Housing and Mortgage Markets with Climate-Change Risk: Evidence from Wildfires in California*

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Abstract

This paper studies the effects of climate-driven events on the housing and mortgage markets. We merge property-level data on all California wildfires from 2000 to 2018, mortgage and property characteristics, household finances, and weather. We find a significant increase in mortgage delinquency and foreclosure after a fire in the devastated areas, but these effects *decrease* in the size of the fire. We argue that this results from coordination externalities afforded by large fires and frictions in the insurance markets, which lead to rebuilding in the devastated areas and to increases in home sizes, house prices, income and wealth. Our results suggest that recent large losses, combined with regulatory distortions, cast doubt on the ability of insurance companies and mortgage lenders to absorb climate-related losses and assess mortgage risk.

Key words: Housing, mortgages, climate-change risk, moral hazard.

JEL codes: G21

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1 Introduction

Climate change is increasing the likelihood of extreme seasonal wildfire conditions across California (Goss et al., 2020) and is expected to lead to significant increases in both the frequency and severity of destructive weather events globally.[1] In 2019 alone, Kramer and Ware (2019) list 15 weather-related disasters causing more than $1 billion in damage each — and well over $100 billion in total — the most costly being a series of wildfires that broke out in California in October 2019, causing damage estimated at over $25 billion (Querolo and Sullivan, 2019) and leaving millions without power as the Northern California utility company, Pacific Gas & Electric, shut down parts of its network to avoid causing additional fires. Large disasters in the U.S. caused $96.4 billion in damages in 2020, the fourth-highest inflation-adjusted total since 1980. The costliest 2020 events were Hurricane Laura ($19 billion) and the Western wildfires ($16.5 billion),[2] including the 2020 August Complex, the largest wildfire in California history, which burned over 1 million acres.[3] In 2021, the Dixie fire is already the second largest wildfire in California history; at 41% containment the fire suppression costs alone have reached $365 million.[4]

This paper investigates both the site-specific probability of California wildfire events as well as the ex-post effect of these wildfires on residential house prices and size, household demographics and wealth, mortgage default, and property-insurance risk. First, we focus on the climate related determinants of California wildfires using digitized maps to identify the physical boundaries of thousands of California wildfires as identified by the California Department of Forestry and Fire Protection (CalFire) as well as geospatial measures for the meteorological characteristics (measured as daily averages of hourly data), topographical features, degree of urbanization, and vegetative coverage for 1.5 kilometer square grids covering of all California from May through October (2000 through 2015). Second, our detailed location specific data on wildfire incidence, property, mortgage, and household characteristics allows us to analyze both the short- and long-term effects of wildfires on key housing- and mortgage-related performance outcomes such as house price dynamics and mortgage default. Third, CalFire scientists have established very precise burn-area boundaries for the vegetative wildfires in California. This allows us to identify the exact properties that are inside the wildfire burn area and to merge our panel of geoprocessed data for properties, mortgages and households with the geographic "treatment" areas (those directly affected by fires) and "control" areas (nearby, but just outside the burn area). We construct two control areas: a one- and a two-mile ring just outside the burn-area boundary. The one-mile control area is in view of the fire but not physically affected; the two-mile ring experienced neither physical nor visual fire exposure.

The treatment and control structure of our data allows us to analyze the effect of climate-related disasters on the housing and mortgage markets in a difference-in-differences framework. Mortgage lenders require fire casualty insurance, so our analysis affords a deeper exploration of the possible

[1] See Flannigan et al. (2009); Moritz et al. (2012); Wotton et al. (2010).

[2] See NOAA's "Billion-Dollar Weather and Climate Disasters" https://www.ncdc.noaa.gov/billions/.

[3] See https://www.fire.ca.gov/media/4jandlhh/top20_acres.pdf.

[4] https://wildfiretoday.com/2021/08/26/the-number-of-residences-destroyed-in-dixie-fire-increases-to-690/

role of frictions in the insurance markets. Prior studies of climate-related natural disasters have found that disaster recovery serves as an ex post coordinating mechanism, allowing for rapid gentrification in some affected areas.[5] In addition, the cost and challenges of negotiating insurance and meeting rebuilding requirements could lead to elevated mortgage default. Our analysis allows us to quantify the risks of losses and to identify important policy vulnerabilities of the inextricably linked casualty insurance and mortgage capital markets. Given the extensive literature on mortgage-default options and their exercise,[6] household expectations of changes in housing and household wealth should affect the decision to default on all mortgages.

Overall, our focus on the the empirical estimation of site-specific wildfire incidence coupled with our quasi-experimental design allows us to address four key empirical questions. First, is it possible to predict ex ante which housing locations have elevated wildfire risks given pre-conditions such as their vegetative, topographic, and meteorologic features as well as their exposure to the WUI? Second, is there evidence of long-run post-fire differentials between treatment and control areas in the quality of the housing stock, house price dynamics, and household demographics and wealth — all possible indicators of gentrification? Third, given the post-fire effects on the housing stock and household wealth, what are the mortgage default risks of wildfires? Fourth, given the growing climate related risks of wildfire in California, how sustainable is the current pricing of fire casualty insurance and the associated benefits to the mortgage market under state insurance regulations?

Our empirical estimates of the incidence of California wildfires indicate that key meteorological features such as the direction and speed of the wind, the humidity levels, and maximum temperature are important as are the slope of the site, its elevation and the density of vegetative coverage. In sample estimates, of the site specific probability of wildfire risk in October do not match the California Department of Insurance's (CDI) deterministic risk maps especially for the CDI defined "zero" risk areas. Our sensitivity analyses indicate that a shock to the maximum temperature for a day in October would have the largest incremental effect on wildfire risk, both ceteris paribus and accounting for correlations across the meteorological features. One- and two-standard-deviation shocks to the maximum temperature lead to an overall change in the daily probability of wildfire of 0.16%–0.32%. Similarly, the estimated incremental number of houses burned on an October day due to these overall marginal shocks is between 12,464 and 24,293.

Our empirical results for the ex post effects of wildfires indicate that fires cause a 1.46% house-size increase and a 3.44% house-price increase in the treatment group (fire areas) relative to their respective control groups (not in these burn areas) five years after large wildfires. In addition, the increase in household income and wealth are 5.25% and 2.14% higher in fire areas than in the control areas. Moreover, we study the spill-over effects of climate-driven events. First, we find that the post-fire positive effects on house prices also affect nearby zones that did not burn. Specifically, we find that the increase in house prices 5 years after the wildfire is, on average, 1.79% higher in the immediate rings outside the fire areas (*Control1*) than in a second ring with houses located

[5] See Contardo et al. (2018); Florida (2019); Freeman (2005); Lee (2017); Olshansky et al. (2008); van Holm and Wyczalkowski (2019); Weber and Lichtenstein (2015).

[6] See Deng et al. (2000); Foster and Van Order (1984); Kau et al. (1993, 1995); Stanton and Wallace (2018).

between 1 and 2 miles away from the fire edges (*Control1to2*). We also document a 5-year higher increase in income and wealth of 6.96% and 2.37%, respectively, in *Control1* vs. *Control1to2* areas.

Unsurprisingly, we find a significant increase in mortgage delinquency and foreclosure after a fire event when we do not control for the size of the fire: after a fire, the probabilities of delinquency and foreclosure are 0.40% and 0.30% higher, respectively, in the treatment than in the control group. However, we also find a more subtle result: the level of default and foreclosure *decreases* in the size of the wildfire. Specifically, for big fires, the decrease in the probability of delinquency is 87.1% higher in the treatment group than in the ring from the fire-zone edge to 1 mile outside the fire zone (i.e., the decrease is 5.8% in the treatment group and 3.1% in the control group). We argue that this results from the coordination externalities afforded by large fires, whereby county requirements to rebuild to current building codes and casualty-insurance-covered losses work together to assure that the rebuilt homes will be modernized and thus more valuable than the pre-fire stock of homes.

2 Determinants and probabilities of climate-driven events

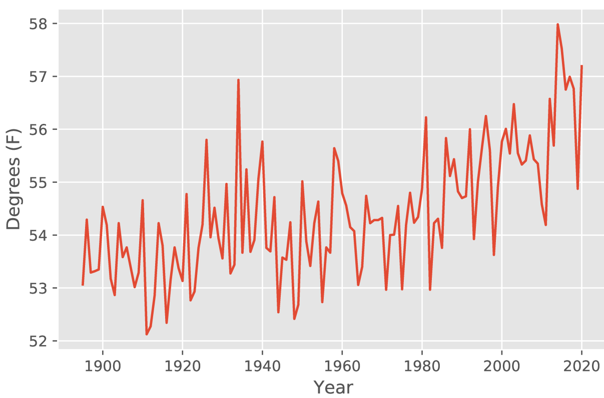
This section analyzes the determinants of climate-driven events (subsection 2.1) and estimates their probabilities of occurrence at a detailed geographical level (subsection 2.2). Overall, there are weather variables (e.g, temperature, humidity, and wind characteristics), physical attributes of the areas affected (e.g., slope, elevation, percentage of vegetative site coverage), and presence of seasonality are relevant in most types of extreme climate-driven events. We focus our analysis on wildfires in California, though our methodology and estimation procedure is broad and can be used to study any type of climate-driven event including hurricanes, heat waves, floods, droughts, and storms.

