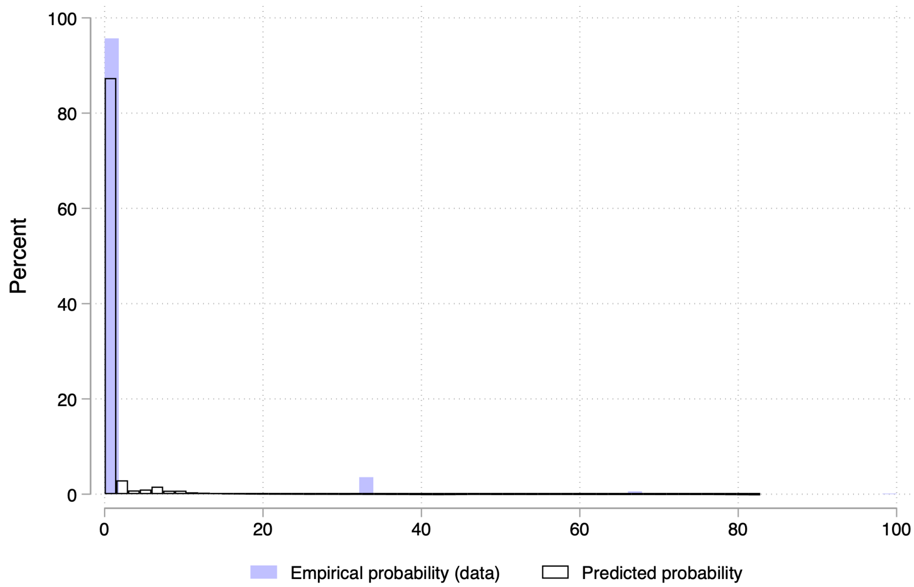


Notes: This figure calculates average land development and total number of housing units within 250m and 1km of the point of origin for wildfire incidents between 2001 and 2003. Land development is measured in 2001, and the number of housing units is measured in 2000. Section 3 and Appendix A describe the data sources in more detail.

Figure B.15: Suppression costs per fire and per acre

Notes: This figure plots suppression costs per fire (panel A) and per square kilometer (panel B) using numbers from CalFIRE for the entire state, inflated to 2019 US dollars using the Consumer Price Index. Section 3 and Appendix A describe the data sources in more detail.

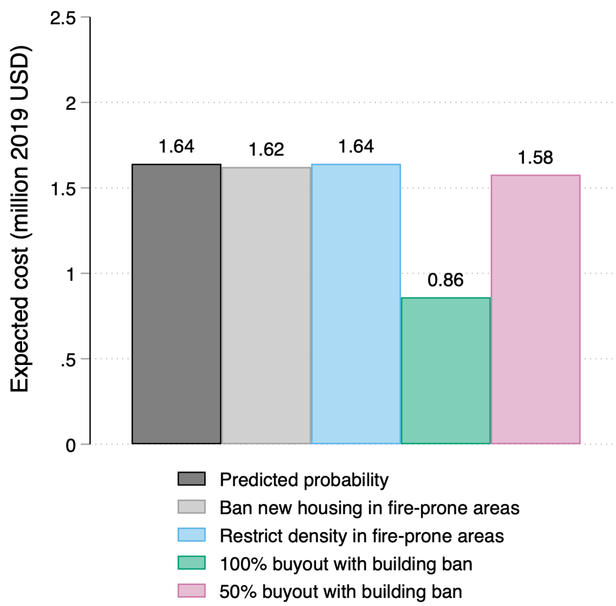
Figure B.16: Empirical and predicted wildfire probabilities, 2016-2018



