Environmental Externalities of Urban Growth: Evidence from the California Wildfires

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Abstract

Does residential development at the urban edge increase the probability and cost of wildfires in California? I use geospatial data to show that the probability of wildfires increases as previously undeveloped land becomes developed, but decreases at higher levels of development until the probability of wildfire reaches zero. At very low housing densities, an additional housing unit increases the probability of wildfire by .01-.02 percentage points over a baseline probability of 1.53. This translates into an increase the probability of wildfire from 1.53 to 4.34 percent when housing density increases from 30 to 130 units per km^2. I then calculate costs for a set of wildfires under counterfactual patterns of housing development. Due to the non-monotonic relationship between development and wildfire probability, restricting some but not all development in fire-prone areas can have a larger impact on wildfire probability. I discuss how land use restrictions in safe areas relate to higher expected costs of wildfires.

1 Introduction

Between 1990 and 2020, 16 million houses were built in previously undeveloped land in the United States (Radeloff et al., 2023). Regulations limiting the construction of new housing near city centers, together with population growth, have driven new development to the urban edge (Burchfield et al., 2006). The cost of wildfires also increased increased during that period. In 2021, total wildfire suppression costs were nearly \$4.2 billion dollars, 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).

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In this paper, I study the relationship between urban growth and wildfire costs in California. Wildfire costs may increase as urban areas expand into previously undeveloped land for a number of reasons. First, the probability of wildfire incidents may increase with housing or land development. All else equal, greater 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 be taking into account the marginal contribution of new development to wildfire probability, which would lead 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, but does not regulate new construction in fire-prone areas.

I estimate the impact of development on the probability of wildfires using two empirical approaches. The first uses cross-sectional data and an instrumental variable to identify the exogenous impact of the development on wildfire probability. I also use a long difference specification to measure the effect of changes in development on changes in wildfire probability. I find that the probability of wildfires increases as previously undeveloped land becomes developed, but decreases at higher levels of development until the probability of wildfire reaches zero. At very low housing densities, an additional housing unit increases the probability of wildfire by .01-.02 percentage points over a baseline probability of 1.53. This translates into an increase the probability of wildfire from 1.53 to 4.34 percent when housing density increases from 30 to 130 units per km^2.

I then show that, as land at the urban edge becomes developed, 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 greater when homes locate near fire-prone wildland (Haas, Calkin and Thompson, 2013; Barrett, 2018; Xu, Webb and Evans, 2019; Schoennagel et al., 2017). I show that fires are allowed to 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 .0018 square kilometers (.43 acres).

Lastly, I calculate counterfactual wildfire probabilities and suppression cost under four alternative residential development patterns. I find that restricting or removing *some* housing units away from the urban edge may not impact the probability of wildfires, and may actually 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 0.

I use data from California to estimate the impact of developing the urban edge on wildfire costs. 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 on average more affordable than those in lower risk areas (Ellis, 2020),

[1] The Insurance Information Institute calculated potential reconstruction values in 2020, using the cost of materials and labor needed to rebuild after total destruction of the residential structure. Calculations factor in pricing variations due to different geographic locations.

all else equal. Importantly, many of the state's jurisdictions 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; Molloy, 2020).

This paper contributes to three main literatures. First, it contributes to the nascent literature on housing supply and adaptation to climate change. Closest to this paper is work by Ospital (2022), which estimates that land use regulations explained 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 a lower bounds at low levels of development, but upper bounds at higher levels. Hsiao (2023) finds evidence that policies intended to help with climate adaptation can lock households into high risk areas. To the best of my knowledge, this is the first paper to estimate the effects of climate "agnostic" land use policies on the risk of wildfires, or any natural disaster, occuring.

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). 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 larger carbon footprint due to automobile emissions (Kahn, 2000; Glaeser and Kahn, 2010; Kahn and Walsh, 2015). As urban areas expand, there may be environmental externalities for which economists have not yet accounted, particularly where forests, grassland, shrubs and wetland (the "wildland") are being developed. Most of the land developed between 2001 and 2019 in the United States was previously wildland.[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). My paper complements simulation-based work on the impact of urban growth in 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.

Furthermore, this paper builds on the literature on the economics of environmental disasters, and in particular the nascent literature in economics studying wildfires. Liao and Kousky (2022) estimates the impact of wildfires on municipal budgets in California. There is also a nascent literature on wildfire mitigation and suppression (Baylis and Boomhower, 2023, 2021; Kunreuther et al., 2022), and on the costs of wildfires in mortgage markets (Biswas, Hossain and Zink, 2023) and in terms of exposure to pollution (Burke et al., 2021, 2022). My paper is the first one, to the best of my knowledge, to estimate the excess probability and cost of wildfires due to urban growth induced by housing supply restrictions. My results indicate

[2]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).

that it is not possible to provide wildfire forecasts without making assumptions about how developers and households respond to and intensify (or mitigate) wildfire risk.

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 the probability of wildfires. Section 5 estimates the impact of urban growth on wildfire-related costs. Section 6 estimates counterfactual expected wildfire costs under alternative development patterns. 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, 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. Two inputs are necessary for a wildfire to start and spread: 1) fuel and 2) a source of heat. As a simplification, I can write the fire production function as

$$\mathbf{1}\left[Ignition\right] = a(Fuel, Spark) \tag{1}$$

where $\mathbf{1}\left[Ignition\right]$ is an indicator function that equals 1 when a fire ignites, $a(\cdot)$ is a function such that $Fuel$ and $Spark$ are complements, and $a(0, Spark) = 0$ and $a(Fuel, 0) \approx 0$. 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 ignition, fire size B can be written as

$$B = b(Fuel, Wind, Hilliness, Suppression) \tag{2}$$

where $b(\cdot)$ is a function increasing in fuel, wind and hilliness, and decreasing in suppression, with $\lim_{Fuel \to 0} b(\cdot) = 0$ (Narayanaraj and Wimberly, 2012; Finney et al., 2015; Alexandre et al., 2016; Paulo M. Fernandes et al., 2016; Abatzoglou et al., 2018). Additionally, 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 enough, but 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 both *spark* and *fuel*, potentially affecting ignition and growth propensity of wildfires. Wildfire experts have increasingly documented the impact of human influence on the rate of fire activity and the length of the fire season (Balch et al., 2017; Syphard et al., 2017). In California, 89 percent of all wildfire incidents between 2001 and 2018 were human-caused, either 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) (Figure 2A).[3] Though larger incidents were more likely to be caused by lightning than smaller incidents, naturally-sparked wildfires only make up 30 percent of wildfires larger than 300 acres (Figure 2B). The spatial distribution of incidents also suggests a relationship between wildfire ignition and land development (Figure 1). Incidents in California were geographically concentrated: most incidents took place near urban areas in Southern California and in along the central valleys and mountainous regions. Moreover, wildfires in undeveloped areas *near* exurban or suburban settlements were also more likely to have human causes (Appendix Figure B.2).[4] Thus, holding the availability of fuel constant, increasing human settlement at the urban fringe will increase the probability of ignition.

The aggregate impact of urban growth on wildfire ignitions is ambiguous because 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 constructed in 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 on wildfire costs of increasing human presence in fire-prone areas. Total wildfire costs can be written as C, a function of wildfire probability, and direct and indirect fire costs. Let N denote the number of "potential" fires. Assuming the cost of incidents that never materialize are 0, we have:

$$C = \int_{n \in [0,N]} \mathbf{1}\left[Incident_n\right] \cdot C_n(B_n) dn \tag{3}$$

where $\mathbf{1}\left[Ignition\right]$ is the indicator function that equals 1 if fire opportunity n ignites, and

[3] 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.

[4] 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. Incidents that are small or are suppressed without firefighter help are less likely to be registered. The data may therefore be undercounting incidents in remote areas, and those that are 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. It is therefore likely that fires in both developed and undeveloped areas are underreported.

the cost of incident n $C_n(B_n)$ depends on the size of the fire B. 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).

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

$$\begin{aligned} \mathbf{1}\left[Ignition\right](d) &= a(Fuel(d), Spark(d)) \\ B(d) &= b(Fuel(d), Wind, Hilliness, Suppression(d)) \end{aligned}$$

and assuming that $N \to \infty$ such that $\partial N/\partial d \approx 0$, then the impact of increasing human settlement in fire-prone areas can be written as

$$\frac{\partial C}{\partial d} = \int_{n\in[0,N]} \left(\frac{\partial \mathbf{1}\left[Incident_n\right]}{\partial d} \cdot C_n(B_n) + \mathbf{1}\left[Incident_n\right] \cdot \frac{\partial C_n(B_n)}{\partial dev} \right) dn \tag{4}$$

Equation (4) shows that development can impact wildfire costs in two ways. The first mechanism is "ignition", which captures the change in 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. This paper focuses on the externalities imposed by development, so I focus on the ignition channel and limit the exposure channel to suppression costs.[5] Section 4 estimates the impact of sprawl on ignition, and Section 5 estimates the impact on incident size and suppression efforts. In the next section, I describe my dataset and the variables I construct to estimate the components of equation (4).

3 Data

The foundation of my data is a grid of pixels measuring 1km-by-1km, which cover all of California, excluding islands. I use pixels as my unit of measurement so that I can 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. For instance, municipal boundaries may shift with land development, such that I cannot directly compare growing jurisdictions over time, particularly if new development takes place in unincorporated areas. Similarly, the coverage 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 aforementioned concerns, while keeping the area of my units of analysis small enough to capture the effect of development on wildfire risk.

I then map several geospatial datasets to this grid to measure the following variables:

[5] Baylis and Boomhower (2023) show that households in fire-prone areas do not incur the full cost of fire suppression. Endogenous suppression costs and effort constitute a fiscal externality, so I include suppression in my estimates.

Development: I employ two measures of development. "Land development" measures 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 is assigned to a land cover category, based on vegetation and surface imperviousness. For each pixel in my grid, 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 are undevelopable as they correspond to the Pacific Ocean, large bays (e.g. the San Francisco Bay) or large lakes (e.g. Lake Tahoe). My second measure of development, "housing development1", captures 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). Appendix Figure B.6 shows the correlation between these two measures of development in 2001/2000, and 2016/2010.

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. Using this data, I calculate empirical wildfire probability in each pixel i as the mean of wildfire realizations over some period.[6]

I also use 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 include 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 2). However, 42.4 percent of incidents have the cause listed as "Missing data/not specified/undetermined" (Figure 2). Wildland fire investigators use factors such as burn patterns and first responder testimony to determine wildfire cause.[7] Distinguishing naturally 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 harder to tell apart, especially when there's limited evidence on the source of the ignition. Appendix Figure B.3 shows that the share of incidents with unknown cause increases over

[6] I define empirical wildfire probability as follows:

$$P(incident)_i = \frac{1}{T' - T} \sum_{t \in [T,T']} \mathbf{1}(incident_{i,t})$$

where t indicates the year and $[T, T']$ corresponds to the time period between T and T'.

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

time, suggesting that the investigation has not concluded or has not reached a determination. I replicate my results without fires of unknown cause as robustness.

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 to 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 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 California Energy Commission (2023). I use digital elevation data from 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). Lastly, I map my grid onto state and national park maps and measure the share of each pixel that is in a park and thus is undevelopable (National Park Service, 2019; California State Parks, 2022).

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 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 between 2001 and 2016, when 11.2 percent of pixels became more developed.[8] Housing density increased by 5.2 units between 2000 and 2010, over a baseline mean of 36 housing units per squared-kilometer in 2000. Appendix Table C.1 also shows that there is wide variation in determinants of land development. 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 one quarter of their land is undevelopable due to hillside steepness (Saiz, 2010). Some pixels are also entirely contained in national or state parks, thus being legally undevelopable. Finally, pixels vary in their access to transportation and electricity infrastructure. The average pixel is nearly 10 kilometers away from the nearest electric line, and 60 kilometers from the 1947 freeway plan.

4 Impact of urban growth on ignition

The probability of wildfire incidents varies cross-sectionally with land development and housing density. Figure 3 regresses average ignition probability between 2001 and 2003 on a spline of levels of land development (panel A) and housing density (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. The average probability in undeveloped pixels was .76 percent, while the average probability

[8] Appendix Figure B.12 plots a histogram of changes in pixel area that is developed. Negative changes mainly reflect the conversion of recreational open land into agricultural land.

for pixels 15-20 percent developed was 5.13 percent. Pixels with 200 to 400 housing units, i.e. housing density of 200-400 units per squared-kilometer, had almost five times the wildfire probability of pixels with no housing units (4.16-4.72 vs. .84 percent). This initial increase in ignition probability suggests that human settlement may play a role in increasing wildfire risk. However, the relationship between development and ignition probabilities is non-monotonic. At higher levels of development (over 80 percent developed), increases in development can actually decrease 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 ignition risk is highest in moderately developed areas. The probability of fires was approximately 5.5 percent for pixels 30 to 55 percent developed, and 4.2 where housing density was between 100 and 400 houses per pixel.

OLS estimates in the cross-section may not estimate the causal impact of changes in land or housing 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, then those areas will be more developed, all else equal. In this case, OLS will understate the relationship between on ignition. Moreover, if underlying wildfire risk is increasing over time in some areas, then these areas might experience relatively slower development than areas with similar wildfire probabilities at baseline, whose risk did not change. In this case, cross-sectional OLS estimates that pool ignition 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. The second is long differences, similar to Taylor and Druckenmiller (2022). I show results for both of my measures of development, "land development" and "housing development", in each of the empirical strategies.

4.1 Cross-sectional instrumental variable approach

I estimate the exogenous effect of land 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:

$$d_i = \alpha_1 + \alpha_2 \text{log distance 1947 plan}_i + \zeta_i \tag{5}$$

$$P(ignition)_i = \beta_1 + \beta_2 d_i + X_i' \beta_3 + \eta_i + \varepsilon_i \tag{6}$$

where $P(ignition)_i$ 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 in wildland in 2001). The identifying assumption is that distance to the proposed network is orthogonal to changes in wildfire risk during my window of analysis, i.e. log distance 1947 plan$_i \perp \eta_i$. The 1947 plans were designed to facilitate trade and national defense, and 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. One could argue that distance to the 1947 highway plan correlates with other factors that impact wildfire risk. For instance, if power lines were laid next to planned highways, instead of actual ones, then my instrument would capture distance to one potential cause of wildfires. Appendix Figure B.5 maps the location of powerlines 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.

Table 1 estimates equations (5) and (6). Panel A shows the results when d is measured as share developed in 2001, while panel B uses the number of housing units in 2000. Increasing a pixel's distance to the 1947 freeway plan by 1 percent decreases development by 2.280 percentage points (panel A, column 1) and decreases the number of housing units in the pixel by 20 houses, approximately two thirds of the average pixel's density (panel B, column 1). Appendix Figure B.7 plots the first stage relationships, and shows that pixels further away from the 1947 plan were less developed in 2001 and had fewer housing units in 2000.