2.1 Determinants of climate-driven events: application to California wildfires

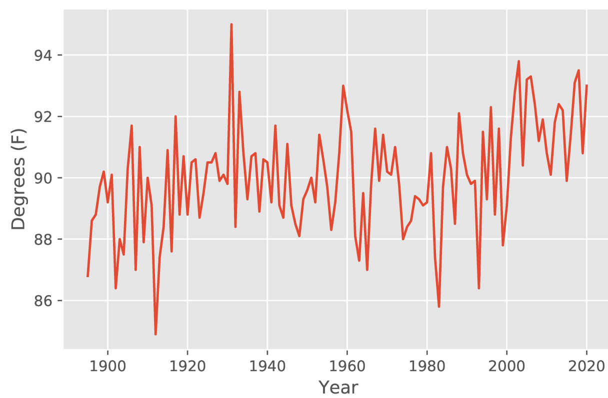
Climate change has an effect on weather patterns, which influence the intensity and the frequency of extreme environmental events, such as wildfires, hurricanes, storms, droughts, heat waves, and floods. Figure 1 shows that the the Western U.S. has become significantly hotter and dryer over time. Average temperature, maximum temperature, and cooling-degree days[7] show a positive trend over the period 1895–2020, while precipitation exhibits a negative trend over the same period.

At the same time, both the number of events and their severity have increased in many areas around the world, including the Western U.S. Focusing on wildfires in California, the area burned each year in California increased 5-fold between 1972 and 2019. (Williams et al., 2019), and the 2020 California (and Western U.S.) fire season was worse still, fueled (see Masters, 2021) by "the hottest August through October period in western U.S. history; the fourth-highest levels of October drought on record; an unusual dry lightning event caused by the remnants of an August Northeast Pacific tropical storm; and a once-in-a-generation offshore wind event in September." The total area burned in California in 2020 was more than double the previous annual maximum, and 2020

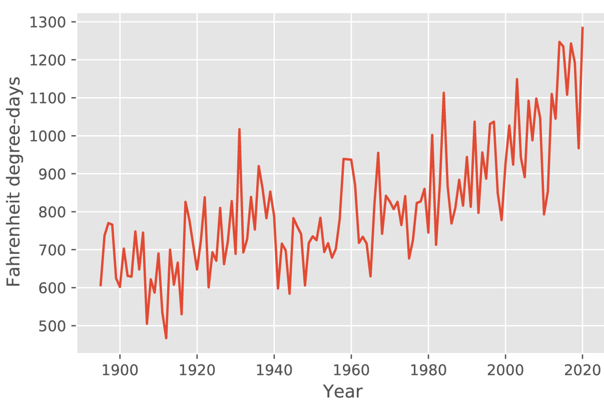
[7]Cooling-degree days are a measure of how hot the temperature was on a given day or during a period of days.



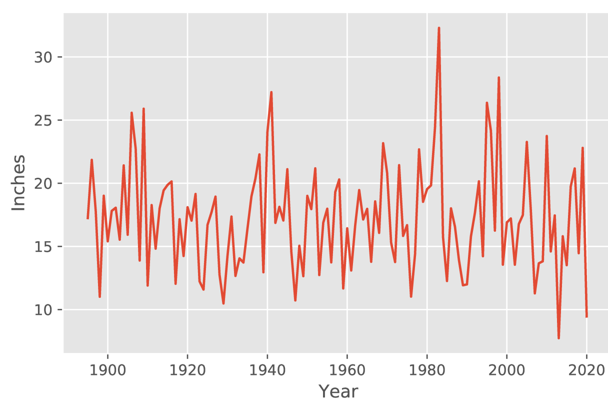
(a) **Average temperature**



(b) **Maximum temperature**



(c) **Cooling degree days**



(d) **Precipitation**

Figure 1: **NOAA annual weather statistics for the Western U.S. (annual, 1895–2020).** Source: https://www.ncdc.noaa.gov/cag/regional/time-series.

saw five of the six largest fires ever recorded in the state, including the August Complex fire, the first ever in California to burn over 1 million acres.[8] In 2021, California experienced the Dixie fire, the second largest wildfire in its history, which started on July 14. As of August 28 it had burnt 756,768 acres and 1,275 structures had been destroyed.

Figure 2 shows: i) the high statewide incidence of large wildfires (Panel a); ii) the significant exposure of its largest and highest density urban areas to the wildland urban interface (Panel b); iii) important recent increases in the mean July 2018 temperature relative to the historical mean July temperature from 1971 to 2000 (Panel c); and iv) important decreases in the mean July 2018 precipitation level relative to the historical July mean precipitation levels from 1971 to 2000 (Panel d). Panel a includes the 2018 fire season, in which California experienced 1,823,153 acres burned in wildland and wildland-urban-interface (WUI) fires, more than any other state in the country.[9] The 2018 fire season in California also marked the occurrence of the then-most-disastrous single fire incident in the state's history, the Camp Fire, which burned 142,000 acres, destroyed 18,085 structures, and killed 85 people. Although WUI growth rates are not shown in Panel b, according to the United States Department of Agriculture, National Forest Service, between 1990 and 2010 California experienced a 33.8% (1,117,087 houses) increase in residential WUI exposure — the second highest growth rate in the country.[10] The longer-term growth rates, again not shown in Panel c, are also important in that California's average air temperatures began rising at a faster annual rate starting in 1980, with 2014 through 2017 being notably warm.[11] Similarly the growth trends reported in Panel d indicate that California has become drier over time and that for five of the eight years between 2007 and 2016 the Palmer Drought Severity Index fell below -3, indicating severe to extreme drought.[12]

Recent studies (Raymond et al., 2020; Tilloy et al., 2019) show that multiple weather-related and physical characteristics drive climate-related events. For example, precipitation, evapotranspiration, antecedent soil moisture, and temperature are the drivers of droughts. Wildfires are mainly a result of climate, vegetation, topography, and human activities that interact dynamically in space and time (see Marlon et al., 2012).

In California, extreme fire behavior is often associated with strong offshore winds. Most notably, the Santa Ana winds have been the driving force behind many of Southern California's most devastating fires (Billmire et al., 2014; Govell and Cao, 2017; Guzman-Morales et al., 2016; Jin et al., 2013; Kochanski et al., 2013), as have the Diablo winds of Northern California with their similarly low relative humidity, high temperatures, and very high wind speeds (Bowers, 2018;

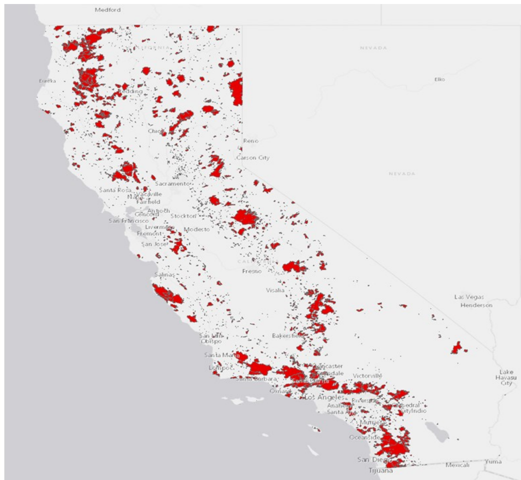
[8] See Oliver Milman and Vivian Ho, "California Wildfires Spawn First 'Gigafire' in Modern History," The Guardian, Oct. 6, 2020, https://www.theguardian.com/us-news/2020/oct/06/california-wildfires-gigafire-first; Priya Krishnakumar and Swetha Kannan, "The Worst Fire Season Ever. Again." Los Angeles Times, Sept. 15, 2020, https://www.latimes.com/projects/california-fires-damage-climate-change-analysis/.

[9] National Interagency Fire Center, National Report of Wildland Fires and Acres Burned by State, https://www.predictiveservices.nifc.gov/intelligence/2018_statssumm/fires_acres18.pdf.