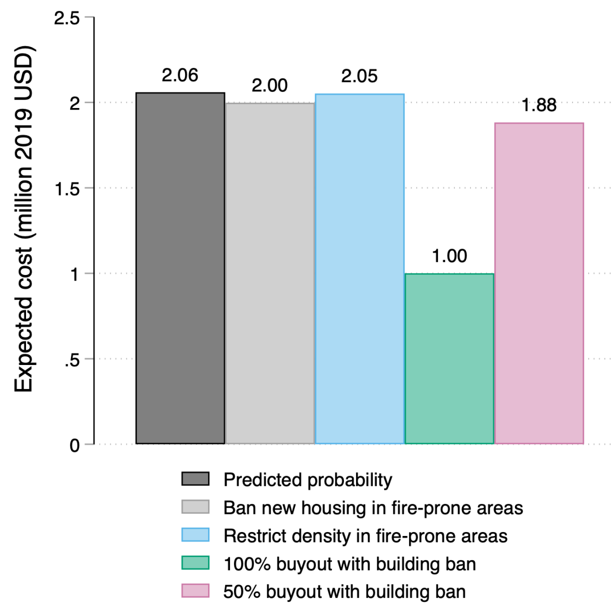
Notes: This figure plots the distribution of empirical wildfire probability (blue) and the distribution of fitted values of wildfire probability (black/white). I estimate the predicted probability of wildfire in each pixel using the IV results from Table 1, panel A. I then add the no-development predicted change in wildfire probability to the 2001-2003 estimated probability. Finally, I use the estimates from Figure 4 to predict wildfire probability given observed changes in housing supply. The correlation between the empirical and predicted probabilities in 2016-2018 is .2224.