The rest of Table 1 estimates equation (6) using OLS and the IV approach. Panel A, column 3 estimates that a 1 percentage point increase in share of pixel developed increases the probability of wildfire by .108 percentage points, or (.108/1.53≈)7 percent at low levels of development.[9] Note that the OLS and IV estimates are similar in magnitude, with the IV estimates being larger, suggesting that OLS indeed provides a lower-bound estimate. Columns 4 and 5 replicate columns 2 and 3, but control for the share of the pixel covered in wildland in 2001. These regressions allow for heterogeneity in the impact of developing land near wildland vegetation, versus converting cropland or barren land. At low levels of development and high share wildland (6.25% and 77.7%), a 1 percentage point increase in share of pixel developed increases the probability of wildfire by .218 percentage points, or (.218/1.53≈)14.2 percent. Panel B shows similar patterns to Panel A, but at smaller magnitudes. One additional house increases wildfire probability by 1.21-2.17 basis points, or .8-1.4 percent at a housing density of 36 houses per kilometer squared.

Appendix Figure B.10 replicates columns 2 and 3 by incident cause, and shows that human-caused fires become more likely. Equipment use, undetermined human cause, arson/incendiarism, debris and open burning, and smoking are the causes most responsive to cross-sectional increases in development. Lightning-caused fires, on the other hand, become less likely as low-development pixels become more developed. 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 relate differently to urbanization. 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 fire 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 zero percent developed pixels, and Panel B restricts to pixels with 0 housing units. I then estimate equation (6) using development in pixels within 1 kilometer instead of own-pixel development share. Column 3 in Panel A estimates that a 1 percentage point increase in development within

[9]The average pixel was 6.25 percent develped in 2001, as shown in Appendix Table C.1.

1 kilometer of wildland increases the probability of wildfire by .811 percentage points, which constitutes a doubling of the ignition probability. The results in Panel B are qualitatively similar, but larger: one additional house within 1 kilometer of wildland increases wildfire probability by 8.38-13.2 basis points, or 9.4-14.7 percent at an average housing density of 2 houses per kilometer squared. Appendix Table C.3 replicates Table 2, but uses a 5km ring around each undeveloped pixel instead of a 1km ring. These results indicate that development not only increases the probability of wildfires where land is being developed, but also increases the likelihood of ignition in nearby wildland.

4.2 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 flexible 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. Appendix Figure B.11 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.12 describes the distribution of changes in development for both of my metrics (share of pixel developed and number of housing units).

Table 3 shows the regression coefficients for the long difference regressions where $f(\cdot)$ is a linear function of d_i. Column 1 estimates the impact of increasing share of pixel developed, while columns 2 and 3 respectively estimate the impact of additional housing units in level and log. The constants in columns 1 and 2 indicates that wildfire probability did not change over time for the average pixel. However, an increase in share of pixel developed of 1 percentage point between 2001 and 2016 leads to an increase in incident probability of .109 percentage points ($.109/1.53 \approx 7.1$ percent). The estimates in column 3 for the impact of change in housing are qualitatively similar, though smaller. Adding one housing unit between 2000 and 2010 increases the probability of an incident in that pixel by 1.01 basis points ($.01/1.53 \approx .7$ percent). Columns 2 and 4 replicate columns 1 and 3, but allow non-monotonicity in the impacts of development on wildfire probability over time. The coefficient on the quadratic term is negative for both measures of development. These estimates support the model of ignitions described in Section 2, which posits that ignitions increase in development while there is fuel available, but then decreases as concrete replaces grasses, or as housing becomes denser.

Figure 4 further illustrates the non-monotonic relationship between development and the probability of wildfire ignition. Panel A shows the non-parametric relationship between the change in developed land cover between 2001 and 2016, and the change in empirical wildfire probability between 2001-2003 and 2016-2018. The probability of wildfires increases as land becomes more developed, but only initially. Moreover, the relationship between land development and wildfire probability is non-monotonic. A 5 percentage point increase in development corresponds to an average increase in wildfire probability of 1.8 percentage points, while a 20 percentage point increase corresponds to an increase of 5.8 percentage points. The average yearly empirical probability in 2001-2003 was 1.53 percent, the average pixel was 6.25 percent developed in 2001 and the average change in development was 3.46 percentage points (Appendix Table C.1). Thus, at the mean the elasticity of wildfire development with respect to land development is $(1.8/1.5)/(3.46/6.25) \approx 2.17$. These findings are also robust to comparing the empirical probability in 2001-2005 to 2014-2018, but estimates are noisier due to the 2005-2008 period having a much more active fire season (Appendix Figure B.4).

Panel B replicates Panel A using housing units as a proxy for development. I bin decreases in number of housing units below 500, and increases above 1500 to handle outliers and for readability. As in Panel A, we see that the initial increase in number of housing units increases the probability of wildfires. Once the number of new units reaches approximately 500 units per square kilometer, the impact of additional housing on ignition becomes statistically indistinguishable from zero. The data also suggest that small *decreases* in the number of housing units are also associated with increases in wildfire probability. The pattern in Panel B makes sense in light of Figure 3B and Appendix Figure B.12, absent mismeasurement of housing density.[10] In pixels with housing density around 300/km^2, adding or removing 10 units still keeps the pixel in the highest probability region, and may in fact move the pixel along the housing-ignition curve. This figure illustrates the fundamental issue surrounding land use policy in fire-prone areas: some, low-density development increases wildfire risk more than high-density development.

Finally, I show that increases in neighbors' development over time increases own-pixel wildfire probability (Appendix Table C.6). Column 1 restricts the sample to pixels whose share developed stayed constant between 2001 and 2016. There are two types of pixels in my sample that don't become more developed: those that were already completely developed, and those that were inframarginal with regards to new construction. Column 1 estimates the average long difference impact of neighboring development for those two sets of pixels, and indicates that i) on average, wildfire probability *decreased* over time in these pixels, but ii) a 1 percentage point change in development within 1 kilometer increases wildfire probability between 2001-2003 and 2016-2018 by .416 percentage points. Column 2 further restricts the sample to pixels that were undeveloped in 2001 *and* did not become more developed by 2016. For those pixels, the probability of fire did not change with development over time. The average change in neighbor's development was close to 0, suggesting that this subset of pixels is selected and likely inframarginal for new development. Columns 3 and 4 replicate columns 1 and 2, but for new housing units. These regressions again indicate that the set of pixels that did not gain housing units and whose neighbors gained housing units is highly selected (the average pixel with 0 housing units only had 1.2 houses within 1 kilometer).

[10]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.

5 Impact of urban growth 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 suppression wildfires, though there are also costs associated with 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.14 describes the size of wildfire incidents in my data. Panel A shows that the vast majority of fires in California between 2001 and 2018 were smaller than .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 over time. Average incident size fluctuated year-on-year, but trended up.

I estimate the impact of development on suppression costs as follows. First, I calculate average development, total housing units and total land value within some distance of each incident's point of origin. Table 4 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 .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 units 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 translates into a decrease in fire size from .446 acres to .445 acres.

One could argue that fires are mechanically smaller near areas of greater land value–in other words, fires started by humans can be put out by humans. Appendix Table C.8 suggests that this relationship is not mechanical, since lightning-caused fires are also smaller when nearby property value is higher. Moreover, the cost of suppression per fire has increased faster than the probability of incidents, suggesting that humans who start fires are unable to suppress them costlessly (The Pew Charitable Trusts, 2022).[11]

I can nevertheless place bounds on the change in suppression costs. The cost of suppressing one kilometer squared of fire in areas with at least some very low density housing ranges from \$220 thousand to 360 thousand dollars (Mietkiewicz et al., 2020), though suppression costs per kilometer squared averaged \$427,730 between 2001 and 2003, and reached \$1.060 million in 2009. If development is 1 percentage point higher within 250 meters of the average wildfire incident, then the .85 percent reduction in fire size would cost \$375-\$730 dollars per incident.

[11] Appendix Figure B.17 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.

Similarly, an additional housing unit within 250 meters implies fires that are .436 percent smaller, which corresponds to additional \$384-\$747 suppression dollars per fire. Notably, higher density corresponds to smaller impacts on fire size, which is in line with findings in Baylis and Boomhower (2023).

6 Discussion

Consider equation (3), reproduced below, which captures the aggregate cost of wildfires as a function of ignition probability, fire size and damages:

$$C = \int_{n \in [0,N]} \mathbf{1}\left[Incident_n\right] \cdot C_n(B_n) dn$$

In this section, I calculate counterfactual wildfire costs in 2001-2003 and 2016-2018, given alternative housing development patterns and results from Sections 4 and Section 5. I then discuss how relaxing housing supply restrictions closer to the urban core relates to the different land development patterns, and therefore to the counterfactual wildfire costs.

I consider four counterfactual housing distributions. *Counterfactual 1* reallocates 100 percent of housing units in pixels with housing density below 1200/km^2 to pixels with density above 2500/km^2. Recall that the probability of ignition in the latter set of pixels is statistically indistinguishable from zero (Figure 3B). *Counterfactual 2* reallocates 50 percent of housing units in pixels with housing density below 1200/km^2 to pixels with density above 2500/km^2. *Counterfactual 3* and *Counterfactual 4* respectively reallocate 100 and 50 percent of housing units in pixels with housing density below 300/km^2 to pixels with density above 2500/km^2. Once I calculate the counterfactual housing densities, I calculate counterfactual wildfire probabilities using the results from Figure 3B. I restrict my attention to the probability of wildfire in pixels with low housing density (i.e., below 1200/km^2).

At lower housing density levels, the impact of decreasing housing density is mixed. Figure 5A plots the average wildfire probability in 2001-2003 against the counterfactual average probabilities. Moving all housing units away from low density to medium/higher density areas decreases the average probability of wildfires from 3.04 percent to .83 percent in counterfactual 1, and .80 percent in counterfactual 3. However, reducing housing density by half–either in all low density pixels, or only in the lower density ones–does not decrease the expected probability of wildfires by much (3.04 percent relative to 2.8 percent). This relates back to the findings from Figures 3B and 4B. Reallocating some housing units from low density to high density areas moves pixels along the inverse-U curve representing the relationship between housing and wildfire probability. Some of the pixels have low enough housing density that removing half of housing units brings the pixel close enough to a density of 0, but other pixels are moved to higher probability of wildfires. For instance, removing 700 housing units from a pixel with density of 1000 units per squared kilometer moves that pixel to the highest probability region of Figures 3B. Figure 5B calculates the counterfactual average number of yearly incidents between 2001-2003, given the yearly fire probabilities from Panel A. The counterfactuals where only 50 percent of housing is re-allocated predict a higher number of incidents, relative to the counterfactuals with 100 percent of reallocation and the incident-level data.

Are there inefficiently too many wildfire incidents? Households, developers and jurisdictions are not accounting for the impact of an additional housing unit on wildfire risk, and therefore housing development along the urban edge constitutes an externality. An additional housing unit in downtown San Diego does not change the probability of wildfire in those pixels, or in the neighboring developed pixels. However, new development in low (moderately) developed areas along the urban edge might increase (decrease) the probability of wildfires. Housing supply regulations in low-risk areas don't account for the additional probability of ignition in higher risk, less regulated areas. Moreover, density limitations are likely preventing areas from densifying and facing lower wildfire risk.

These externalities are costly. Panel C computes the counterfactual suppression spending, given the counterfactual fire probability and number of incidents. Suppose the distribution of fire sizes remains constant, such that the median incident burns .2 acres, or .0008 km^2. Suppression costs per squared kilometer range from $220-360 thousand dollars (Mietkiewicz et al., 2020), though, according to CalFIRE data, the average suppression cost per kilometer squared between 2001-2003 was approximately $427,730 (measured in 2019 dollars).[12]. I estimate total predicted burn area, holding the median incident area fixed. I then multiply the total burn area by $220,000 to calculate predicted suppression costs. Finally, I subtract the counterfactual suppression costs from the estimated cost, given the actual yearly number of incidents between 2001 and 2003. Panel C.i plots this measure of excess suppression costs for the counterfactuals. Counterfactuals 1 and 3 predict savings of .21-.32 million dollars per year in suppression spending, assuming that fires retain their median size. Counterfactuals 2 and 3, however, predict a large enough increase in the number of incidents, such that more money is spent on fire suppression. Panel C.ii allows for fire size and suppression needs to change endogenously with development. In Panel C.ii, I allow both incident probability and fire size to vary. I assign the median incident size for the counterfactual housing density, calculate total predicted burn area, multiply the area by $220,000 as in Panel C.i, and calculate excess suppression costs for the counterfactuals. The results in Panel C.ii are qualitatively similar to those in Panel C.i, though the differences in suppression spending are larger in absolute value for all counterfactuals. Appendix Figure B.18 re-calculates Panel C using average incident size, rather than the median, which changes qualitatively the results in Panel ii. That is because the average incident size is much larger in pixels with no housing units, so as housing gets reallocated, the counterfactual calculation assumes the fires in those undeveloped pixels will be 120 acres (Appendix Figure B.14).

7 Conclusion

In this paper, I provided evidence that wildfires become more likely as urban areas expand into previously undeveloped areas. An additional housing unit increases the probability of wildfire by .01-.02 percentage points over a baseline probability of 1.53. Land and housing development at the urban edge also impose spillovers on undeveloped areas outside of the urban edge. I extrapolate the additional suppression cost associated with an additional house near fire's point of ignition, showing that additional development increases the need for suppression

[12]See Appendix Figure B.17 for further details on suppression costs

spending at lower levels of development. Finally, I calculate counterfactual wildfire probability and costs under alternative housing allocations. I find that restricting or removing *some* housing units away from the urban edge may not impact the probability of wildfires, and may actually 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 0.

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 (above 1200 units per square kilometer, according to my data). Housing supply regulations that limit density in already developed places distort development 1) in areas where an additional unit brings efficiency gains, as well as 2) in undeveloped or low development areas where an additional unit imposes a social cost.