[10] See https://www.nrs.fs.fed.us/data/wui/state_summary/

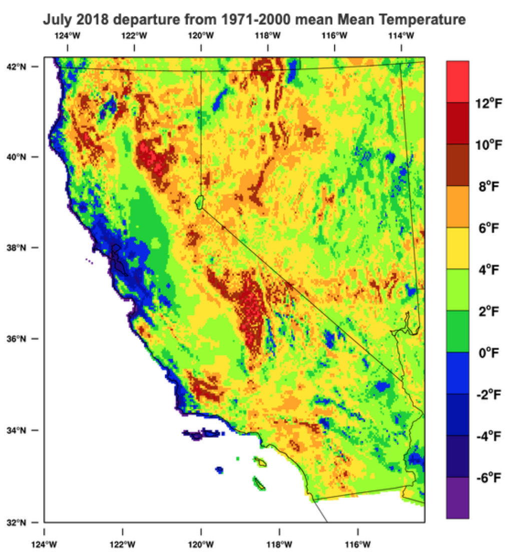
[11] See *California Office of Environmental Health Hazard Assessment, Climate Change Indicator Report, 2018*, https://oehha.ca.gov/media/downloads/climate-change/report/2018indicatorssummary.pdf.

[12] https://oehha.ca.gov/media/downloads/climate-change/report/2018indicatorssummary.pdf.

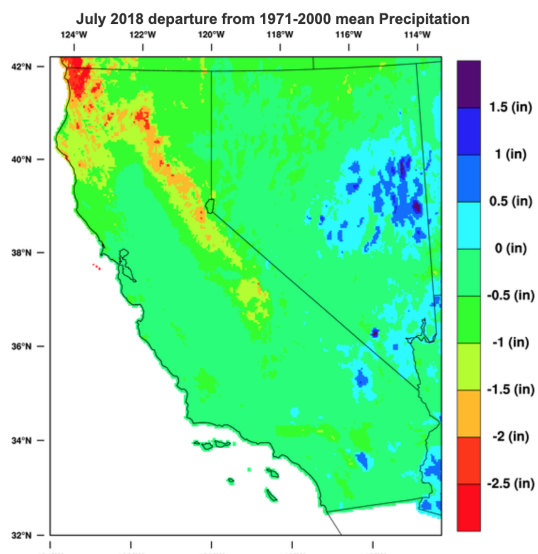


(a) **Wildfires 2000 to 2018**

(b) **Wildland Urban Interface, 2019**



(c) **2018 Mean temp. deviation**



(d) **2018 Mean precip. deviation**

Figure 2: **California wildfire incidence, Wildland Urban Interface (WUI), maximum temperature and precipitation deviations from 1971–2000 averages.** Panel a presents the geographic location of wildfires in California, 2000 to 2018, shown in red, as designated by the California Department of Forestry and Fire Protection. Panel b presents the wildland Urban Interface (WUI) in 2019, shown in tan (Source: https://www.arcgis.com/home/item.html?id=a4985d64969743db8feddf01c96c9435 ArcGIS Living Atlas of the World, SILVIS Lab, University of Wisconson-Madison, Multi-Resolution Land Characteristics Consortium). Panels c and d, respectively, show the July 2018 mean departure from the 1971–2000 mean temperature and mean precipitation from 1971 through 2000. (Source: https://cefa.dri.edu/Westmap/westmappass.php).

Keeley and Syphard, 2019; Liu et al., 2021). The National Weather Service first defined a Santa Ana wind as a northeasterly to easterly wind over 25 knots (Small, 1995) and Diablo winds are now defined similarly by their speed, direction, and relative humidity (Bowers, 2018; Liu et al., 2021). Interestingly, the minimum relative humidity of Diablo and Santa Ana winds has decreased significantly in recent years, especially in October, which suggests that the drying effects of these winds has become more severe with time, possibly leading to an increase in both the chance of fires and their destructive potential (Bowers, 2018; Liu et al., 2021). Population growth is also associated with these wind-driven fires, since the presence of larger populations increases the probability that humans, or human infrastructure, can provide an ignition source.[13]

Given the determinants of the climate-driven fire events that are identified above, we now focus on developing a tractable empirical specification to evaluate the probabilities of climate-driven fire events in California. In the following subsection, we propose a reduced form empirical specification to the obtain estimates for the seasonal probabilities of site-specific fire risk in California, drawing upon on the meteorological pre-conditions of extreme fire weather conditions identified in the forecasting models of Goss et al. (2020) as well as site specific characteristics such as topography, vegetative coverage, and degree of urbanization from the environmental literature (Bowers, 2018; Liu et al., 2021; Marlon et al., 2012).

2.2 Probability of climate-driven events: estimation using data on California wildfires

The first step towards understanding the effects of climate risk on the housing and mortgage markets is the evaluation of the probabilities that a specific house will experience a climate-driven event. Therefore, we set up a methodology to estimate the probability $p = p(c, l, t)$ of occurrence of a type of climate-driven event, c, in a location, l, at time, t, using the determinants of these events.

Consider a reduced-form model with three sets of predictors of a type of climate-driven event, $X_{weather}(c, l, t)$, $X_{physical}(c, l, t)$, and $X_{season}(c, l, t)$, which denote a vector of weather variables, a vector of physical characteristics of the grid where each specific house is located, and a vector of seasonal variables (e.g., month of the year), respectively, and one binary (Bernoulli) response variable $Y(c, l, t)$, where $p(c, l, t) = \mathrm{P}(Y(c, l, t) = 1)$. All of the predictors depend on the type of the climate-driven event, c, the specific grid in which the house is located, l, and the time, t; however, to simplify notation we drop references to c, l, and t from now on. We assume a linear relationship between the predictor variables and the log-odds of the climate-driven event Y. This relationship can be written in the following form:

$$\log \frac{p}{1-p} = \beta_0 + \beta_{weather} X_{weather} + \beta_{physical} X_{physical} + \beta_{season} X_{season}, \tag{1}$$

where β_0 is a constant and β_i are the model's parameters.

[13] Human ignitions account for essentially all of these wind-dominated fires, not just in California, but nationwide (Abatzoglou et al., 2018).

We estimate the parameters of this model using data on California wildfires. The meteorological data used in this study were provided by Vahmani et al. (2019). The data are simulated using a regional climate model (the Weather Research Forecasting (WRF) model)[14] coupled with an Urban Canopy Module (UCM)[15] to downscale historical North American Regional Reanalysis (NARR) data[16] to create weather measurements in 1.5 by 1.5 kilometer grids for urban areas and 4.5 by 4.5 kilometer grids for rural areas of California. Ground-based measurements using National Oceanic and Aeronautical Administration (NOAA) measurement station data were used to validate the simulations.

Our weather data are measured as daily averages of hourly data, and we use all urban and rural grids that contain at least one single-family residential house with a mortgage. For each grid-day, we have daily measures of the maximum temperature, wind velocity, the relative humidity, an indicator variable for northeasterly and southeasterly wind direction (as a control for Diablo and Santa Ana winds), and indicator variables for the peak periods for these winds. Our daily measurements from 2000 to 2015 are for the months of May to October, which are considered the California fire season.

Table 1 presents the results of the logistic regression in equation (1) of the daily probability that a grid is within a CalFire burn area — the areas shown in red in Panel a of Figure 2. In addition to the meteorological information for each grid, we also include measures for the slope and elevation of the centroid of each grid.[17] The slope and elevation data are important because Santa Ana and Diablo winds are also driven by the mountainous terrain of California, which can cause offshore winds to transition to down-slope winds associated with rapidly warming and drying airflow as they descend at high velocity on the lee of the mountain ranges (Whiteman, 2000). Finally, we have two measures of WUI characteristics obtained by geoprocessing California WUI maps: the percentage of vegetative and urban development coverage at the latitude and longitude of each grid centroid.[18]

As shown in Table 1, our logistic regression indicates a strong positive relationship between the probability of a wildfire and grid-level average wind speed, the average maximum temperature, the slope and the elevation, and the percentage of vegetative coverage. Average relative humid-

[14]The WRF Model is a next-generation numerical weather prediction system with meteorological applications across scales from tens of meters to thousands of kilometers. It works at a mesoscale or intermediate scale between the scale of microclimates and of weather systems, on which storms and other weather phenomena take place. WRF was developed through a collaborative partnership among the National Center for Atmospheric Research (NCAR), the National Oceanic and Atmospheric Administration (represented by the National Centers for Environmental Prediction (NCEP) and the (then) Forecast Systems Laboratory (FSL)), the Air Force Weather Agency (AFWA), the Naval Research Laboratory, the University of Oklahoma, and the Federal Aviation Administration (FAA).