Figure B.17: Difference in suppression spending, assuming median fire size

A. Fixed suppression costs

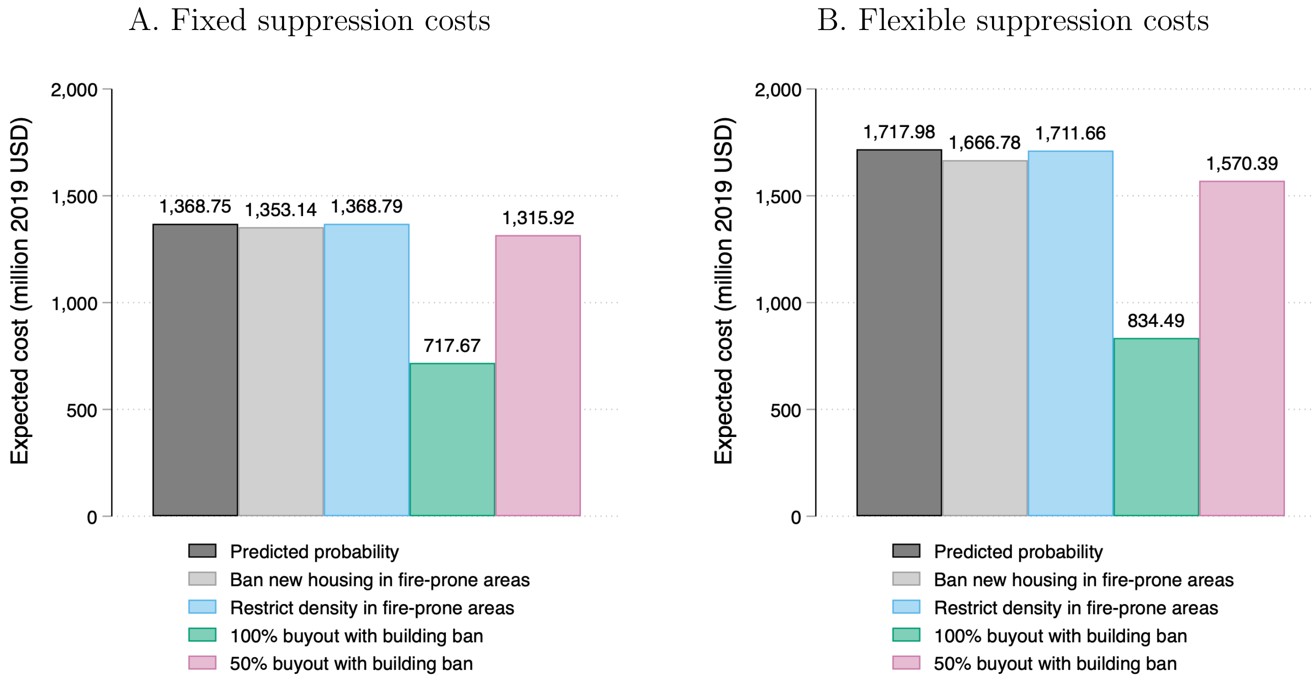


B. Flexible suppression costs



Notes: This figure replicates panels B and C of Figure 5, assuming that the average wildfire is the size of the median wildfire between 2001 and 2018. Section 6 describes the counterfactuals in greater detail. Counterfactuals that hold suppression efforts fixed assume that the average incident burns .0008 km^2, which was the median fire size between 2001 and 2018. Counterfactuals that allow suppression costs to adjust with changes in housing supply, according to the coefficient in Table 3A, column 2. I assume suppression costs are USD$220,000 per square kilometer (Mietkiewicz et al., 2020). Expected costs are the sum of suppression cost per kilometer times average fire size, weighted by the wildfire probability calculated in Figure 5A.

Figure B.18: Difference in suppression spending, assuming higher suppression cost per km^2



Notes: This figure replicates panels B and C of Figure 5, assuming that cost to suppress each square kilometer of wildfire is \$442,565. Section 6 describes the counterfactuals in greater detail. Counterfactuals that hold suppression efforts fixed assume that the average incident burns .17 km^2, which was the average fire size between 2001 and 2018. Counterfactuals that allow suppression costs to adjust with changes in housing supply, according to the coefficient in Table 3A, column 2. Expected costs are the sum of suppression cost per kilometer times average fire size, weighted by the wildfire probability calculated in Figure 5A.

C Appendix Tables

Table C.1: Summary statistics

	Mean	SD	P50	P90
% pixel developed, 2001	6.25	17.54	0.00	11.85
% Low/medium intensity	5.69	15.38	0.00	11.59
% High intensity	0.56	4.29	0.00	0.00
% pixel wildland, 2001	77.66	35.69	97.23	100.00
% forest	23.70	35.09	0.00	88.98
% shrub or grass	52.84	40.23	57.67	100.00
% wetlands	1.12	6.69	0.00	0.64
% pixel wildland if developed	65.09	39.73	89.57	98.84
% pixel crop/pasture/hay, 2001	10.16	27.67	0.00	57.40
% that became more developed, 2001-2016	11.20	31.53	0.00	100.00
Pp. change in development if >0, 2001-2016	3.46	9.64	0.27	8.82
Housing units, 2000	20.89	126.86	0.00	8.00
Change in no. units, 2000-2010	2.60	24.74	0.00	1.27
Average yearly fire probability (%)	1.74	5.26	0.00	5.56
Lightning-caused	0.23	1.21	0.00	0.00
Human-caused	1.52	5.14	0.00	5.56
Average yearly fire probability, 2001-2003 (%)	1.53	8.16	0.00	0.00
Number of fire incidents, 2001-2018	0.39	1.76	0.00	1.00
% pixel with slope > 15%	39.17	39.08	28.00	95.00
Distance to 1947 highway plan (km)	60.44	47.49	48.52	133.74
Distance to electricity transmission cable (km)	9.69	13.90	4.85	24.18
% pixel in State or National Park	10.76	30.99	0.00	100.00
Total property value ($ M)	6.99	34.36	0.47	5.40
N	407,963			

Notes: This table summarizes characteristics of the pixels in the data. Section 3 describes the data in greater detail.