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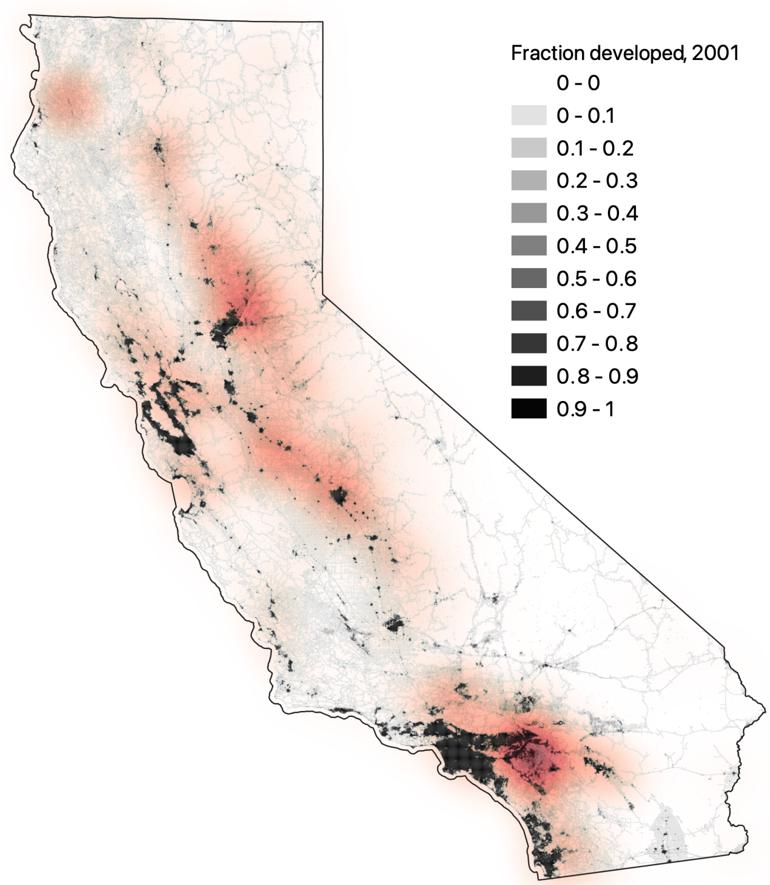
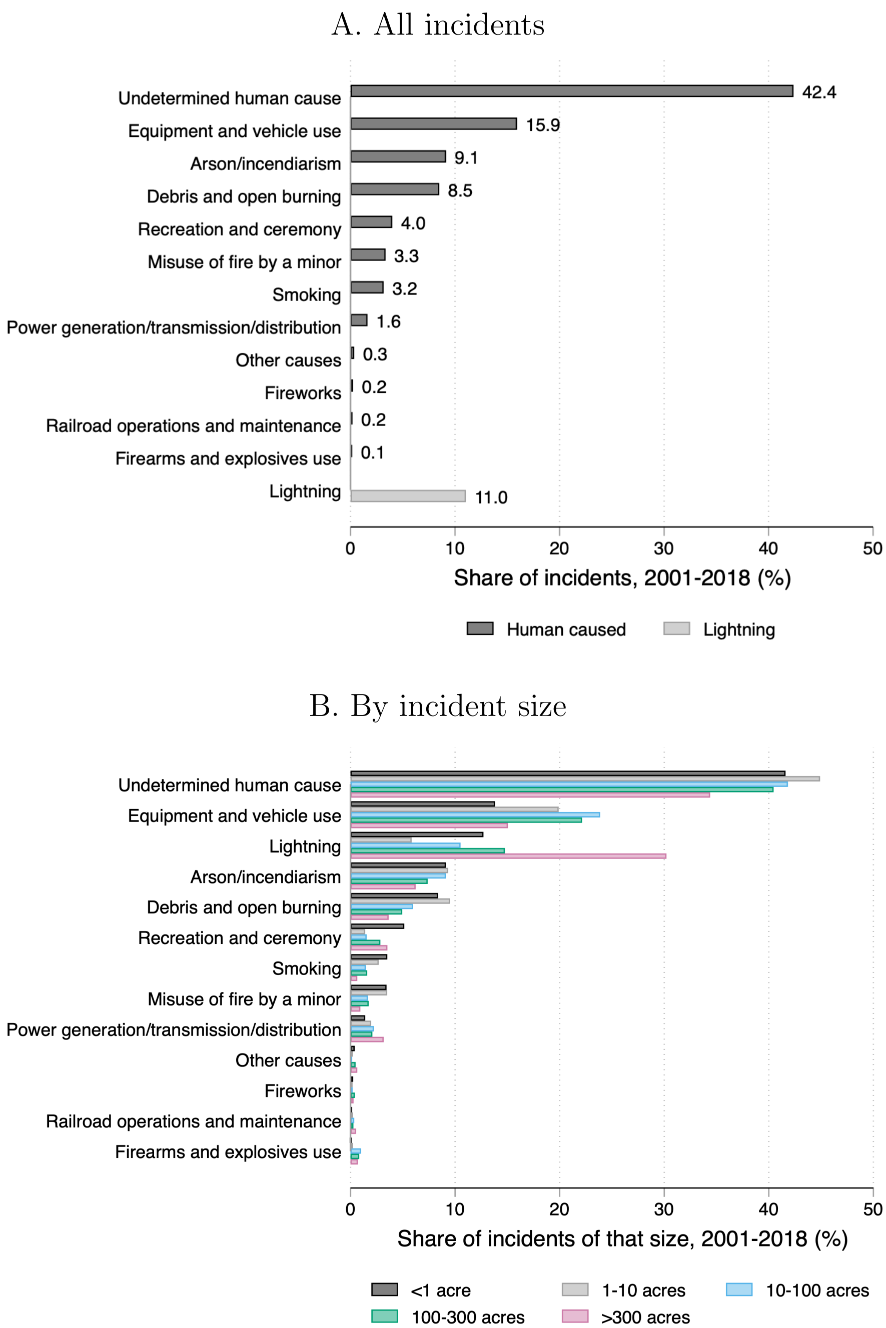
Figure 1: Most wildfire incidents between 2001 and 2018 were located near developed areas



Notes: This figure overlays a heatmap of fire incidents from 2001 to 2018, onto developed landcover in California in 2001. Darker colors indicate greater 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.

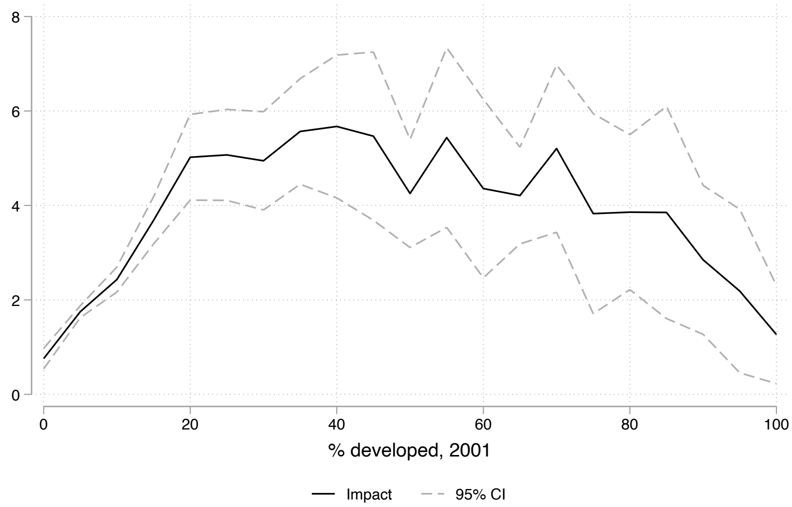
Figure 2: Cause of fire incidents in California, 2001-2018



Notes: This figure shows the share of wildfire incidents reported in California between 2001 and 2018, by cause. Panel B replicates Panel A by incident size. Section 3 and Appendix A describe the data in more detail. Appendix Figure B.14 shows the distribution of wildfire incidents by size.

Figure 3: Cross-sectional impact of development on probability of ignition, 2001-2003

A. Share of pixel developed (2001)

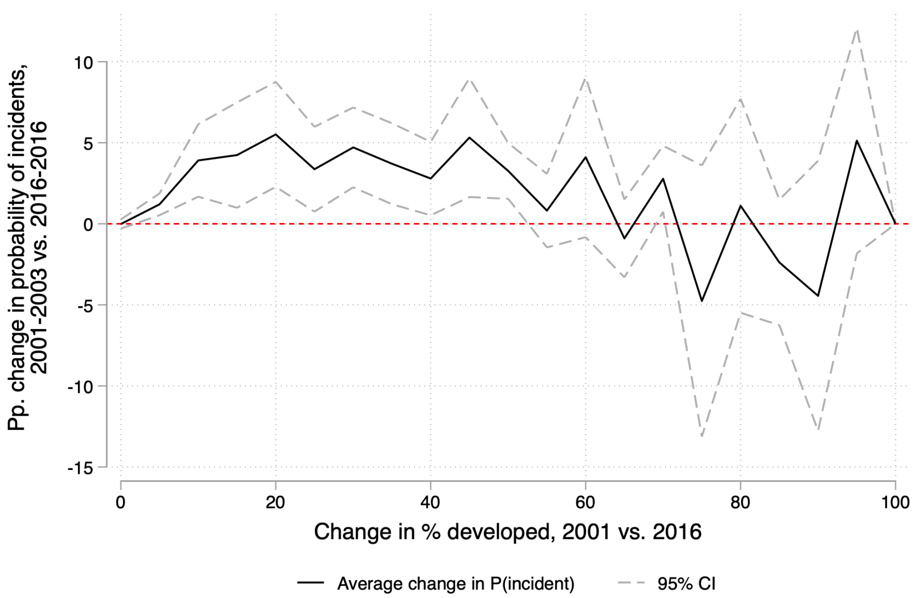


B. Number of housing units (2000)

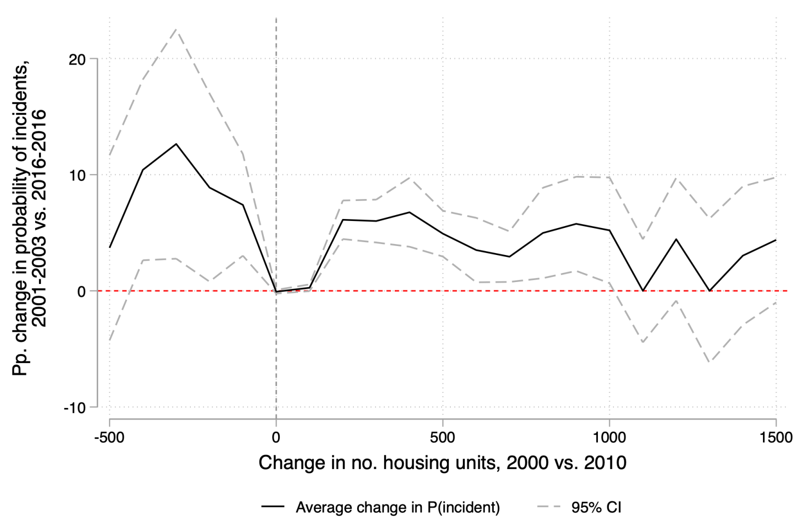
Notes: This figure plots the results of OLS regressions of fire probability in 2001-2003 on a spline of development bins. Panel A measures development as share of the pixel developed in 2001. Bins are 5 percentage points wide. Panel B replicates A using housing units in 2000. Bins in the Panel B are 100 housing units wide. I top-code housing density 2500 since inly 601 pixels have number of housing units above 2500, and their average incident probability is .0046 percent. Section 3 and Appendix A describe the data in more detail.

Figure 4: Long difference impact of development on probability of ignition at low levels of development

A. Change in share of pixel developed

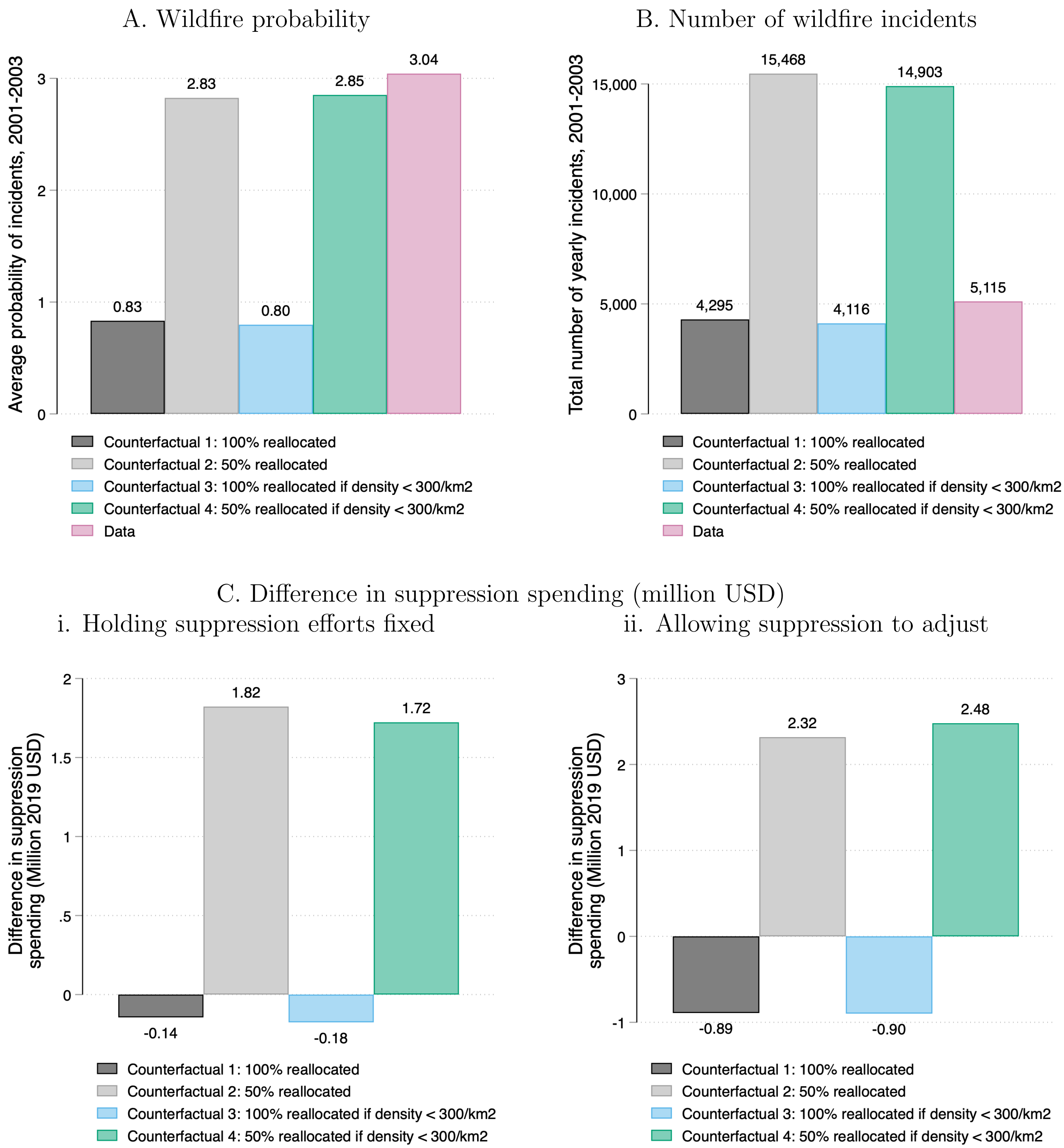


B. Change in number of housing units



Notes: This figure summarizes the average change in fire probability over time, given different magnitudes of change in pixel development. The change in probability of ignition is measured using 2001-2003 and 2016-2018 averages. Panel A measures change in development as the difference in share of pixel developed in 2016, and share developed in 2001. Bins are 5 percentage points wide. Panel B replicates Panel A using changes in number of housing units between 2000 and 2010. Bins in the Panel B are 100 housing units wide. Panel A restricts the analysis to pixels that were 0-60 percent developed in 2001, and Panel B limits the sample to pixels with housing density below 2500 housing units per squared kilometer, following the results from Figure 3. Appendix Figure B.12 summarizes the average change in development, given initial levels of land development and number of housing units. Appendix Figure B.16 replicates this figure A using 5-year moving averages, rather than 3-year.