[15]The purpose of the coupled model is to provide more accurate forecasts for urban regions by accounting for features such as shadowing from buildings, the reflection of short- and longwave radiation, the wind profile in the canopy layer, and multi-layer heat transfer equations for roof, wall and road surfaces (see https://ral.ucar.edu/solutions/products/urban-canopy-model).

[16]See https://psl.noaa.gov/data/gridded/data.narr.html.

[17]These were computed using topographical RASTER data from https://www.usgs.gov/core-science-systems/ngp/tnm-delivery/gis-data-download?qt-science_support_page_related_con=0qt-science_support_page_related_con and geoprocessing this information using QGIS software to compute slope.

[18]These data were obtained from the Silvis Lab for Spatial Analysis For Conservation and Sustainability at the University of Wisconsin (see https://frap.fire.ca.gov/mapping/maps/).

ity and the percentage of urban coverage, as expected, have statistically significant and negative association with grid wildfires. The easterly direction of the wind has a statistically significant positive relationship with the probability that the grid was involved in a wildfire, as do the months of September and October. October, as expected, is the most severe month.

Table 1: **Probability of climate-driven events. Application to California wildfires.** This table presents the logistic regression analysis of the probability that a grid with single family homes and mortgages will experience a wildfire as detailed in equation (1). The data are a panel at the grid-day level. We use average daily measurements at the latitude and longitude centroid of each grid for the months of May through October from 2000 through 2015. The daily grid measures include maximum temperature, wind speed, relative humidity, the slope of the grid and its elevation, and two measures for the wildland urban interface of the grid, the percentage of urban coverage and the percentage of vegetative coverage. We also include two measures for the direction of the wind as indicator variables for northeasterly and southeasterly winds and two measures for California's historical peak fire season, September and October. Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the .01%, 1%, and 5% levels, respectively.

	Coef.	Std. Error
β_0, constant	-10.7559***	0.039
$\beta_{weather}$:		
Wind Speed	0.3976***	0.005
Maximum Temperature	0.4854***	0.018
Relative Humidity	-0.2549***	0.016
Northeasterly Wind	0.3743***	0.031
Southeasterly Wind	0.3921***	0.032
$\beta_{physical}$:		
Slope	0.4003***	0.011
Elevation	0.2821***	0.011
Percentage of Urban Site Coverage	-0.0429*	0.021
Percentage of Vegetative Site Coverage	0.0677***	0.018
β_{season}:		
September	1.9573***	0.042
October	3.2897***	0.043
Observations	28,978,800	
Pseudo R-squared	0.16	

Figure 3 presents a heatmap for the grid-level wildfire probability estimates for Northern and Southern California for the months of June of 2015 (panel a) and October of 2015 (panel b). As shown, in the probability scales over the four submaps, the average monthly probabilities of wildfires range from essentially zero to more than 3.3%. Additionally, areas with a combination of steeper topography and relatively higher temperatures are persistently red and the areas with significant but not the highest probabilities of big fires stretch over wider areas of the coastal zones than are shown in the deterministic maps.

To better interpret the wildfire probability estimates reported in Table 1 and panels (a) and (b) of Figure 3, we present a map, shown in panel (c), of the deterministic wildfire hazard codes that have been assigned by the California of Department of Insurance (CDI) for Northern and Southern

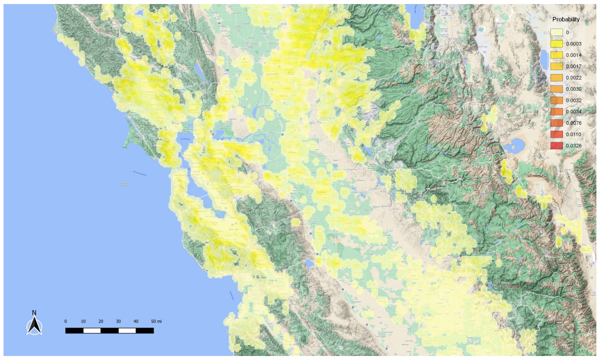
California properties. As shown, there are three designations of risk: code 3 for high; code 2 for moderate; code 1 for lower; all other areas are code 0 (not shown), the lowest risk. Along the coastal areas, the code-3 zones tend to run along the western facing slopes of the coastal range and along natural breaks in the coastal range that link dry interior areas with the western slopes. In the interior, the code-3 zones are at the base of the eastern facing side of the coastal range. Both along the coast and in the interior, the code-2 areas lie in areas with flatter topography that abuts the code-3 higher risk zones. Finally, the code-1 areas abut the code-2 zones, but in areas with lower elevation.

Table 2 presents our average daily grid estimates for the June and October probability of wildfire in 2015 organized by the CDI hazard code designation of the grid. As shown in the table, in the peak fire-season month the estimated levels of the probability of urban wildfire for hazard code 0 through and 2 are quite flat, especially between codes 1 and 2. Though the difference between the means for codes 1 and 2 is statistically significantly different from zero magnitude of the differences between these two designations is not very large certainly compared with the difference between code 2 and code 3. The flat risk assessment structure of the current hazard codes is the basis for fire casualty insurance premia in California. The soundness of the California insurance market is currently the subject of much debate (we discuss these in more detail in Section 7) due to possible distortions induced by three important features of the pricing and regulation of fire casualty insurance in the state (see Dixon et al., 2019). First, the CDI prohibits the use of probabilistic wildfire models, such as the model estimated above, in rate setting. Second, while the CDI does allow for adjustment factors to increase rates for high-risk properties, these scaling factors must be approved by the CDI, and insurers claim that the factor structure is too flat. Third, the CDI does not allow insurers to include the reinsurance margin as an expense in the rate-approval process. We will re-consider the merits of the flat deterministic risk structure in Section 6 where we discuss shocks to the exogenous meteorological data and their effects on the expected post fire value of the California housing stock.

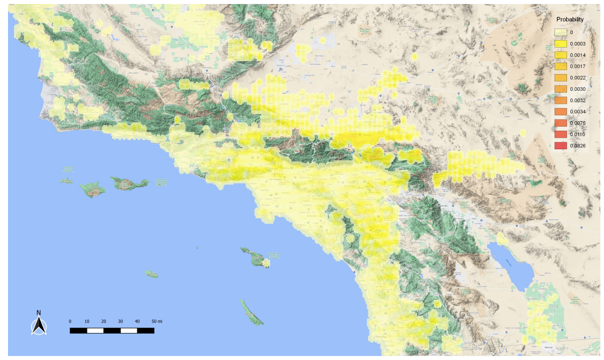
Table 2: **Probability of wildfires by hazard code groups.** This table shows the average daily probability of wildfire estimates for grids with single family residential houses and mortgages for each of the California Department of Insurance (CDI) hazard code assignment of the grid. The average daily probability of wildfire has been estimated using the logistic regression in equation (1).

CDI Hazard Codes	Grid Count	Logistic Regression Daily Probability Estimates			
		June		October	
		Mean	Std. Dev.	Mean	Std. Dev.
0	8,613	0.000034	0.000044	0.000712	0.000875
1	1,304	0.000055	0.000044	0.001045	0.000695
2	1,134	0.000069	0.000061	0.001259	0.000814
3	1,659	0.000070	0.000067	0.002021	0.001518

Our empirical strategy to quantify the effect of these distortions is based on natural experiments determined by the confluence of the random weather and ignition events that have led to wildfire