Table C.2: Table 1 with linear $g(z)$ and $h(\cdot)$

Panel A. Number of housing units

	No. units	$100 \cdot$ P(wildfire)	
	(1)	(2) OLS	(3) IV
Dist. 1947 highway (km)	-0.328		
	(0.120)		
No. housing units		0.000181	0.0367
		(0.00101)	(0.0140)
Observations	407,960	407,960	407,960
Dep. var. mean	20.887	1.529	1.529
F-stat	7.480	0.032	6.879
Kleibergen-Paap Wald F-stat			7.480
Cragg-Donald Wald F-stat			1,841.550

Panel B. Share of pixel developed

	% developed	$100 \cdot$ P(wildfire)	
	(1)	(2) OLS	(3) IV
Dist. 1947 highway (km)	-0.0756		
	(0.0213)		
% developed		0.0282	0.160
		(0.0123)	(0.0464)
Observations	407,960	407,960	407,960
Dep. var. mean	6.252	1.529	1.529
F-stat	12.569	5.255	11.825
Kleibergen-Paap Wald F-stat			12.569
Cragg-Donald Wald F-stat			5,194.770

Notes: This table replicates Table 1 with linear $g(z)$ and $h(d)$ instead of splines. This table estimates the cross-sectional impact of increasing number of housing units in 2000 and development in 2001 on the probability of wildfires. Standard errors are conservatively clustered at the county level and estimated via two-step GMM. Appendix Table C.1 shows summary statistics for the analysis sample. Appendix Tables C.3, C.4 and C.5 characterize the complier pixels.

Table C.3: Characterization of compliers by hillside slope, distance to powerlines and distance to highway

Panel A. Number of housing units		% pixel steep		Log(dist. powerline)		Log(dist. freeway)	
	(1) Full sample	(2) Below 50%	(3) Above 50%	(4) Below 1.58	(5) Above 1.58	(6) Below 3.26	(7) Above 3.26
Log dist. 1947 highway	-11.50	-13.65	-2.937	-12.93	-0.175	-12.40	-1.028
	(3.335)	(4.289)	(1.185)	(3.627)	(0.105)	(3.809)	(0.655)
Ratio		1.187	0.255	1.124	0.015	1.078	0.089
Observations	407,960	204,903	203,057	203,980	203,980	203,980	203,979

Panel B. Share of pixel developed		% pixel steep		Log(dist. powerline)		Log(dist. freeway)	
	(1) Full sample	(2) Below 50%	(3) Above 50%	(4) Below 1.58	(5) Above 1.58	(6) Below 3.26	(7) Above 3.26
Log dist. 1947 highway	-2.280	-2.446	-0.219	-2.301	-0.0423	-2.168	-0.593
	(0.413)	(0.469)	(0.159)	(0.460)	(0.0896)	(0.478)	(0.338)
Ratio		1.073	0.096	1.009	0.019	0.951	0.260
Observations	407,960	239,500	168,460	203,980	203,980	203,980	203,979

Notes: This table estimates the first stage equation 5 for different subsamples, using linear $g(z)$. Column 1 uses all pixels in my dataset, replicating column 1 in Appendix Table C.2. Column 2 restricts the sample to pixels where less than 50 percent of the area has hillside slope above 15 degrees, while column 3 restricts the sample to pixels where over 50 percent of the pixel is considered too steep for development (Saiz, 2010). Columns 4 and 5 respectively compare the first stage for pixels with log distance to the nearest powerline below and above the median log distance of 1.58 log points. Columns 6 and 7 respectively compare the first stage for pixels with log distance to the nearest state of federal highway below and above the median log distance of 3.26 log points. I include the ratio of each subgroup's first stage to the first stage for the full sample in the spirit of Angrist, Imbens and Rubin (1996). Standard errors are conservatively clustered at the county level and estimated via two-step GMM. All regressions include county fixed effect to control for underlying differences in wildfire probability.