Figure 5: Counterfactual probability and costs



Notes: This figure calculates counterfactual wildfire probabilities (Panel A), number of wildfire incidents (Panel B), and suppression savings (Panel C) for a set of four counterfactuals. *Counterfactual 1* reallocates 100 percent of housing units in pixels with housing density below 1200/km^2 to pixels with density above 2500/km^2. Recall that the probability of ignition in the latter set of pixels is statistically indistinguishable from zero (Figure 3B). *Counterfactual 2* reallocates 50 percent of housing units in pixels with housing density below 1200/km^2 to pixels with density above 2500/km^2. *Counterfactual 3* and *Counterfactual 4* respectively reallocate 100 and 50 percent of housing units in pixels with housing density below 300/km^2 to pixels with density above 2500/km^2.

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

Panel A. Share of pixel developed	% developed	P(wildfire)			
	(1)	(2) OLS	(3) IV	(4) OLS	(5) IV
Log dist. 1947 highway	-2.280***				
	(0.413)				
% developed		0.0282**	0.108**	0.0277**	0.218**
		(0.0123)	(0.0350)	(0.0115)	(0.0990)
% wildland				-0.0550	4.300*
				(0.256)	(2.255)
Observations	407,960	407,960	407,960	407,960	407,960
Dep. var. mean	6.252	1.529	1.529	1.529	1.529
F-stat	30.436	5.255	9.555	2.961	2.433
Kleibergen-Paap Wald F-stat			30.436		8.511
Cragg-Donald Wald F-stat			12603.794		2,794.906

Panel B. Number of housing units	No. units	P(wildfire)			
	(1)	(2) OLS	(3) IV	(4) OLS	(5) IV
Log dist. 1947 highway	-20.29***				
	(5.819)				
No. housing units		0.0000744	0.0121**	-0.000205	0.0217**
		(0.000495)	(0.00482)	(0.000414)	(0.00954)
% wildland				-0.725**	3.318*
				(0.340)	(1.782)
Observations	407,960	407,960	407,960	407,960	407,960
Dep. var. mean	36.091	1.529	1.529	1.529	1.529
F-stat	12.154	0.023	6.349	2.977	2.705
Kleibergen-Paap Wald F-stat			12.154		10.326
Cragg-Donald Wald F-stat			5,246.164		1,292.220

Notes: This table estimates the cross-sectional impact of increasing development and number of housing units on the probability of wildfires. Standard errors are conservatively clustered at the county level. All regressions include county fixed effect to control for underlying differences in wildfire probability. Appendix Table C.2 replicates this table without controlling for county fixed effects. Appendix Table C.1 shows summary statistics for the analysis sample. $^{*}p < .10$ $^{**}p < .05$ $^{***}p < .01$

Table 2: Cross-section impact of development within 1km on fire probability in undeveloped pixels

Panel A. Share developed	% developed	P(wildfire)			
	(1)	(2) OLS	(3) IV	(4) OLS	(5) IV
Log dist. 1947 highway	-0.0959**				
	(0.0343)				
% developed within 1km		0.149***	0.811**	0.151***	1.058**
		(0.0314)	(0.301)	(0.0302)	(0.467)
% wildland				0.353*	-1.564
				(0.190)	(1.082)
% wildland within 1km				-0.00190	0.0260
				(0.00241)	(0.0160)
Observations	224,686	224,686	224,686	224,686	224,686
Dep. var. mean	0.537	0.756	0.756	0.756	0.756
F-stat	7.813	22.459	7.265	11.456	4.036
Kleibergen-Paap Wald F-stat			7.813		11.983
Cragg-Donald Wald F-stat			1,102.756		676.780

Panel B. Number of housing units	% developed	P(wildfire)			
	(1)	(2) OLS	(3) IV	(4) OLS	(5) IV
Log dist. 1947 highway	-1.451**				
	(0.579)				
Housing units within 1km		0.000561	0.0838**	0.000587	0.132**
		(0.000413)	(0.0325)	(0.000396)	(0.0625)
% wildland				-0.289*	-1.696**
				(0.152)	(0.722)
% wildland within 1km				0.00350	0.0369**
				(0.00258)	(0.0174)
Observations	295,406	295,406	295,406	295,406	295,406
Dep. var. mean	2.336	0.896	0.896	0.896	0.896
F-stat	6.271	1.846	6.669	3.741	2.238
Kleibergen-Paap Wald F-stat			6.271		5.185
Cragg-Donald Wald F-stat			247.734		105.602

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 zero percent developed pixels, and Panel B restricts to pixels with 0 housing units. I then estimate equation (6) using development in pixels within 1 kilometer instead of own-pixel development share. Standard errors are conservatively clustered at the county level. 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. $^{*}p < .10$ $^{**}p < .05$ $^{***}p < .01$

Table 3: Long difference impact of change in development on fire probability

	(1)	(2)	(3)	(4)
Δ % developed, 2001-2016 (pp)	0.109***	0.385***		
	(0.0233)	(0.0810)		
Δ % developed (sq)		-0.00543***		
		(0.00114)		
Δ housing units, 2000-2010			0.0101***	0.0143***
			(0.00227)	(0.00346)
Δ housing units (sq)				-0.00000367**
				(0.00000144)
Constant	0.152	0.113	0.140	0.127
	(0.116)	(0.109)	(0.116)	(0.114)
Observations	407,960	407,960	407,960	407,960
R-squared	0.001	0.003	0.002	0.002
Avg P(incident), 2001-2003	1.529	1.529	1.529	1.529
Avg. initial development	6.252	6.252	36.091	36.091
Avg. Δ development	0.371	0.371	5.178	5.178

Notes: This table estimates the long difference regressions for the impact of increasing development and number of housing units on the probability of wildfires. Standard errors are conservatively clustered at the county level. Appendix Table C.1 shows summary statistics for the analysis sample. $^{*}p < .10$ $^{**}p < .05$ $^{***}p < .01$

Table 4: Impact of development on wildfire size

Panel A. 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***	-6.364***	-6.364***	-6.364***
	(0.00000151)	(0.00000153)	(0.00000188)	(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

Panel B. 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***	-6.364***	-6.364***	-6.364***
	(0.000000704)	(0.000000725)	(0.000000977)	(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

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 easier interpretation. Regressions control for county, year and incident cause fixed effects. Appendix Figure B.15 plots the average land development and total housing units within 250m and 1km of wildfire incidents. $^{*}p < .10$ $^{**}p < .05$ $^{***}p < .01$

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:

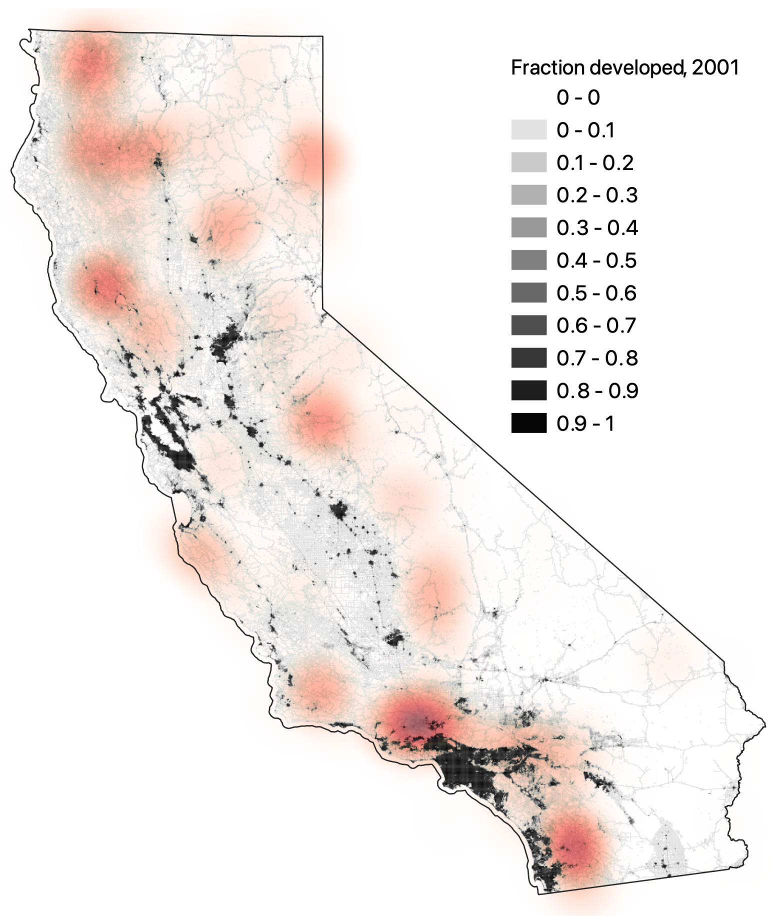
- Open water: areas of open water, generally with less than 25% cover of vegetation or soil.
- Developed, open space: areas with a mixture of some constructed materials, but mostly vegetation in the form of lawn grasses. Impervious surfaces account for less than 20% of total cover. These areas most commonly 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 complexes, 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.

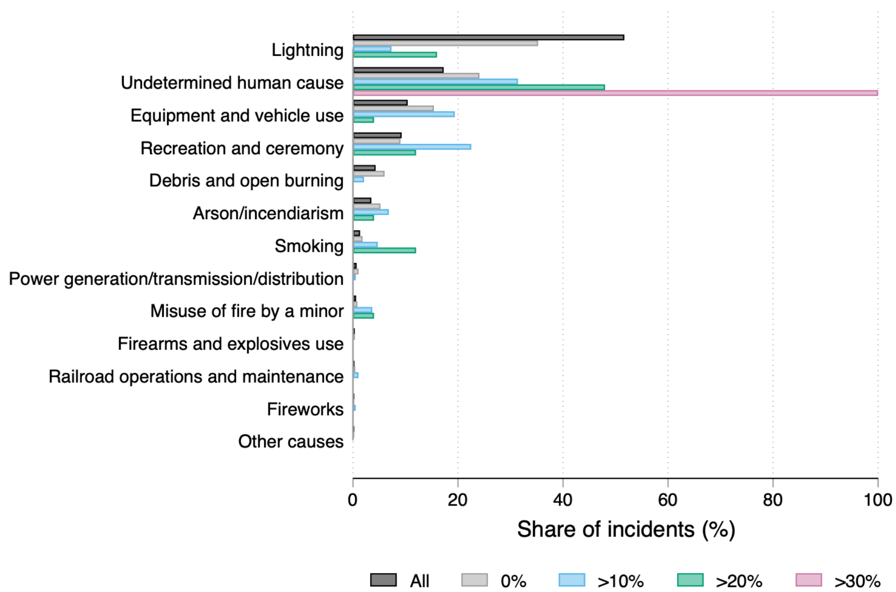
B Appendix Figures

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



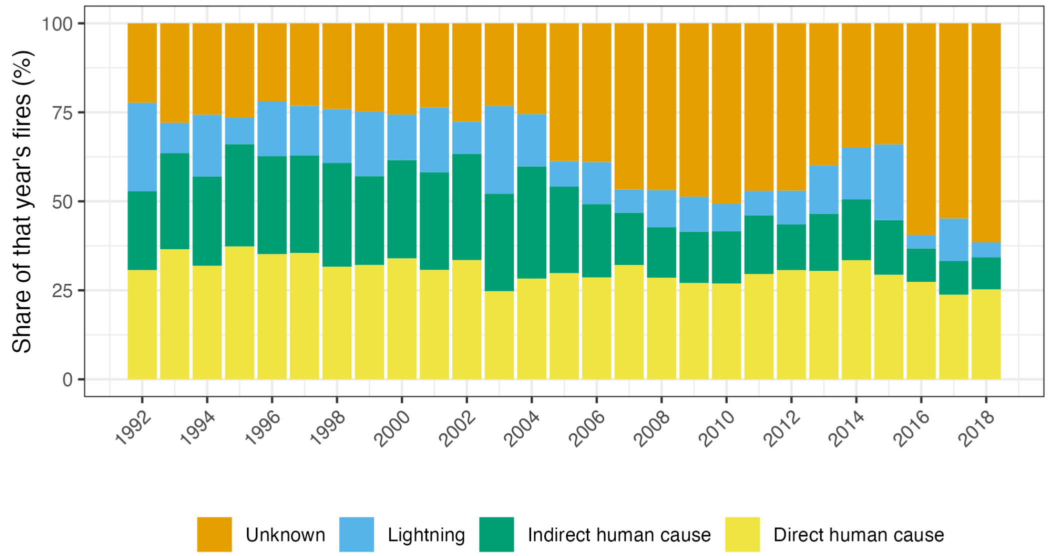
Notes: This figure replicates Figure 1 and maps overlays a heatmap of fire incidents from 2001 to 2018, onto developed landcover in California in 2001, but weighs incidents by their size. Darker colors indicate greater density of incidents. Section 3 and Appendix A describe the data in more detail.