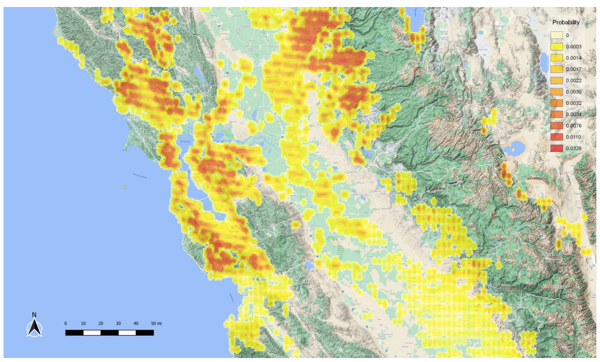


i. Northern California

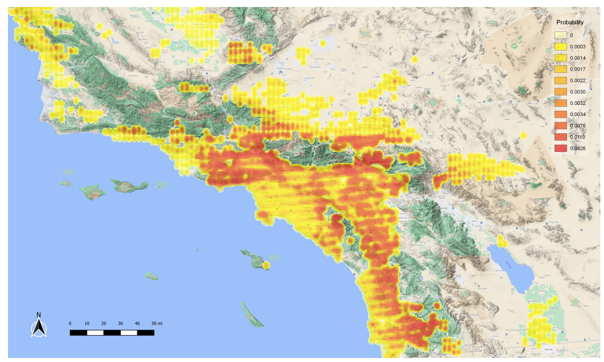


ii. Southern California

(a) Estimated probabilities in June

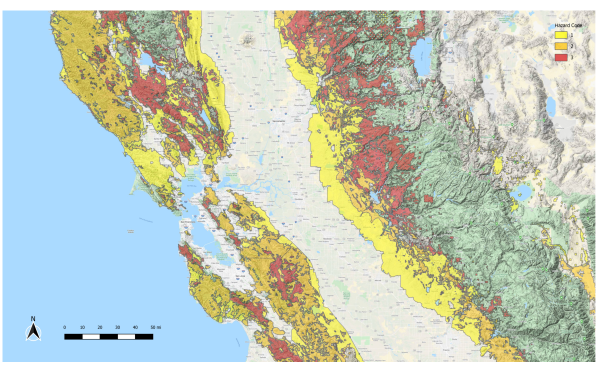


i. Northern California

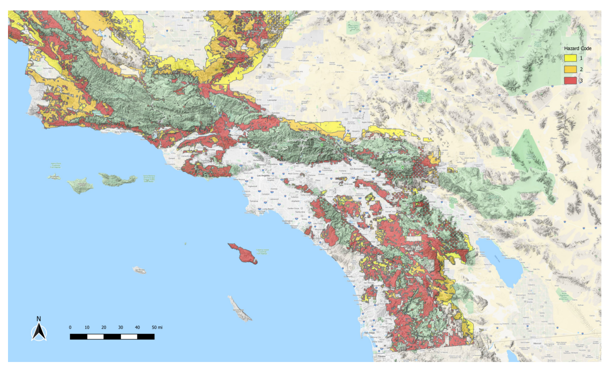


ii. Southern California

(b) Estimated probabilities in October



i. Northern California



ii. Southern California

(c) Deterministic probabilities

Figure 3: **Estimated fire probabilities.** This figure presents the estimates of the wildfire probabilities at the grid level for the months of June and October of 2015 in panels a and b, respectively. Panel c shows the deterministic fire codes from CalFire (see https://osfm.fire.ca.gov/divisions/wildfire-planning-engineering/wildland-hazards-building-codes/fire-hazard-severity-zones-maps/)

natural disasters in California. We first describe how we use difference-in-differences approaches to study the effects of these largely climate-driven events on the dynamics of the housing markets (house size and prices), gentrification (income and wealth), and the household's mortgage-default decisions (default and delinquency). Moreover, we analyze the mechanisms that drive these effects, namely the frictions in the housing and insurance markets, since fire insurance is required for *all* residential mortgages.[19]

3 Property-level empirical strategy

In this section, we develop the empirical strategy that we use to study the effects of insured climate-related events on the housing and mortgage markets. Although there is now a growing literature that considers the effects of climate change on the health of the U.S. financial system,[20] no existing papers focus on the relationship between climate-driven events such as wildfires, ex post house price and size dynamics, household demographics, and residential mortgage performance accounting for the pervasive effects of casualty insurance on these outcomes.[21] Most housing-related papers in the existing climate finance literature focus on whether inundation and sea-level risks are capitalized into house prices (see Baldauf, Garlappi, and Yannelis, 2020; Bernstein, Gustafson, and Lewis, 2019; Gibson and Mullins, 2020; Giglio, Maggiori, Rao, Stroebel, and Weber, 2021; Keenan, Hill, and Gumber, 2018; Murfin and Spiegel, 2020; Ouazad and Kahn, 2021). Another strand of this literature focuses on the effects of current and forecasted inundation risks on real estate valuations and flood insurance premiums (see Baldauf et al., 2020; Gibson and Mullins, 2020) or the effects of low flood insurance subscription rates on the incentives of banks to securitize (see Ouazad and Kahn, 2021).[22] Only one empirical paper explicitly models the ex post default outcomes of mortgages on homes damaged by flooding (see Billings et al., 2020).

3.1 Wildfires: a natural experiment

The treatment and control assignment of properties associated with each of the California wildfires provides a quasi-experimental design to address our empirical analyses. Consequently, we geolocalize all the properties with mortgages in our database, as well as the shapes of the wildfires, which we obtain from the California Department of Forestry and Fire Protection (Cal-Fire). We define our treatment group as the set of mortgages that are inside a wildfire zone in the event of a fire. We define the dummy variable *Fire*, which takes the value 1 if the active mortgage falls inside the

[19]Fire insurance is bundled as a secondary risk within the typical homeowner policy, so its pricing is not as directly observable to consumers as that of, say, flood insurance. Notice that the decision to rebuild a mortgaged home after a large wildfire is made by the borrower, given their insurance coverage and the requirements of county and local building codes among other frictions.

[20]See Bernstein et al. (2019), Ouazad and Kahn (2021), and a recent special issue of the *Review of Financial Studies*.

[21]The exception is Garnache and Guilfoos (2019), who study wildfires and house prices. However, this working paper focuses not on the direct effect of wildfires, but rather on the effect of burn-scar view on real estate prices.

[22]Ouazad and Kahn (2021) base their analysis on forward-looking expectations of default for *newly* originated mortgages, rather than the current stock of houses and loans.

wildfire zone and 0 otherwise. We consider a ring 1 mile around the perimeter of the wildfire zone, *Control1*. The set of mortgages that fall in *Control1* conform the control group for the baseline specification.

We also define a second control group using a dummy variable, *Control1to2*, that takes the value 1 if the property is inside the ring between 1 and 2 mile distance outside the limit of the fire area (i.e., ring outside the *Control1* ring). This second control group will allow us to use *Control1* as a treatment group in some specifications and, therefore, be able to quantify the externalities and spillover effects of climate events to nearby areas.

We use the San Diego Witch Creek complex fire as an example to explain the assignment of properties in treatment and control groups. This wildfire started on October 21, 2007 and was contained on November 13, 2007. The ignition event was the random confluence of wind-induced arcing of a power line located roughly 20 meters above the ground and a strong Santa Ana wind (see Billmire et al., 2014; Govell and Cao, 2017; Guzman-Morales et al., 2016; Jin et al., 2013; Kochanski et al., 2013). The wildfire caused five deaths and led to the evacuation of more than 1,000,000 residents — the largest evacuation in California history.[23] The insured damages from the fire were $1.3 billion.[24] As of 2020, the Witch Creek fire is the fourteenth-largest wildfire (in terms of size) in modern California history and the sixth-most destructive wildfire (in terms of costs) on record in California.[25]

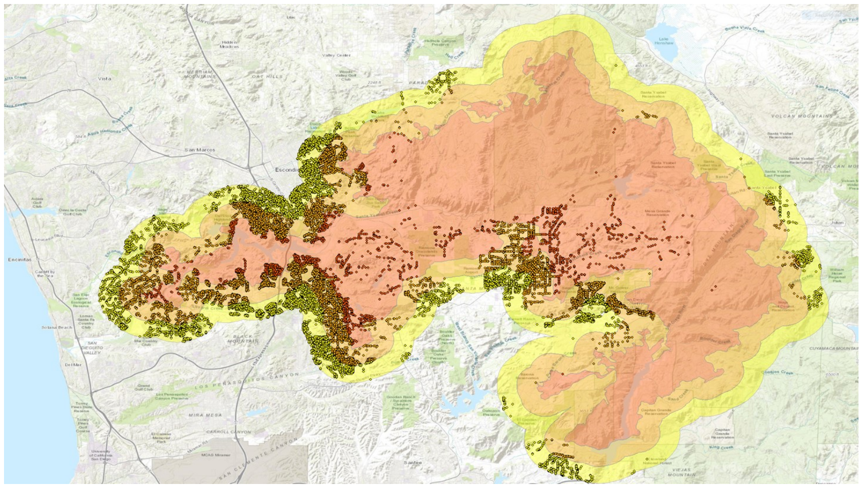
Figure 4a shows the properties within the CalFire-designated burn area and two peripheral rings, computed by the authors, at distances of 1 and 2 miles, respectively. CalFire's burn area designation includes all properties with total or partial burn damage. The properties within the 1-mile periphery did not burn, but were often visually exposed to the remains of the fire whereas the 2-mile area had neither visual nor actual exposure to the fire. As shown in Figure 4b, nearly all of the burn area and peripheral zones are in or abut the WUI. These areas are characterized by i) significant vegetative fuel loads that are more likely to carry wildfire and thus develop into intense fire events; ii) steeply sloped terrain; iii) south-facing slopes where vegetation is typically drier, thus leading to increased fire intensity and higher potential for ignition (see Jeffrey et al., 2019; Simon, 2017).