Table C.4: Characterization of compliers by vegetation

Panel A. Number of housing units		% in state or national park		% barren/desert		% crop	
	(1) Full sample	(2) Below 50%	(3) Above 50%	(4) Below 50%	(5) Above 50%'	(6) Below 50%	(7) Above 50%
Log dist. 1947 highway	-11.50	-11.73	-0.248	-12.04	-0.0503	-15.50	-1.112
	(3.335)	(3.352)	(0.304)	(3.434)	(0.153)	(4.870)	(0.336)
Ratio		1.019	0.022	1.047	0.004	1.347	0.097
Observations	407,960	369,579	38,378	391,148	16,809	365,454	42,504

Panel B. Share of pixel developed		% in state or national park		% barren/desert		% crop	
	(1) Full sample	(2) Below 50%	(3) Above 50%	(4) Below 50%	(5) Above 50%'	(6) Below 50%	(7) Above 50%
Log dist. 1947 highway	-2.280	-2.304	-0.117	-2.382	-0.00487	-2.892	-0.536
	(0.413)	(0.421)	(0.112)	(0.420)	(0.119)	(0.643)	(0.118)
Ratio		1.011	0.051	1.045	0.002	1.269	0.235
Observations	407,960	369,579	38,378	391,148	16,809	365,454	42,504

Notes: This table continues Appendix Table C.3, and estimates the first stage equation 5 for different subsamples, using linear $g(z)$. Column 1 uses all pixels in my dataset, replicating column 1 in Appendix Table C.2. Column 2 restricts the sample to pixels where less than 50 percent of the area is in a state or national park, while column 3 restricts the sample to pixels where over 50 percent of the pixel is contained in a state or national park. Columns 4 and 5 respectively compare the first stage for pixels where below or above 50 percent of the land cover is barren. Columns 6 and 7 replicate columns 4 and 5 based on crop, pasture and hay's share of land cover. I include the ratio of each subgroup's first stage to the first stage for the full sample, in the spirit of Angrist, Imbens and Rubin (1996). Standard errors are conservatively clustered at the county level and estimated via two-step GMM. All regressions include county fixed effect to control for underlying differences in wildfire probability.

Table C.5: Characterization of compliers by wildland share of land cover

Panel A. Number of housing units	(1) Full sample	(2) 0-25%	(3) 25-50%	(4) 50-75%	(5) 75-100%
Log dist. 1947 highway	-11.50	-16.41	-5.212	-2.507	-0.373
	(3.335)	(3.840)	(1.341)	(0.990)	(0.139)
Ratio		1.427	0.453	0.218	0.032
Observations	407,960	67,255	15,463	19,928	305,309

Panel B. Share of pixel developed	(1) Full sample	(2) 0-25%	(3) 25-50%	(4) 50-75%	(5) 75-100%
Log dist. 1947 highway	-2.280	-3.089	-2.088	-1.078	-0.156
	(0.413)	(0.760)	(0.527)	(0.457)	(0.0772)
Ratio		1.355	0.916	0.473	0.068
Observations	407,960	67,255	15,463	19,928	305,309

Notes: This table continues Appendix Table C.3, and estimates the first stage equation 5 for for pixels that were in 2001 were less than 25 percent, 35-50 percent, 50-75 percent or 75-100 percent wildland, using linear $g(z)$. I include the ratio of each subgroup's first stage to the first stage for the full sample in the spirit of Angrist, Imbens and Rubin (1996). Standard errors are conservatively clustered at the county level and estimated via two-step GMM. All regressions include county fixed effect to control for underlying differences in wildfire probability.

Table C.6: Replication of Table 1 without county fixed effects

Panel A. Number of housing units	100 · P(wildfire)	
	(1) OLS	(2) IV
No. housing units (0,300]	0.00950	0.153
	(0.00406)	(0.116)
No. housing units (300, .)	-0.0142	-0.284
	(0.00555)	(0.230)
Observations	407,960	407,960
$Prob(d < 1)$	0.918	0.918
F-stat	5.732	1.064
Kleibergen-Paap Wald F-stat		1.773
Cragg-Donald Wald F-stat		51.151