Figure B.2: Cause of fire incidents in undeveloped areas, given nearby development, 2001-2018



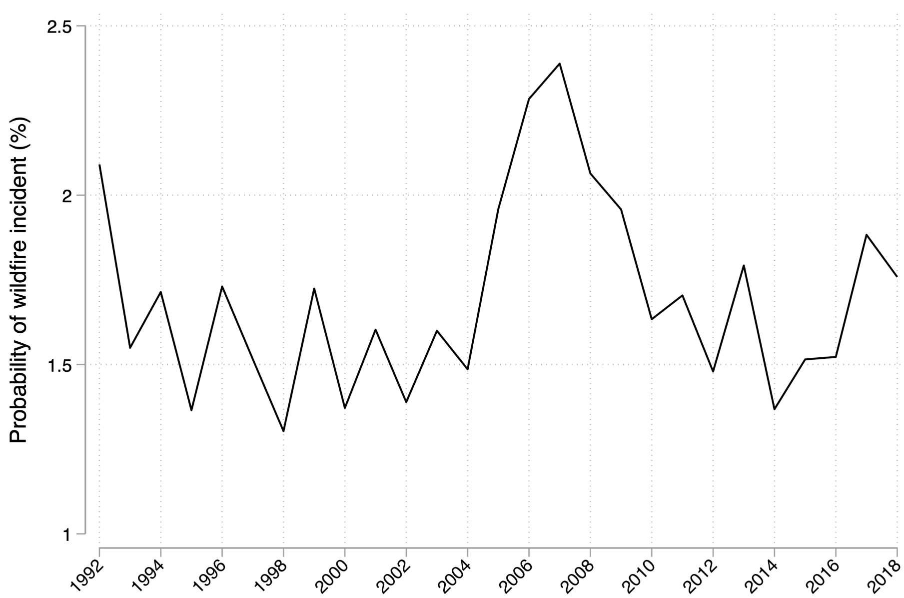
Notes: This figure describes the causes of fire incidents that started in completely undeveloped areas of California. "All" denotes all incidents in undeveloped areas. The other categories restrict to undeveloped areas with p% developed within 1 kilometer, where $p \in \{0, > 10, > 20, > 30\}$. Section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

Figure B.3: 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.4: Empirical wildfire probability by year, 1992-2018

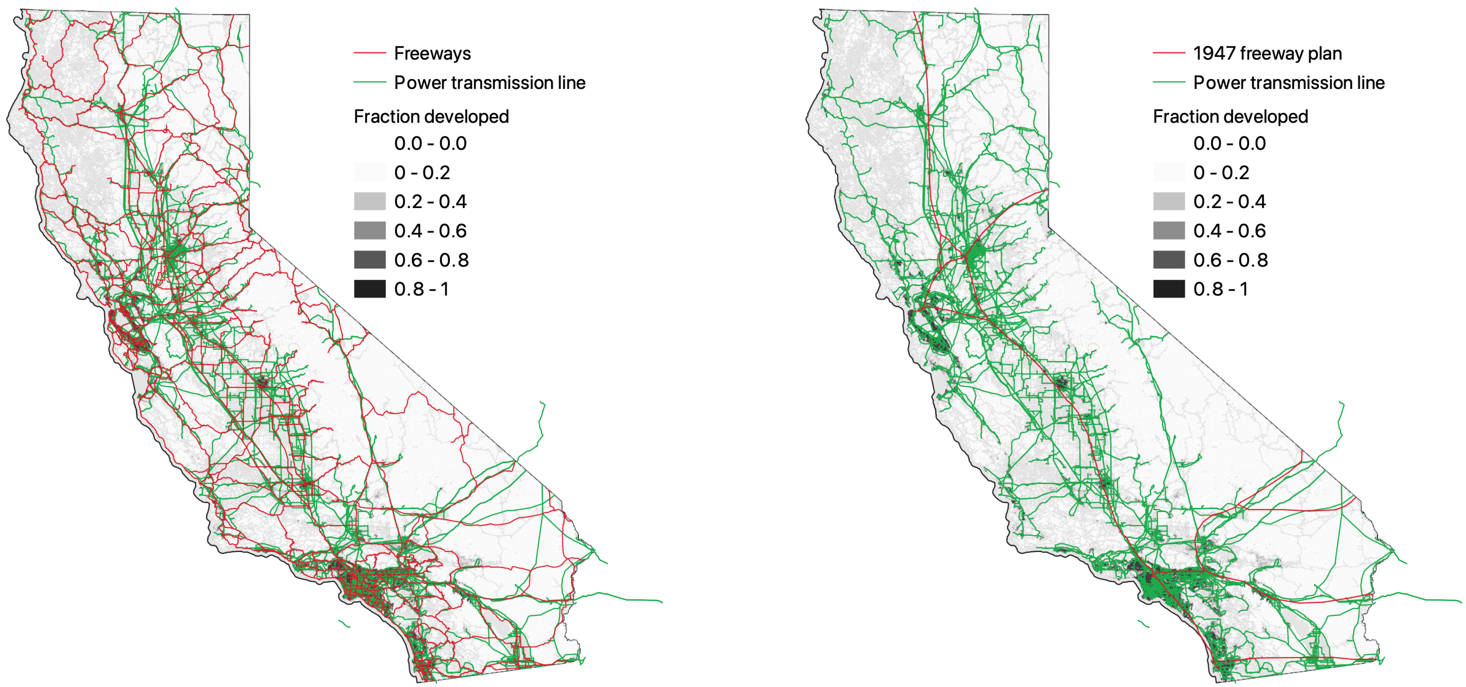


Notes: This figure shows the number of fire incidents reported in California between 1992 and 2018, by year. Section 3 and Appendix A describe the data in more detail.

Figure B.5: Spatial relationship between transmission lines, highways and developed land

A. 2021 freeway map

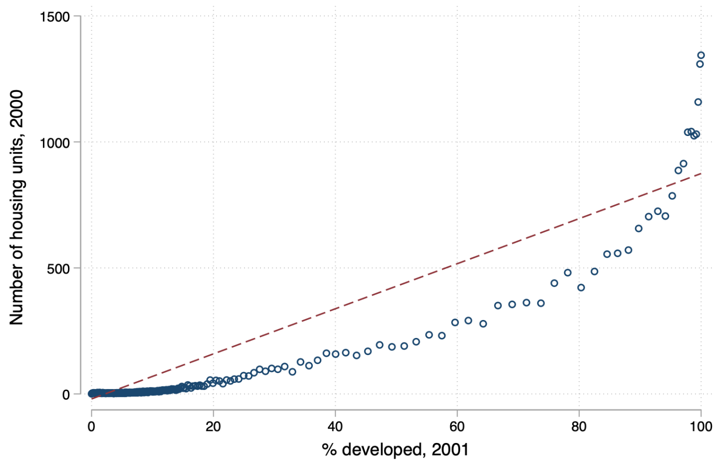
B. 1947 freeway plan



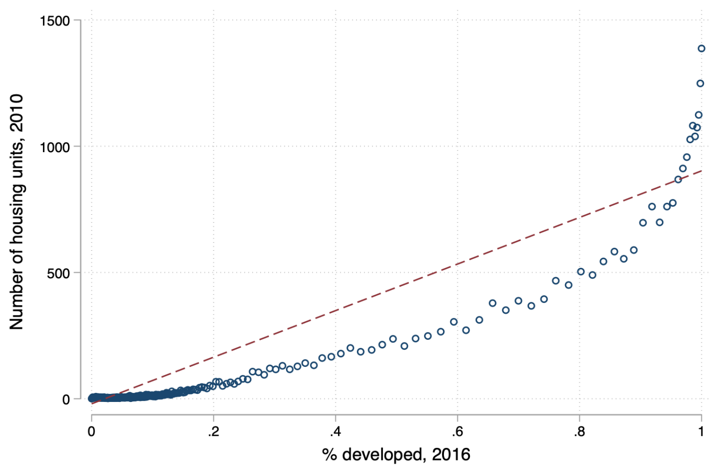
Notes: This figure maps California's power transmission lines and freeways against the rate of land development. Panel A maps 2021 state and federal freeways from Caltrans (2021). Panel B maps the 1947 freeway plan from Brinkman and Lin (2022). Section 3 and Appendix A describe the data in more detail.

Figure B.6: Correlation between development and housing units

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



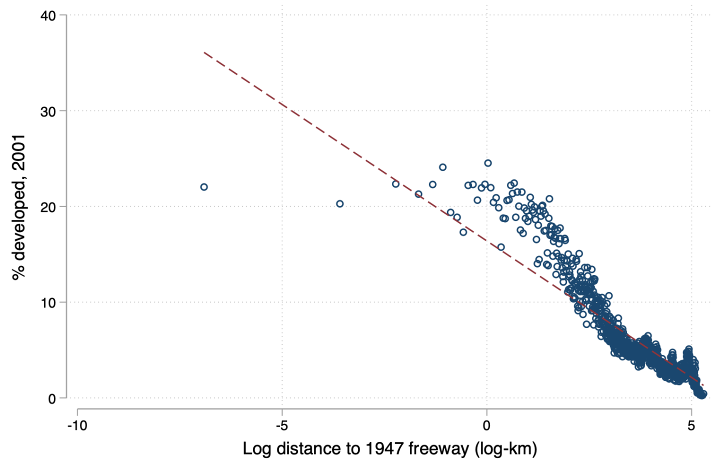
B. Share developed (2016) vs. housing units (2010)



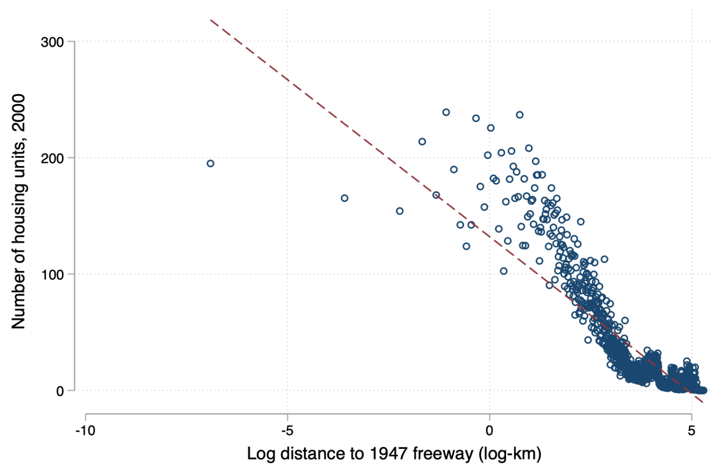
Notes: This figure plots the cross-sectional relationship between this paper's measures of development: share of land developed and number of housing units. Panel A plots land development data for 2001 and housing data for 2000, while Panel B compares data for 2016 and 2010 respectively.

Figure B.7: Correlation between development and log distance to 1947 freeway plan

A. Share developed



B. Number of housing units

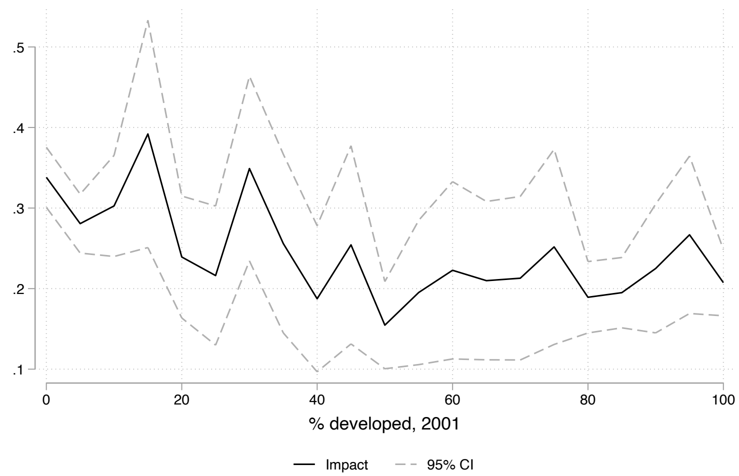


Notes: This figure plots the first stage relationship between log distance to the 1947 freeway plan (measured in kilometers), and share of pixel developed in 2001 (Panel A) and number of housing units in 2000 (Panel B).

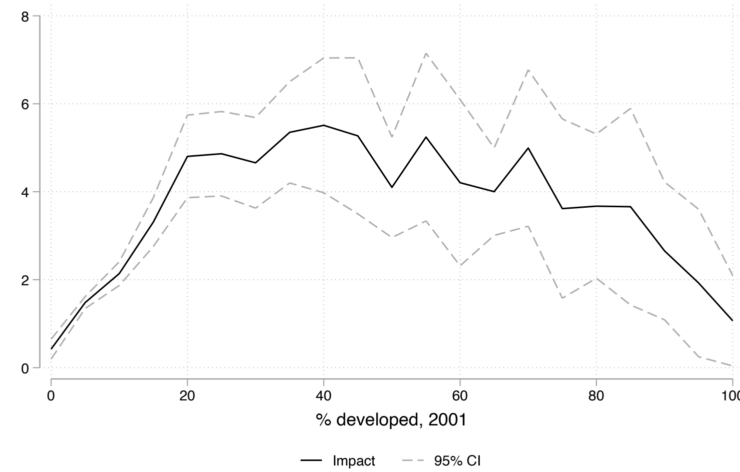
Figure B.8: Cross-sectional relationship between development and probability of ignition, by incident cause

A. Share developed

(i) Lightning

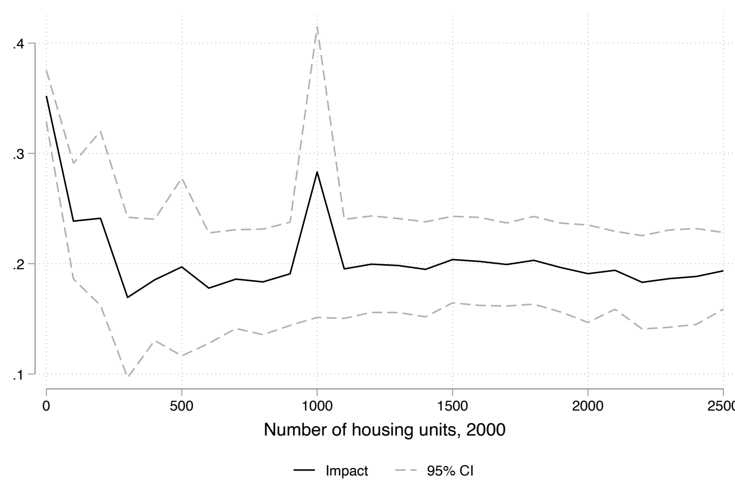


(ii) Human



B. Number of housing units

(i) Lightning

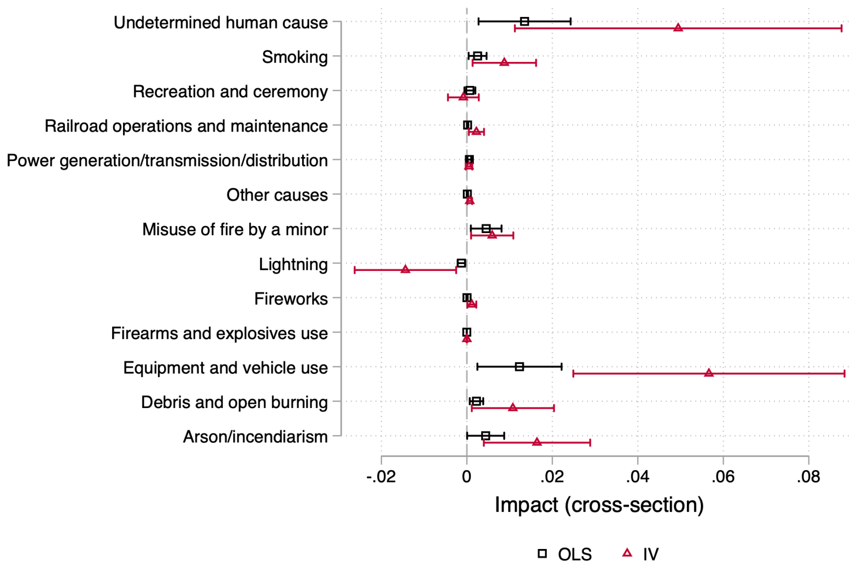


(ii) Human

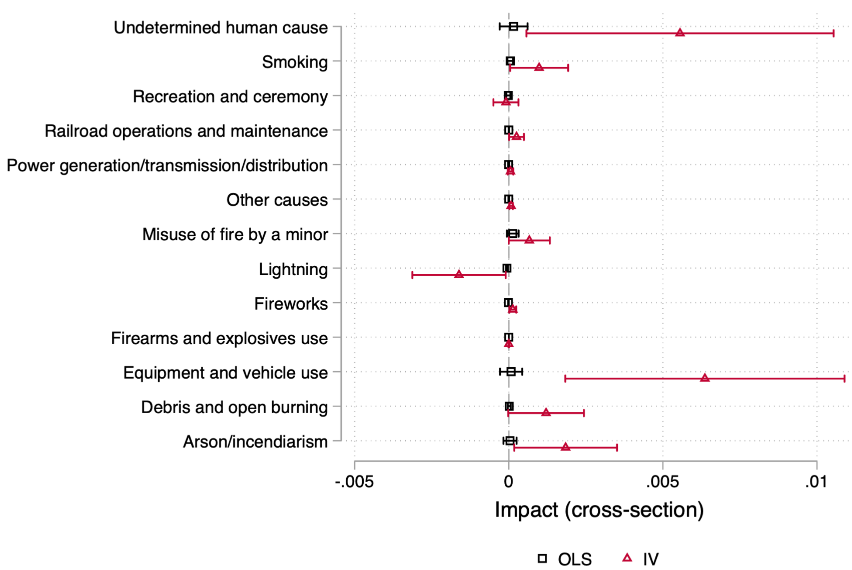
Notes: This figure replicates Figure 3 by incident cause (lightning vs. human-caused). This figure plots the results of OLS regressions of fire probability in 2001-2003 on a spline of development bins. Panel A shows the probability of lightning-caused fires by bin, while Panel B shows the probability of human-caused fires. Panel A measures development as share of the pixel developed in 2001. Bins are 5 percentage points wide. Panel B replicates A using housing units in 2000. Bins in the Panel B are 100 housing units wide. I top-code housing density 2500 since inly 601 pixels have number of housing units above 2500, and their average incident probability is .0046 percent. Section 3 and Appendix A describe the data in more detail.