The Witch Creek fire destroyed 1,446 single family residential homes. Since 2003 San Diego County Planning and Development Services, as with most other California counties and municipalities, has required all fire-related repaired and rebuilt homes to be built to meet current building codes. Under current San Diego County building codes, all roofing must be class A (fire-resistant composite shingles or tile), home exteriors must be built using non-combustible material (stucco, masonry, or cement fiber board), windows are required to have welded metal corners to prevent glass from falling out as well as dual glazed units with a minimum of one tempered pane, and no

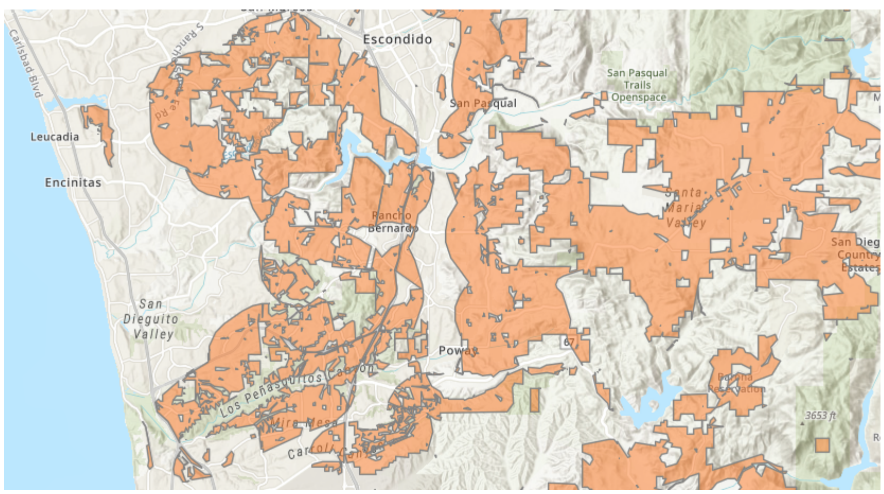
[23] Demian McLean and Peter J. Brennan "California Fires Rout Almost 1 Million People, Kill 5". *Bloomberg*, October 24, 2007.

[24] Tomas Girnius, Tyler Hauteniemi, and Scott Stransky, "California Wildfire: How Large Can The Losses Be?," *AIRCurrents*, August 2008.

[25] CalFire, "Top 20 Most Destructive California Wildfires," September 10, 2020.



(a) **Mortgaged property locations, burn area, 1- and 2-mile peripheral rings**



(b) **WUI of the San Diego Witch Fire Area**

Figure 4: **San Diego Witch Fire, properties with mortgages and the WUI.** Panel a shows the location of the properties with mortgages affected by the 2007 Witch wildfire. It shows the treatment group area in red, the *Ring 0-1* area in organge, and the *Ring 1-2* area in yellow. Panel b shows the WUI for the Witch Fire area in 2019 (Source: https://www.arcgis.com/home/item.html?id=a4985d64969743db8feddf01c96c9435 ArcGIS Living Atlas of the World, SILVIS Lab, University of Wisconson-Madison, Multi-Resolution Land Characteristics Consortium).

homes are allowed to be rebuilt with unenclosed underfloors, among other restrictions.[26] In addition, San Diego County, as well as the rest of the State of California, has earthquake requirements for newly constructed homes such that "modern open-type houses with large glass openings, split-level houses, and multi-story houses..., since 1954, have had to meet higher standards of seismic design in order to obtain a building permit."[27] These higher standards may require shear wall, larger and deeper concrete piers with reinforced steel, and tie-downs for the foundations.

3.2 Household decisions and wildfires

In a frictionless world, households with fire casualty insurance might be indifferent to wildfires, because homeowner policies amount to a promise to pay the lesser of the policy face value or the amount needed to replace the destroyed property minus a deductible.[28] As a result, wildfires should not have any effect on households' decisions. However, in fact, households face many frictions associated with negotiating settlements, rebuilding, understanding state-level insurance laws and their own policies, keeping their mortgages current, or moving to a new home outside the fire area.

To understand the impact of fire risk on housing and mortgage markets and post-fire gentrification, it is useful to focus on the revealed preferences of mortgagors with casualty insurance who were located within the burn-areas of these wildfires. The size, and even the direction, of the effect of a wildfire on mortgage performance is not a priori clear. For example, default could increase after a wildfire because of homeowners' short-term liquidity issues or it could decrease because homeowners could rebuild a home in a rebuilt neighborhood with the proceeds of the insurance settlement. Of course, the value today of a just-burnt-down house is lower than immediately before the fire, and the event of a fire may increase the perceived likelihood of additional fires in the future. As pointed out by Campbell et al. (2011), rational decisions about complicated financial products require considerable information on terms and conditions that households may have limited ability or inclination to process. Negotiated settlements on casualty policy claims significantly exacerbate this risk to households due to the infrequency of such events and the trauma associated with potentially devastating financial losses (see Feinman, 2017; Molk, 2018; Schwarcz, 2017).

We summarize the important features of fire insurance in California in Appendix A. The main conclusion from this discussion is that homeowners have a strong incentive to rebuild following a loss of a home due to a wildfire, and there are also incentives in the policies to build a larger, better house than was there before. These incentives are magnified by the fact that everyone in the neighborhood is rebuilding at the same time.

[26] See https://www.sandiegocounty.gov/pds/docs/pds664.pdf.

[27] See https://www.sandiegocounty.gov/content/dam/sdc/pds/advance/oldgp/seismicsafetyelement.pdf.

[28] Barseghyan et al. (2013) find in a large sample of about two million U.S. insurance policies that only 1.6% of households had insurance policies with deductibles exceeding $1,000.

4 Data

Our database is unique. We assemble data from multiple sources to be able to observe property characteristics, households' attributes, and mortgage components, as well as to determine treatment and control groups and the determinants of climate events. Our data serve to effectively test the effects of climate-change risk on the housing and mortgage markets for two main reasons. First, we use a micro approach based on geolocalized matches of databases at the property-level, which allows us to take advantage of the quasi-natural experiment provided by wildfires; most of the recent studies use data matched at the zip code or county levels. Second, we can study the long-run effects of climate risk using a large panel.

Table 3: **Summary statistics: House and mortgage characteristics.** The table presents the summary statistics by variable for the merged panel data set from 2000 to 2018. The summary statistics are organized by data source. Housing variables come from ATTOM Data Solutions. Mortgage variables come from McDash Black Knight Financial Services. Treatment and control variables are calculated by identifying all the properties geolocated in the fire (treatment) area or in Control1 or Control1to2 of any of the wildfires in the CalFire maps for the period 2000 to 2018.

Housing variables:					
Only Treatment and Control Areas	Mean	Std. Dev.	Min.	Max.	Obs.
House value	624,380	577,535	0	66,500,000	7,550,244
Size (sq. ft.)	2,140	1,023	0	18,410	9,669,864
Num. bathrooms	2.54	0.97	0	33	9,669,864
Num. bedrooms	3.50	0.97	0	74	9,669,864
Num. rooms	4.3	4.3	0	67	4,547,460
Mortgage variables:					
Only Treatment and Control Areas	Mean	Std. Dev.	Min.	Max.	Obs.
Original loan amount	439,831	315,353	3000	16,500,000	4,547,460
Original property value	659,139	590,709	0	66,500,000	4,524,228
Original interest rate	0.0537	0.0170	0.0002	0.1400	4,547,359
Original credit score	703.56	68.87	0	900	3,936,179
Original term (months)	356.25	62.99	35.00	616.00	4,545,750
LTV	0.745	0.518	0.01	1.22	4,510,658
GSE dummy	0.016	0.127	0	1	4,547,460
Mortgage age (years)	4.88	3.54	0	18	4,547,460
Treatment and Control:					
Only Treatment and Control Areas	Mean	Std. Dev.	Min.	Max.	Obs.
Fire (Treatment)	0.0645	0.2456	0	1	4,547,460
Control1	0.44	0.50	0	1	9,669,864
Control1to2	0.53	0.50	0	1	9,669,864
Fire area (acres)	289.52	387.46	0.00	1559.59	4,547,460

4.1 Housing characteristics, house prices and mortgages

We focus on owner-occupied, single-family residential data in California using a customized panel data set obtained from ATTOM Data Solutions. The ATTOM data provide an annual snapshot of the physical characteristics (e.g., square footage, number of rooms, etc.) for properties in California from 2000 through 2018, allowing us to measure the annual changes in the physical characteristics of each house from year to year. Our base property sample has 4,004,312 properties. To measure house prices, we use either the transaction value of the property as reported in ATTOM at the transaction data, for houses that sell, or we compute an estimate of the value of the home from the last transaction date using a zip code level price index from Zillow.