Panel B. Share of pixel developed	100 · P(wildfire)	
	(1) OLS	(2) IV
% developed, (0, 50]	0.141	0.433
	(0.0184)	(0.297)
% developed, (50,100]	-0.152	-0.559
	(0.0160)	(0.483)
Observations	407,960	407,960
$Prob(d = 0)$	0.756	0.756
F-stat	45.140	3.022
Kleibergen-Paap Wald F-stat		1.115
Cragg-Donald Wald F-stat		339.584

Notes: This table estimates the cross-sectional impact of increasing number of housing units in 2000 and development in 2001 on the probability of wildfires. The coefficients represent the change in slope from the preceding interval. Standard errors are conservatively clustered at the county level and estimated via two-step GMM. Table 1 controls for for county fixed effects. Appendix Table C.1 shows summary statistics for the analysis sample. Appendix Tables C.3, C.4 and C.5 characterize the complier pixels.

Table C.7: Replication of Table 1 with control for hillside slope and log distance to powerlines

Panel A. Number of housing units

	100 · P(wildfire)					
	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV
No. housing units (0,300]	0.00817	0.288	0.00738	0.294	0.00666	0.376
	(0.00429)	(0.173)	(0.00410)	(0.191)	(0.00411)	(0.333)
No. housing units (300, .)	-0.0128	-0.551	-0.0118	-0.556	-0.0111	-0.716
	(0.00561)	(0.332)	(0.00541)	(0.358)	(0.00540)	(0.630)
% slope > 15%	-0.788	0.643			-0.606	0.794
	(0.299)	(0.909)			(0.279)	(1.343)
Log dist. powerline			-0.0543	0.0659	-0.0499	0.0897
			(0.00860)	(0.0798)	(0.00775)	(0.126)
Observations	407,960	407,960	407,960	407,960	407,960	407,960
$Prob(d < 1)$	0.918	0.918	0.918	0.918	0.918	0.918
F-stat	9.589	1.150	22.693	2.442	19.475	1.096
Kleibergen-Paap Wald F-stat		0.947		0.950		0.536
Cragg-Donald Wald F-stat		17.576		14.516		8.926

Panel B. Share of pixel developed

	100 · P(wildfire)					
	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV
% developed, (0, 50]	0.134	0.948	0.129	0.643	0.127	1.303
	(0.0178)	(0.498)	(0.0175)	(0.278)	(0.0170)	(0.993)
% developed, (50,100]	-0.139	-1.254	-0.138	-0.774	-0.137	-1.694
	(0.0143)	(0.731)	(0.0144)	(0.397)	(0.0143)	(1.376)
% slope > 15%	-0.335	2.096			-0.237	2.826
	(0.247)	(1.292)			(0.237)	(2.399)
Log dist. powerline			-0.0349	0.0477	-0.0335	0.112
			(0.00645)	(0.0388)	(0.00597)	(0.111)
Observations	407,960	407,960	407,960	407,960	407,960	407,960
$Prob(d = 0)$	0.756	0.756	0.756	0.756	0.756	0.756
F-stat	36.653	1.998	31.447	9.067	27.084	1.654
Kleibergen-Paap Wald F-stat		1.077		1.809		0.590
Cragg-Donald Wald F-stat		93.886		173.520		46.148

Notes: This table estimates the cross-sectional impact of increasing number of housing units in 2000 and development in 2001 on the probability of wildfires. "% slope > 15%" denotes the share of the pixel with hillside slope above 15%, which Saiz (2010) finds to be severely constrained for residential construction. "Log dist. powerline" is the logarithm of distance to the nearest power transmission line, measured in kilometers. The coefficients represent the change in slope from the preceding interval. Standard errors are conservatively clustered at the county level and estimated via two-step GMM. Appendix Table C.1 shows summary statistics for the analysis sample. Appendix Tables C.3, C.4 and C.5 characterize the complier pixels.