Figure B.9: Impact of development on probability of ignition by cause

A. Share developed



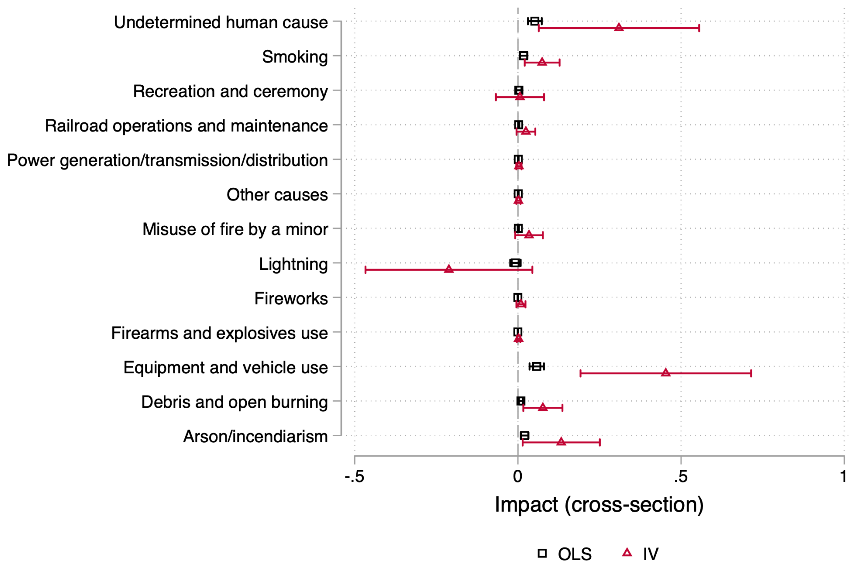
B. Number of housing units



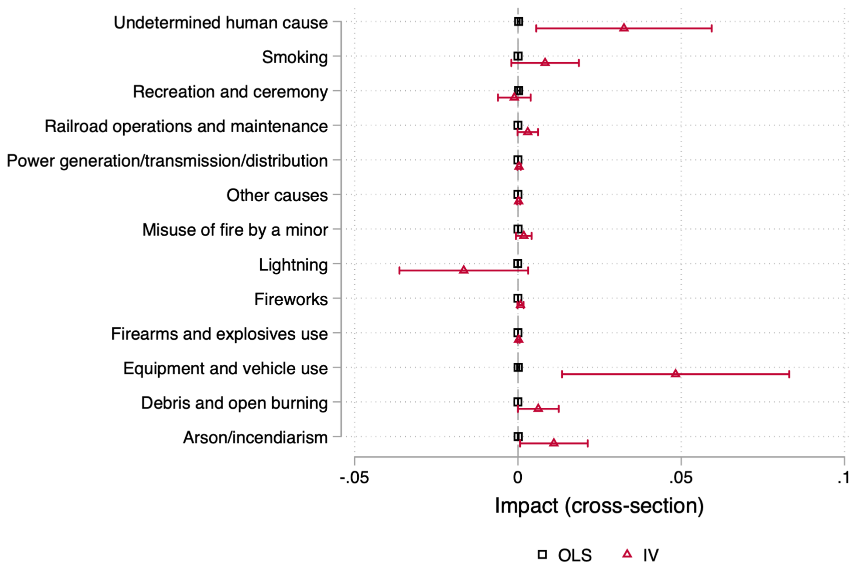
Notes: This figure estimates the cross-sectional impact of increasing development and number of housing units on the probability of wildfires, by wildfire cause. Standard errors are conservatively clustered at the county level. All regressions include county fixed effect to control for underlying differences in wildfire probability. Table 1 estimates these regressions for all incidents.

Figure B.10: Impact of neighboring development on fire probability, by incident cause

A. Share developed



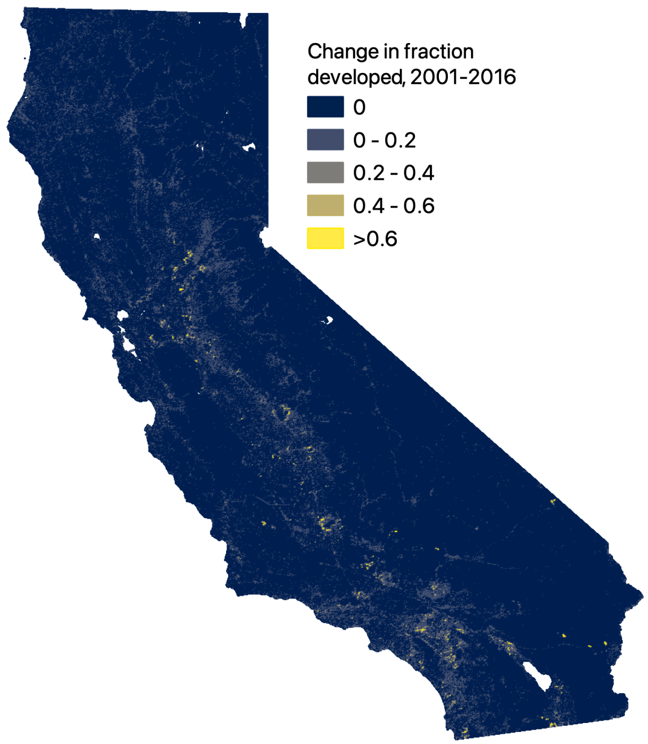
B. Number of housing units



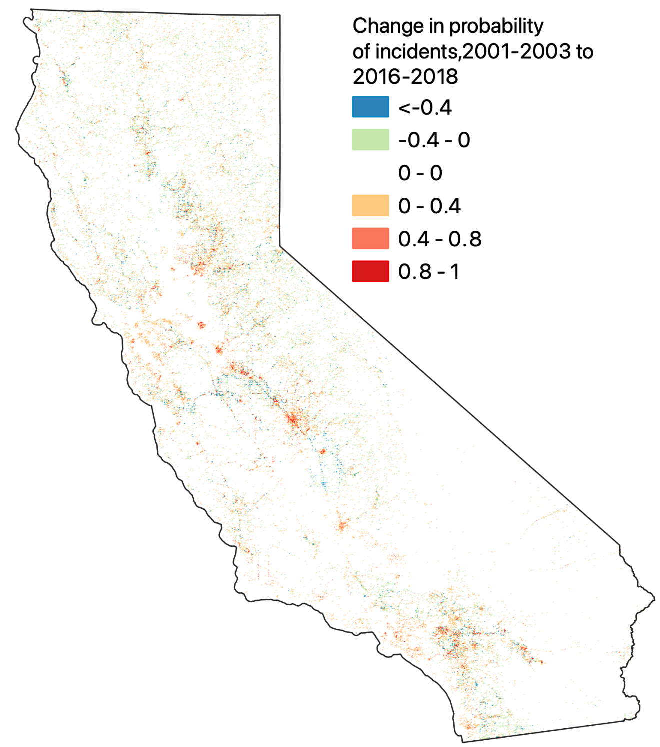
Notes: This figure estimates the cross-sectional impact of increasing neighbors' development and number of housing units on the probability of wildfires, by wildfire cause. Neighbors are the pixels within 1 kilometer of each undeveloped pixel i (Panel A), or each pixel with 0 housing (Panel B). Standard errors are conservatively clustered at the county level. All regressions include county fixed effect to control for underlying differences in wildfire probability. Table 2 estimates these regressions for all incidents.

Figure B.11: Correlation between change in landcover and fire probability

A. Change in share developed



B. Change in probability of incidents

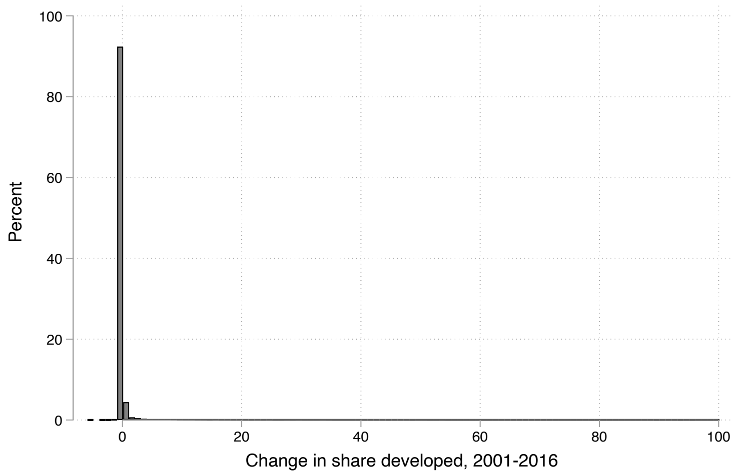


Notes: Panel A maps the change in fraction of pixel land developed for each pixel in my 1km-by-1km grid of California. Panel B maps the change in incident probability from 2001-2003 to 2016-2018 each pixel in my 1km-by-1km grid of California. Section 3 and Appendix A describe the data in more detail. Appendix Figure B.12 plots the distribution of changes in land development between 2001 and 2016.