For our housing and mortgage performance analysis we use a merge of ATTOM and Black Knight McDash loan-level mortgage characteristics and performance data from January 2000 to April 2018, which covers about two-thirds of the mortgage market. These data include information on mortgage characteristics such as the type of mortgage (e.g., ARM, FRM, IO), the interest rate, and the amortization schedule. It also includes information on the borrower such as the FICO score, as well as data on the location, valuation, and physical specifications of property that has been used as collateral. Moreover, this data set contains information of the monthly performance of the mortgage from origination to its final payment. This includes payment status (current or months of delinquency), as well as events such as prepayment, default, and foreclosure. The ATTOM data include not only the latitude and longitude coordinates of each property, but also specific characteristics of the houses collateralizing the mortgages. The final panel mortgage performance data set is measured at monthly time intervals 2000 and 2018.

Table 3 presents the summary statistics for the monthly panel of fixed rate California mortgages. For each mortgage in our sample we include information on its contract characteristics at origination and then we track the mortgage month-by-month until it either prepays or defaults. As shown, the mean loan amount at origination was $439,831 with a standard deviation of $315,353. The mean property value was $659,139 with a standard deviation of $590,709, and the mean loan-to-value ratio was 74.5%.

4.2 Household demographics, income, and wealth

We use data from Data Axle to measure the annual income and wealth of the household residing at each address. Table 4 reports summary statistics for the 2006 through 2018 annual panel of ATTOM data, which has been merged with Data Axle data by year and address for the demographic, income, and wealth characteristics of the occupants of the home. Data Axle's U.S. Consumer Database is the industry's premier consumer database, which is sourced from 100 contributors, is fully rebuilt every month, and includes comprehensive demographic and lifestyle attributes for about 67 million U.S. households from 2006 through 2019. As shown in Table 4, the Data Axle demographic variables include age of household head, marital status of household head, whether the household head is a homeworner, and the ethnicity and race of the household head. More than 70% of the household heads are between 30 and 60 years old; about 4% of household heads are between 25 and 29 years old; and about 17% of the households are older than 60 years old. Seventy percent of the household heads are married, 98% are homeowners, and 71% are Caucasian. Data Axle estimates the annual house value data with hedonic regression models and data from public records, self-reported data, and Census data. The housing and household panel is measured at annual time internals for each property from 2000 to 2018.

The income data are modelled by Data Axle using the MRI/Simmons Survey of the American Consumer. The MRI income data are matched to the name and address of Data Axle's consumer data. Data Axle's income model is estimated on the matched records and then adjusted locally to match census income distributions. The Data Axle model is updated based on changes in Census Bureau data, changes from latest MRI survey, actual changes in the household income, and changes in the Data Axle consumer data. The data used in the Data Axle income model include about 35 individual, household, and consumer life style characteristics and about 26 geo-processed Census data fields.

Data Axle's wealth variable is derived from their WealthFinder model variables using variables such as income, home value, education level, tangible and intangible assets, among others. All of the WealthFinder information is derived from public and self-reported sources found in Data Axle's Consumer Database compilation process. The algorithm does not include any ethnic, racial, religious indicators, or credit data, assuring that biases and Fair Credit Reporting Act guidelines are non-issues.

5 Empirical results: long-run effects on housing, gentrification, and mortgages

In this section we study the causal relationship between wildfires and house size and prices (Section 5.1), households' income and wealth (Section 5.2), and mortgage delinquency and foreclosure (Section 5.3). To do so, we implement a difference-in-differences (DID) approach and a panel spatial autoregressive (SA) model looking at 5-year changes in house size and prices, 5-year changes in household income and wealth, and 6-month changes in mortgage delinquency and foreclosure status from the time of each wildfire, t_0. We choose a 5-year horizon for the analysis of house size, house prices, household income, and household wealth, because full reconstruction and gentrification can take several years to materialize. We choose a 6-month horizon for the analysis of mortgages because decisions on mortgage delinquency or default can occur up to several months after the fire. However, our results are robust to different choices for these horizons.[29]

We implement the treatment and control groups developed in Section 3 and we use the data described in Section 4. The DID model is based on the following empirical specification:

$$Y_{i,t} = \beta_{FA} Fire_i \times Afterfire_{i,t} + \beta_F Fire_i + \beta_A Afterfire_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}, \quad (2)$$

[29] We obtain similar results when we use gaps of 3, 4, and 6 years instead of 5 and when we use gaps of 4, 5, 7, and 8 months instead of 6.

Table 4: **Summary statistics for the annual panel data: household demographics, wealth and income.** The table presents the summary statistics by demographics, wealth, and income variable for the merged panel data set from 2006 to 2018. This data comes from merging the Data Axle database with the ATTOM, McDash Black Knight Financial Services, and the CalFire databases.

Only Treatment and Control Areas	Mean	Std. Dev.	Min.	Max.	Obs.
Income	134,361	98,951	5,000	500,000	43,205
Log(Income)	11.536	0.794	8.517	13.122	43,205
Wealth	3,603,559	1,311,533	145,000	9,654,000	43,205
Log(Wealth)	15.019	0.422	11.884	16.083	43,205
House value	635,788	592,033	0	30,600,000	33,937
Log(House value)	13.14648	0.6240349	9.203938	17.25375	25,529
Dummy age < 25	0.0133	0.1146	0	1	43,205
Dummy age [25,29]	0.0406	0.1975	0	1	43,205
Dummy age [30,34]	0.0756	0.2645	0	1	43,205
Dummy age [35,39]	0.1192	0.3241	0	1	43,205
Dummy age [40,44]	0.1523	0.3594	0	1	43,205
Dummy age [45,49]	0.1657	0.3718	0	1	43,205
Dummy age [50,54]	0.1427	0.3498	0	1	43,205
Dummy age [55,59]	0.1059	0.3077	0	1	43,205
Dummy age [60,64]	0.0789	0.2696	0	1	43,205
Dummy age [65,69]	0.0408	0.1978	0	1	43,205
Dummy age [70,74]	0.0229	0.1498	0	1	43,205
Dummy age > 74	0.0265	0.1608	0	1	43,205
Dummy married	0.7079	0.4547	0	1	43,205
Dummy homeowner	0.9828	0.1300	0	1	43,205
Dummy Caucasian	0.7109	0.4533	0	1	27,632

where $Fire_i$ and $Afterfire_{i,t}$ are dummy variables that take the value one if house i is in the treatment (fire) group and time t for house i is 5 year after the fire, respectively. Notice that we only take the data 5 years before the fire (i.e., $Afterfire = 0$) and from 5 to 9 years after the fire (i.e., $Afterfire = 1$) when we run the DID model specified in equation (2). This approach allow us to take into account the time-to-rebuild and the years that it takes to change after wildfires. $X_{i,t}$ and $\epsilon_{i,t}$ denote a set of controls and the error term, respectively. Let $Y_{i,t}$ denote the dependent variable of each analysis, that is, the log value of house size, house price, income, wealth, and mortgage delinquency and foreclosure for each house or household i at any time t. In all the DID analyses that we perform in this section, we want to test whether the coefficient β_{FA} of the interaction term is positive.

The panel SA model uses the exact geographical location of each house and household and allows outcomes in one location to be affected by outcomes, covariates, and errors from nearby locations. Following Cliff and Ord (1970), Kelejian and Prucha (1999), and Lee (2004) our panel SA model is given by

$$\Delta Y_{i,t} = \beta_F Fire_i + \beta_X X_{i,t} + \lambda W \Delta Y_{i,t-1} + \rho W u_{i,t-1} + \epsilon_{i,t}, \tag{3}$$

where $Fire_i$ is a dummy variable that takes the value one if house i is in the treatment (fire) group. $X_{i,t}$ denotes a set of controls. W is a n $\times$ n spatial-weighting matrix, and $W\Delta Y_{i,t-1}$ and $Wu_{i,t-1}$ are $n \times 1$ vectors referred to as spatial lags. λ and ρ are scalar parameters referred to as spatial autoregressive parameters. Let $\epsilon_{i,t}$ denote an $n \times 1$ vector of innovations and, hence, $\rho W u_{i,t-1} + \epsilon_{i,t}$ corresponds to the error term. Let $\Delta Y_{i,t}$ denote the dependent variable of each analysis, that is, the 5-year change after the fire of the log value of house size, house price, income, and wealth, and the 6-month change after the fire of the mortgage delinquency and foreclosure for each house or household i at any time t. In all the panel SA analyses that we perform, we want to test whether the coefficient β_F is positive.[30]

5.1 Wildfire effects on long-run house size and prices

First, we study climate effects on the size of houses sizes 5 years after a fire event. Table 5 shows the results. Columns [1] and [2] show the estimates from the difference-in-differences (DID) empirical strategy, while columns [3] and [4] show the estimates from the panel spatial autoregressive (SA) model.