Table C.8: Cross-section impact of development within 1km on fire probability in undeveloped pixels

Panel A. Number of housing units

	100 · P(wildfire)			
	(1) OLS	(2) IV	(3) OLS	(4) IV
No. housing units within 1km (0,300]	0.0125	1.031	0.0128	1.226
	(0.00463)	(0.689)	(0.00447)	(0.600)
No. housing units within 1km (300, .)	-0.0181	-3.785	-0.0184	-4.436
	(0.00606)	(3.688)	(0.00586)	(2.910)
% wildland			-0.336	-2.740
			(0.166)	(1.849)
% wildland within 1km			0.00404	0.0356
			(0.00269)	(0.0357)
Observations	303,120	303,120	303,120	303,120
$Prob(d = 0)$	0.765	0.765	0.765	0.765
F-stat	4.930	1.718	5.476	1.260
Kleibergen-Paap Wald F-stat		0.483		0.721
Cragg-Donald Wald F-stat		0.721		0.994

Panel B. Share developed

	100 · P(wildfire)			
	(1) OLS	(2) IV	(3) OLS	(4) IV
% developed within 1km, (0, 50]	0.152	1.079	0.154	0.653
	(0.0313)	(0.662)	(0.0301)	(0.622)
% developed within 1km, (50,100]	-2.136	7147.2	-2.125	-2148.6
	(0.497)	(36676.9)	(0.493)	(2238.1)
% wildland			0.345	-1.105
			(0.189)	(1.021)
% wildland within 1km			-0.00182	0.000944
			(0.00239)	(0.0306)
Observations	224,686	224,686	224,686	224,686
$Prob(d = 0)$	0.576	0.576	0.576	0.576
F-stat	12.333	3.924	9.202	2.964
Kleibergen-Paap Wald F-stat		0.022		0.725
Cragg-Donald Wald F-stat		0.002		0.116

Notes: This table estimates the cross-sectional impact of increasing development within 1 kilometer of undeveloped pixels on own-probability of wildfires. Panel A restricts the sample to pixels zero percent developed in 2001, and Panel B restricts to pixels with 0 housing units in 2000. I then estimate equation (6) using development in pixels within 1 kilometer instead of own-pixel development share. The coefficients represent the change in slope from the preceding interval. Standard errors are conservatively clustered at the county level and estimated via two-step GMM. All regressions include county fixed effect to control for underlying differences in wildfire probability. Appendix Table C.1 shows summary statistics for the analysis sample.

Table C.9: Impact of development on lightning-caused log wildfire size

Panel A. Number of housing units	(1)	(2)	(3)	(4)
Housing units within 250m	-0.0160 (0.00320)			
Housing units within 500m		-0.00234 (0.000610)		
Housing units within 1km			-0.000888 (0.000257)	
Housing units within 2.5km				-0.000234 (0.0000702)
Constant	-6.806 (0.00000116)	-6.806 (0.00000117)	-6.806 (0.000000481)	-6.806 (0.00000335)
Observations	4,063	4,063	4,063	4,063
R-squared	0.106	0.106	0.106	0.106
Indep. var. mean	8.608	40.071	133.215	731.541
Fire size (sq-km)	0.002	0.002	0.002	0.002

Panel B. Share of pixel developed	(1)	(2)	(3)	(4)
% developed within 250m	-0.00899 (0.00240)			
% developed within 500m		-0.0123 (0.00262)		
% developed within 1km			-0.0155 (0.00379)	
% developed within 2.5km				-0.0169 (0.00445)
Constant	-6.806 (0.000000350)	-6.806 (0.00000438)	-6.806 (0.00000364)	-6.806 (0.00000378)
Observations	4,063	4,063	4,063	4,063
R-squared	0.106	0.107	0.107	0.106
Indep. var. mean	14.930	14.121	13.643	11.578
Fire size (sq-km)	0.002	0.002	0.002	0.002

Notes: This table replicates Table 3 for lightning-caused fires. Each observation is a fire incident between 2001 and 2003 in California. All independent variables have been demeaned for more straightforward interpretation. Regressions control for county and year fixed effects.