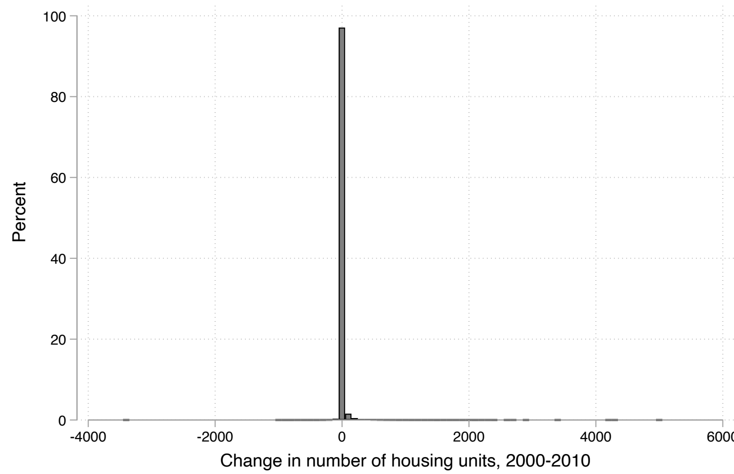
Figure B.12: Change in development

A. Distribution of change in development

(i) Share of pixel developed, 2001-2016

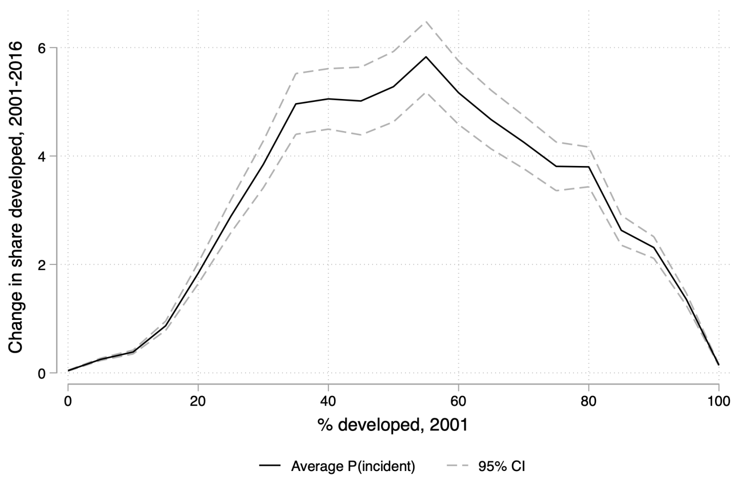


(ii) Number of housing units, 2000-2010

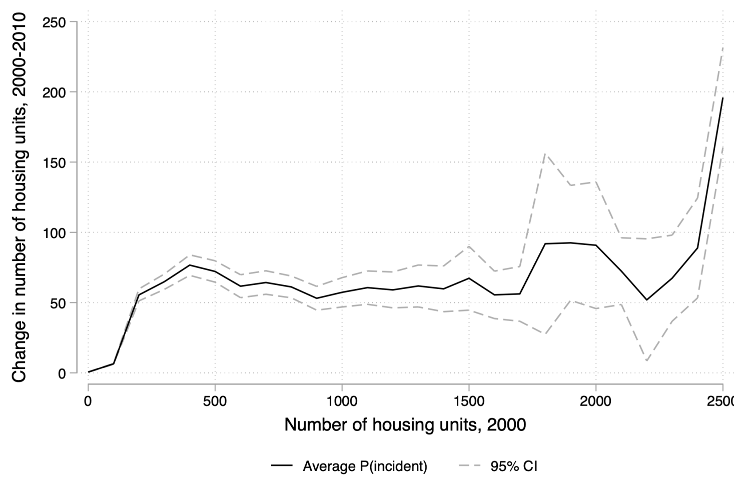


B. Change in development given initial conditions

(i) Share of pixel developed, 2001-2016



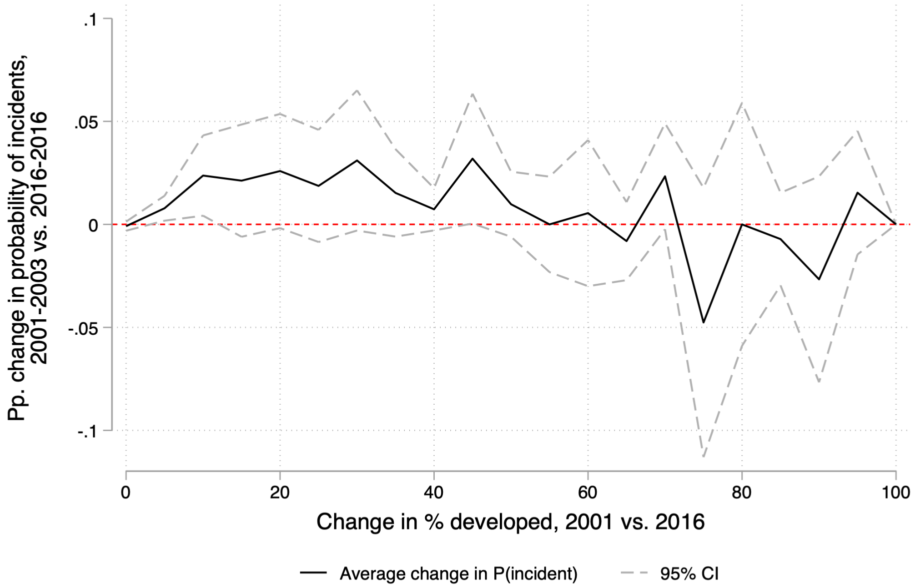
(ii) Number of housing units, 2000-2010



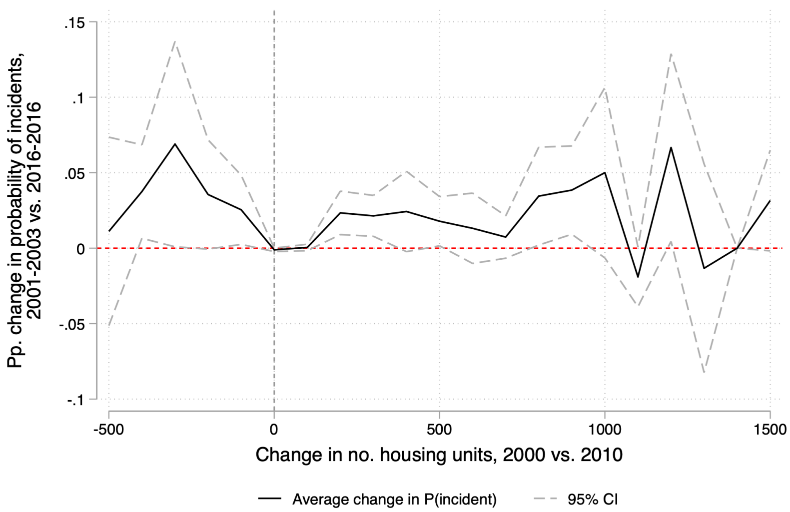
Notes: This figure describes change in development. Panel A shows a histogram of change in share of pixel developed (i) and number of housing units (ii). The change in probability of ignition is measured using 2001-2003 and 2016-2018 averages. Change in development is the difference in share of pixel developed in 2016, and share developed in 2001. Panel B calculates the average change in development across initial development levels.

Figure B.13: Impact of change in development on change in wildfire probability, 2001-2005 vs. 2014-2018

A. Change in share of pixel developed

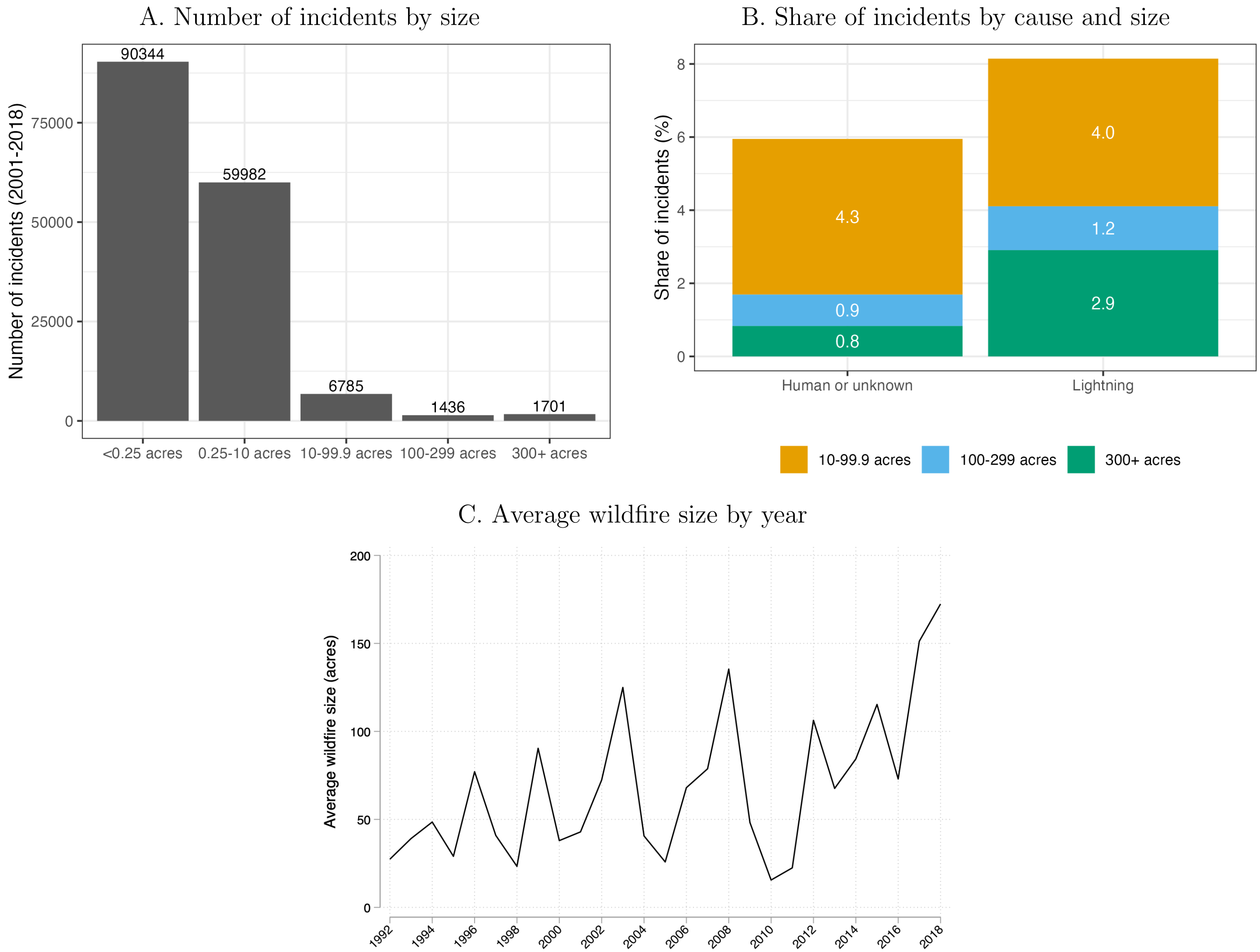


B. Change in number of housing units



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 difference in share of pixel developed in 2016, and share developed in 2001. Bins are 5 percentage points wide. Panel B replicates Panel A using changes in number of housing units between 2000 and 2010. Bins in the Panel B are 100 housing units wide. Panel A restricts the analysis to pixels that were 0-60 percent developed in 2001, and Panel B limits the sample to pixels with housing density below 2500 housing units per squared kilometer, following the results from Figure 3.

Figure B.14: Average fire size

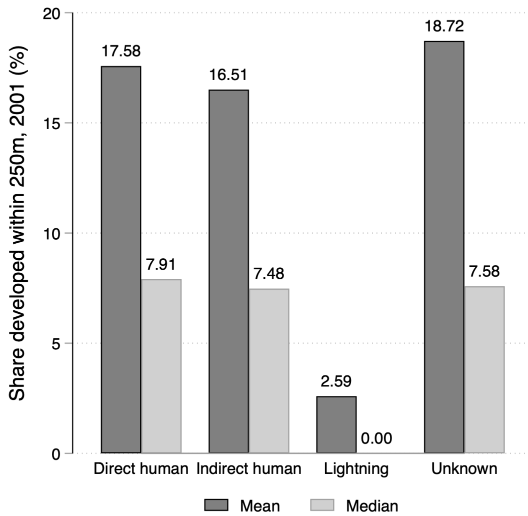


Notes: Section 3 and Appendix A describe the data in more detail.

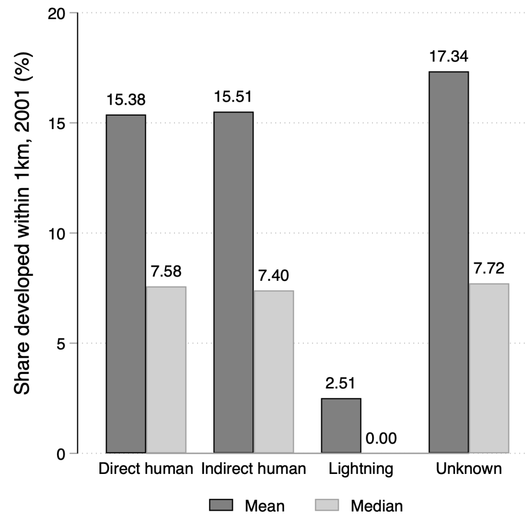
Figure B.15: Development near fire origination spots

A. Share of land developed developed within

250m

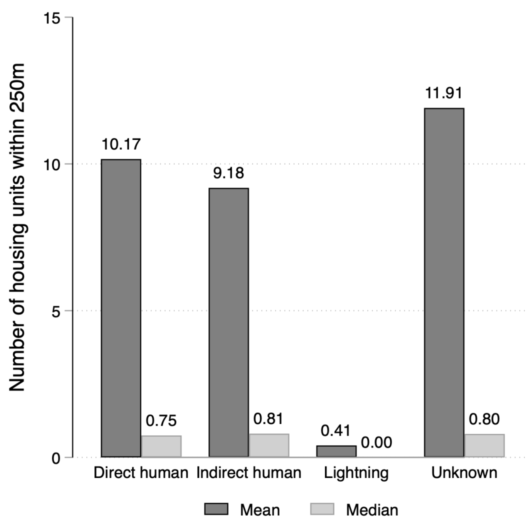


1km

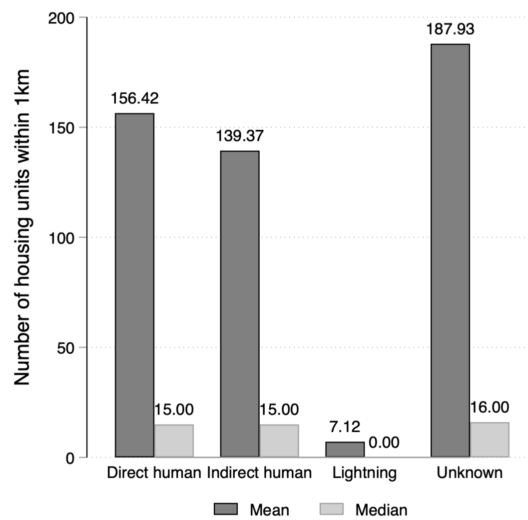


B. Number of housing units within

250m



1km

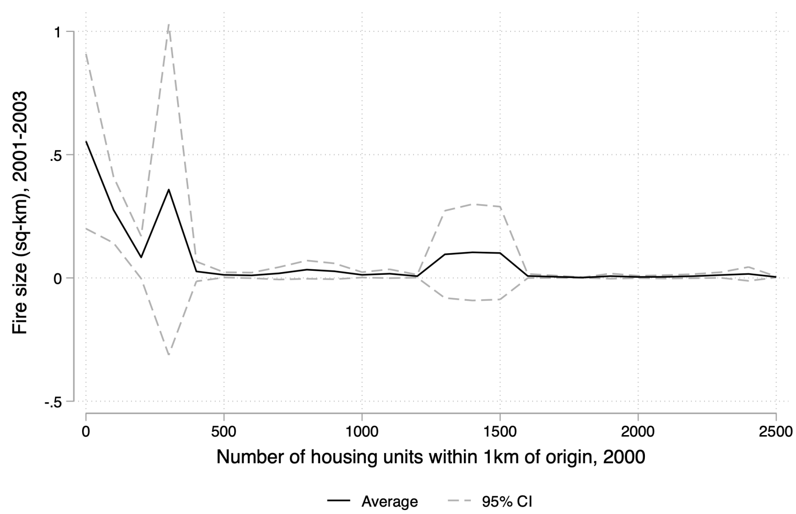


Notes: This figure calculates average land development and total number of housing units within 250m and 1km of the point of origin for wildfire incidents between 2001 and 2003. Land development is measured in 2001, and the number of housing units is measured in 2000. Section 3 and Appendix A describe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

Figure B.16: Relationship between development and incident size

A. Share of pixel developed, 2001

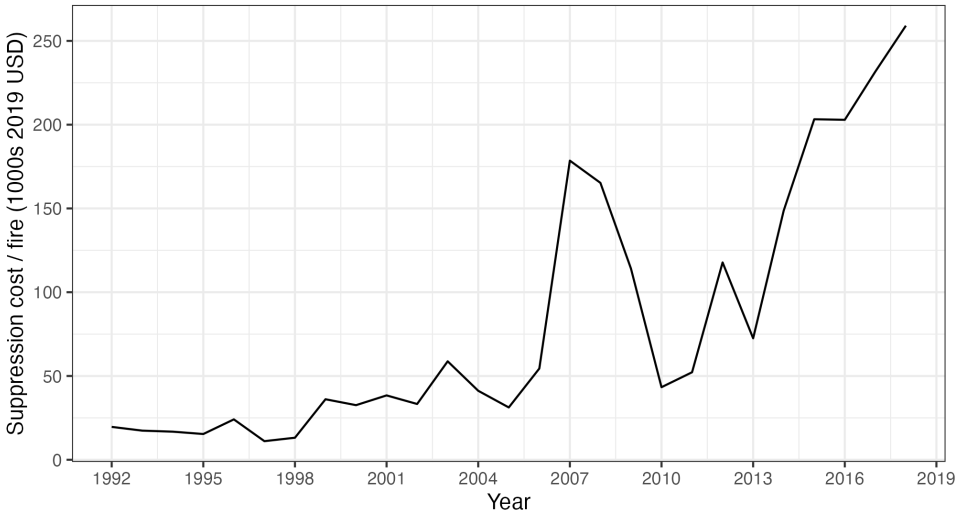
B. Change in number of housing units, 2000



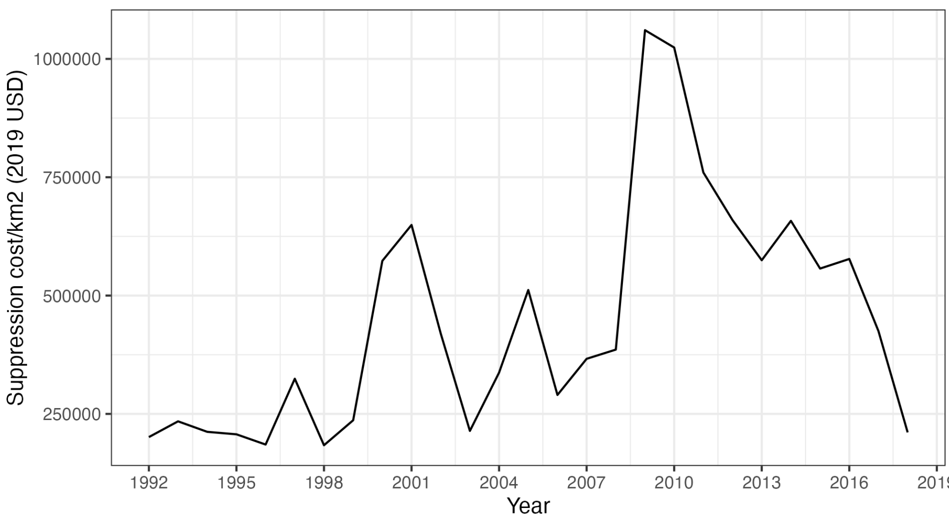
Notes: This figure calculates average incident size given development within 1 kilometer of the incident's ignition point. Panel A measures change in development as the difference in share of pixel developed in 2016, and share developed in 2001. Bins are 5 percentage points wide. Panel B replicates Panel A using the number of housing units in 2000. Bins in the Panel B are 100 housing units wide. The dashed grey lines represent the 95% confidence interval for the estimated mean.

Figure B.17: Suppression costs per fire and per acre

A. Per fire

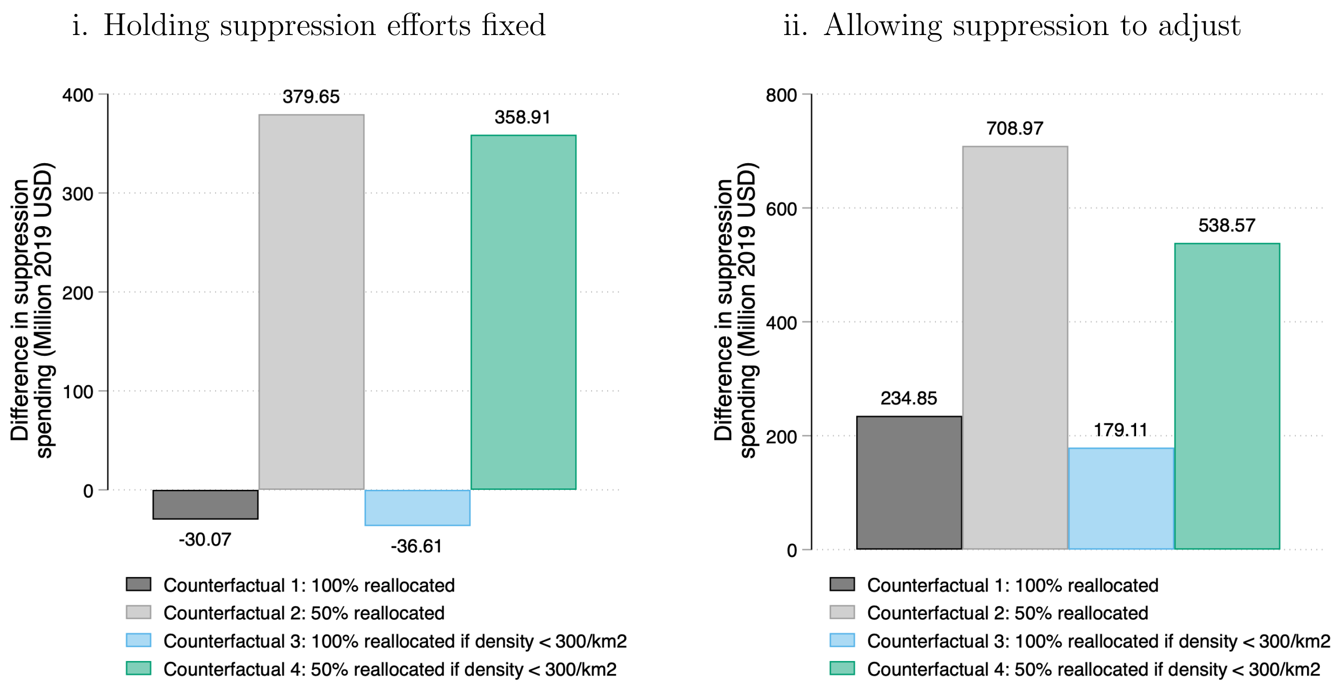


B. Per kilometer squared



Notes: This figure plots suppression costs per fire (Panel A) and per kilometer squared (Panel B) using numbers from CalFIRE for the entire state, inflated to 2019 US dollars using the Consumer Price Index.

Figure B.18: Difference in suppression spending, using average fire size



Notes: This figure replicates Figure 5C using average incident size, instead of median size. *Counterfactual 1* reallocates 100 percent of housing units in pixels with housing density below 1200/km^2 to pixels with density above 2500/km^2. Recall that the probability of ignition in the latter set of pixels is statistically indistinguishable from zero (Figure 3B). *Counterfactual 2* reallocates 50 percent of housing units in pixels with housing density below 1200/km^2 to pixels with density above 2500/km^2. *Counterfactual 3* and *Counterfactual 4* respectively reallocate 100 and 50 percent of housing units in pixels with housing density below 300/km^2 to pixels with density above 2500/km^2.

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	36.09	236.83	0.00	12.00
Change in no. units, 2000-2010	5.18	49.22	0.00	2.86
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: Replication of Table 1 without county fixed effects

Panel A. Share of pixel developed	% developed	P(wildfire)			
	(1)	(2) OLS	(3) IV	(4) OLS	(5) IV
Log dist. 1947 highway	-2.850***				
	(0.695)				
% developed		0.0255**	0.0648**	0.0279**	0.130**
		(0.0109)	(0.0316)	(0.0108)	(0.0663)
% wildland				0.274	2.498*
				(0.369)	(1.379)
Observations	407,960	407,960	407,960	407,960	407,960
Dep. var. mean	6.252	1.529	1.529	1.529	1.529
F-stat	16.834	5.408	4.127	3.477	1.922
Kleibergen-Paap Wald F-stat			16.834		9.362
Cragg-Donald Wald F-stat			26538.269		6,462.853

Panel B. Number of housing units	No. units	P(wildfire)			
	(1)	(2) OLS	(3) IV	(4) OLS	(5) IV
Log dist. 1947 highway	-26.98**				
	(9.103)				
No. housing units		0.000140	0.00684*	0.000000357	0.0122*
		(0.000411)	(0.00371)	(0.000373)	(0.00656)
% wildland				-0.331	1.926*
				(0.390)	(1.147)
Observations	407,960	407,960	407,960	407,960	407,960
Dep. var. mean	36.091	1.529	1.529	1.529	1.529
F-stat	8.784	0.116	3.339	0.362	1.809
Kleibergen-Paap Wald F-stat			8.784		8.017
Cragg-Donald Wald F-stat			12616.985		3,515.716

Notes: This table estimates the cross-sectional impact of increasing development and number of housing units on the probability of wildfires. Standard errors are conservatively clustered at the county level. Table 1 controls for for county fixed effects. Appendix Table C.1 shows summary statistics for the analysis sample. $^{*}p < .10$ $^{**}p < .05$ $^{***}p < .01$

Table C.3: Cross-section impact of development within 5km on probability of ignition in undeveloped pixels

Panel A. Share developed	% developed	P(wildfire)			
	(1)	(2) OLS	(3) IV	(4) OLS	(5) IV
Log dist. 1947 highway	-0.260**				
	(0.0771)				
% developed within 5km		0.0806***	0.299**	0.0798***	0.392**
		(0.0195)	(0.105)	(0.0190)	(0.174)
% wildland				0.367**	-0.675
				(0.148)	(0.632)
% wildland within 5km				-0.00265	0.0167
				(0.00260)	(0.0119)
Observations	224,686	224,686	224,686	224,686	224,686
Dep. var. mean	1.329	0.756	0.756	0.756	0.756
F-stat	11.407	17.115	8.098	8.669	4.371
Kleibergen-Paap Wald F-stat			11.407		20.135
Cragg-Donald Wald F-stat			2,270.170		1,291.304

Panel B. Number of housing units	% developed	P(wildfire)			
	(1)	(2) OLS	(3) IV	(4) OLS	(5) IV
Log dist. 1947 highway	-102.1**				
	(33.60)				
Housing units within 5km		0.0000168	0.00119**	0.0000193	0.00200**
		(0.0000243)	(0.000376)	(0.0000232)	(0.000804)
% wildland				-0.162	-1.540**
				(0.147)	(0.757)
% wildland within 5km				0.00259	0.0382**
				(0.00292)	(0.0189)
Observations	295,406	295,406	295,406	295,406	295,406
Dep. var. mean	165.833	0.896	0.896	0.896	0.896
F-stat	9.231	0.481	10.042	1.436	2.077
Kleibergen-Paap Wald F-stat			9.231		8.260
Cragg-Donald Wald F-stat			1,233.218		481.970

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 zero percent developed pixels, and Panel B restricts to pixels with 0 housing units. I then estimate equation (6) using development in pixels within 1 kilometer instead of own-pixel development share. Standard errors are conservatively clustered at the county level. 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 2 replicates this table using neighbors within 1 kilometer. $^{*}p < .10$ $^{**}p < .05$ $^{***}p < .01$

Table C.4: Long difference impact of change in development on fire probability, 20-60% developed

	(1)	(2)	(3)	(4)
Δ % developed, 2001-2016 (pp)	0.0385*	0.237**		
	(0.0223)	(0.0961)		
Δ % developed (sq)		-0.00474**		
		(0.00187)		
Δ housing units, 2000-2010			0.000304	0.00276
			(0.00135)	(0.00264)
Δ housing units (sq)				-0.00000224
				(0.00000166)
Constant	4.584***	4.307***	4.738***	4.671***
	(0.871)	(0.795)	(0.893)	(0.872)
Observations	12,639	12,639	12,639	12,639
R-squared	0.000	0.001	0.000	0.000
Avg P(incident), 2001-2003	5.148	5.148	5.148	5.148
Avg. initial development	35.163	35.163	122.687	122.687
Avg. Δ development	4.364	4.364	46.527	46.527

Notes: This table estimates the long difference regressions for the impact of increasing development and number of housing units on the probability of wildfires in pixels 20-60 percent developed in 2001. Standard errors are conservatively clustered at the county level. Appendix Table C.1 shows summary statistics for the analysis sample. $^{*}p < .10$ $^{**}p < .05$ $^{***}p < .01$

Table C.5: Long difference impact of change in development on fire probability, housing density below 1500

	(1)	(2)	(3)	(4)
Δ % developed, 2001-2016 (pp)	0.109***	0.386***		
	(0.0234)	(0.0814)		
Δ % developed (sq)		-0.00544***		
		(0.00114)		
Δ housing units, 2000-2010			0.0116***	0.0188***
			(0.00240)	(0.00370)
Δ housing units (sq)				-0.00000823**
				(0.00000246)
Constant	0.119	0.0801	0.105	0.0872
	(0.113)	(0.105)	(0.112)	(0.109)
Observations	406,001	406,001	406,001	406,001
R-squared	0.001	0.003	0.002	0.003
Avg P(incident), 2001-2003	1.533	1.533	1.533	1.533
Avg. initial development	5.816	5.816	24.272	24.272
Avg. Δ development	0.371	0.371	4.658	4.658

Notes: This table estimates the long difference regressions for the impact of increasing development and number of housing units on the probability of wildfires in pixels with housing densithy below 1500 units per squared kilometer. Standard errors are conservatively clustered at the county level. Appendix Table C.1 shows summary statistics for the analysis sample. $^{*}p < .10$ $^{**}p < .05$ $^{***}p < .01$

Table C.6: Long difference impact of neighboring change development on fire probability

	(1)	(2)	(3)	(4)
Δ % developed within 1km (pp)	0.416***	-0.0685		
	(0.0735)	(0.0452)		
Δ housing units within 1km			0.000576	0.000576
			(0.00110)	(0.00110)
Constant	-0.159*	-0.404***	-0.257**	-0.257**
	(0.0852)	(0.0905)	(0.0766)	(0.0766)
Sample	Δ dev. share = 0	Δ dev. share = 0 and dev. 2001 = 0	Δ housing = 0	Δ housing = 0 and housing 2000 = 0
Observations	329,339	223,070	148,851	148,851
R-squared	0.001	0.000	0.000	0.000
Avg P(incident), 2001-2003	1.103	0.749	0.677	0.677
Avg. neigh. initial dev. (%)	3.915	0.525	1.194	1.194
Avg. Δ development, 1km (pp)	0.061	0.018	0.296	0.296

Notes: This table estimates the long difference regressions for the impact of increasing development and number of housing units on the probability of wildfires. Standard errors are conservatively clustered at the county level. Column 1 restricts the sample to pixels whose share developed stayed constant between 2001 and 2016. Column 2 further restricts the sample to pixels that were undeveloped in 2001 *and* did not become more developed by 2016. Columns 3 and 4 replicate columns 1 and 2, but for new housing units. Appendix Table C.1 shows summary statistics for the analysis sample. $^{*}p < .10$ $^{**}p < .05$ $^{***}p < .01$

Table C.7: Impact of potential residential exposure to fire on containment time

Panel A. Share of pixel developed	(1)	(2)	(3)	(4)
% developed within 250m	-0.00309**			
	(0.00108)			
% developed within 500m		-0.00318**		
		(0.00124)		
% developed within 1km			-0.00419**	
			(0.00177)	
% developed within 2.5km				-0.00587**
				(0.00232)
Constant	0.453***	0.453***	0.453***	0.453***
	(0.000109)	(0.000121)	(0.000163)	(0.000176)
Observations	22,913	22,913	22,913	22,913
R-squared	0.017	0.017	0.017	0.017
Indep. var. mean	14.930	14.121	13.643	11.578
Containment time (days)	1.572	1.572	1.572	1.572

Panel B. Number of housing units	(1)	(2)	(3)	(4)
Housing units within 250m	-0.00128*			
	(0.000754)			
Housing units within 500m		-0.000292*		
		(0.000155)		
Housing units within 1km			-0.0000976	
			(0.0000615)	
Housing units within 2.5km				-0.0000259**
				(0.0000128)
Constant	0.453***	0.453***	0.453***	0.453***
	(0.0000386)	(0.0000407)	(0.0000486)	(0.0000463)
Observations	22,913	22,913	22,913	22,913
R-squared	0.017	0.017	0.017	0.017
Indep. var. mean	8.608	40.071	133.215	731.541
Containment time (days)	1.572	1.572	1.572	1.572

Notes: This table regresses number of days until the fire is contained 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. Each observation is a fire incident between 2001 and 2018 in California. All independent variables have been demeaned for easier interpretation. Regressions control for county, year and cause fixed effects. $^{*}p < .10$ $^{**}p < .05$ $^{***}p < .01$

Table C.8: Impact of development on lightning-caused wildfire size

Panel A. 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***	-6.806***	-6.806***	-6.806***
	(0.000000350)	(0.00000438)	(0.00000364)	(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

Panel B. 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***	-6.806***	-6.806***	-6.806***
	(0.00000116)	(0.00000117)	(0.000000481)	(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

Notes: This table replicates Table 4 for lightning-caused fires. Each observation is a fire incident between 2001 and 2003 in California. All independent variables have been demeaned for easier interpretation. Regressions control for county and year fixed effects. $^{*}p < .10$ $^{**}p < .05$ $^{***}p < .01$