Specifically, we find that wildfires cause an extra 1.14% (DID result) to 1.46% (Panel SA result) square footage increase in the treatment group (*Fire*) compared with the control group (*Control1*), even when we use multiple controls and fixed effects (see columns [2] and [4], respectively). The negative coefficient on $\log(size_{t_0})$ indicates that these effects are smaller for initially larger houses. The results are robust to the inclusion of controls for house and fire characteristics, as well as year, month, and zip-code fixed effects.

We also study climate effects on house prices using the same DID and panel SA approaches.

[30] See Drukker et al. (2013) for more details about the estimation of the parameters in panel SA models.

Table 5: **The long-run effects on house size.** This table shows the estimates of the DID and panel SA analyses in house sizes before *versus* after a wildfire. The dependent variable is the logarithm of the house size, $\log(size_t)$ for columns [1] and [2] and the difference between the logarithm of the house size (in sq. feet) 5 years after the fire, $\log(size_{t_0+5})$, minus the logarithm of the house size the month before the fire, $\log(size_{t_0})$ for columns [3] and [4]. *Fire* is a dummy variable that takes the value 1 if the property is inside the fire area (i.e., the treatment group). *Control1* is a dummy variable that takes the value 1 if the property is inside the ring defined by the edge of the fire area and 1 mile distance outside this limit (i.e., the control group). *Afterfire* is a dummy variable that takes the value one 5 years after the fire event and zero before the fire event. We exclude the observations between 0 and 4 years after the fire event for the DID analysis. All specifications include controls for house characteristics, area characteristics, and size of the wildfire. Specifications in [2] and [4] include time and zip code fixed effects. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Approach:	DID	DID	Panel SA	Panel SA
Treatment group:	Fire	Fire	Fire	Fire
Control group:	Control1	Control1	Control1	Control1
Dep. variable:	$\log(size)$	$\log(size)$	$\Delta\log(size)$	$\Delta\log(size)$
	[1]	[2]	[3]	[4]
Fire × Afterfire	0.0103**	0.0114***		
	(0.00516)	(0.00353)		
Fire	0.0552***	0.0536***	0.0138***	0.0146***
	(0.00398)	(0.00354)	(0.00367)	(0.00481)
Afterfire	-0.0098***	0.0117		
	(0.00125)	(0.00860)		
$\log(size_{t_0})$			-0.0647***	-0.0763***
			(0.00251)	(0.00375)
Controls	Yes	Yes	Yes	Yes
Fixed effects	No	Yes	No	Yes
Observations	152,765	152,765	20,483	20,483

Table 6 presents the results of these analyses, showing that wildfires cause an extra 1.14% (DID result) to 4.18% (Panel SA result) house price increase in the treatment group (*Fire*) compared with the control group (*Control1*), even when we use multiple controls and fixed effects (see columns [2] and [5], respectively). Again, the negative coefficient on $\log(price_{t_0})$ indicates that these effects are lower for initially more expensive houses. Since, as shown in Table 5 above, house sizes tend to increase within 5 years from the fire, we also control for the change in house size, $\Delta \log(size_{t_0,t_0+5})$, in columns [3]–[7]. This does not materially change the coefficient on the fire dummy, indicating that our results are not merely driven by an increase in house size. The results are also robust to the inclusion of controls for house and fire characteristics, as well as year, month, and zip-code fixed effects.

Table 6: **The long-run effects on house prices.** This table shows the estimates of the DID and panel SA analyses in house sizes before *versus* after a wildfire. The dependent variable is the logarithm of the house price, $\log(price_t)$ for columns [1] and [2] and the difference between the logarithm of the house price 5 years after the fire, $\log(price_{t_0+5})$, minus the logarithm of the house size the month before the fire, $\log(price_{t_0})$ for columns [3]–[7]. *Fire* is a dummy variable that takes the value 1 if the property is inside the fire area (i.e., the treatment group). *Control1* is a dummy variable that takes the value 1 if the property is inside the ring defined by the edge of the fire area and 1 mile distance outside this limit (i.e., the control group). *Control1to2* is a dummy variable that takes the value 1 if the property is inside the ring between 1 and 2 mile distance outside the limit of the fire area (i.e., ring outside the *Control1* ring). *Afterfire* is a dummy variable that takes the value one 5 years after the fire event and zero before the fire event. We exclude the observations between 0 and 4 years after the fire event for the DID analysis. All specifications except for the one in column [3] include controls for house characteristics, area characteristics, and size of the wildfire in acres. Specifications in [2], [5], and [7] include time and zip code fixed effects. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Approach:	DID	DID	Panel SA	Panel SA	Panel SA	Panel SA	Panel SA
Treatment group:	Fire	Fire	Fire	Fire	Fire	Fire	Fire
Control group:	Control1	Control1	Control1	Control1	Control1	Control1to2	Control1to2
Dep. variable:	$\log(price)$	$\log(price)$	$\Delta\log(price)$	$\Delta\log(price)$	$\Delta\log(price)$	$\Delta\log(price)$	$\Delta\log(price)$
	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Fire × Afterfire	0.0536***	0.0580**					
	(0.01253)	(0.02562)					
Fire	-0.0085	-0.0038	0.0498***	0.0418***	0.0344***	0.0567***	0.0492***
	(0.00973)	(0.02172)	(0.00970)	(0.00982)	(0.00961)	(0.00960)	(0.00927)
Afterfire	0.0413***	-0.0263					
	(0.00307)	(0.07985)					
$\log(price_{t_0})$			-0.1883***	-0.1910***	-0.1820***	-0.1699***	-0.1565***
			(0.00478)	(0.00477)	(0.00552)	(0.00276)	(0.00313)
$\Delta \log(size_{t_0,t_0+5})$			0.2620***	0.2632***	0.2580***	0.2644***	0.2663***
			(0.0173)	(0.0172)	(0.0166)	(0.0102)	(0.0098)
Control1						0.0228***	0.0179***
						(0.00381)	(0.00370)
Controls	Yes	Yes	No	Yes	Yes	Yes	Yes
Fixed effects	No	Yes	No	No	Yes	No	Yes
Observations	118,582	118,582	13,359	13,359	13,359	41,802	41,802

We also study the neighborhood effects of climate-driven events. Columns [6] and [7] of Table 6 show the results of the equivalent approach to columns [4] and [5], but using both *Fire* and *Control1* as treatment groups and the ring located from 1 to 2 miles outside the border of the wildfire, *Control1to2*, as the control group. These results show that there is a significant increase in house prices in the 5-year period after a wildfire event for houses located within a mile of the wildfire border, compared to prices of houses located between 1 and 2 miles away from the fire limit. The increase in house prices 5 years after the wildfire event is, on average, 1.79% higher in the first ring outside the fire area (*Control1*) than in the second ring (*Control1to2*). However, the magnitude of the coefficient for *Control1* is about one third of the one for *Fire*, which indicates that the house price increases due to a wildfire is larger in the *Fire* than in *Control1*, although the latter is significantly higher than in the control group. Overall, these results show that there are neighborhood effects driven by the positive externalities associated with rebuilding.

5.2 Wildfire effects on long-run household income and wealth

Second, we study the impact of climate events on gentrification. Specifically, we study the climate effects on households' income and wealth after five years. Tables 7 and 8 present our results. We find that a wildfire event causes a significant positive change in income 5 years later. Specifically, we find that wildfires cause an extra 5.25% income increase in the treatment (*Fire*) with respect to the control group (*Control1*), even when we use multiple controls and fixed effects (see column [4]).

Additionally, we study the neighborhood effects of climate-driven events on gentrification. Columns [5] and [6] of Table 7 show the results of the equivalent DID approach to columns [3] and [4], but using both *Fire* and *Control1* as treatment groups and the ring located from 1 to 2 miles outside the border of the wildfire, *Control1to2*, as the control group. We find that there is a significant increase in income in the 5-year period after a wildfire event for households located within a mile of the wildfire border, compared with the income of households located between 1 and 2 miles away from the edge of the fire. The increase in income 5 years after the wildfire event is, on average, 6.96% higher in the first ring outside the fire area (*Control1*) than in the second ring (*Control1to2*). However, the magnitude of the coefficient for *Control1* is about one half of the one for *Fire*. Overall, these results confirm that there are neighborhood effects on income. These effects are driven by positive externalities that are associated with replacing a concentrated area of burned older homes with new built-to-code homes similar to the effects found for long-run house prices (see Table 6).

We confirm the significant effects of climate events on gentrification using wealth data at the household level. The results reported in Table 8 show the effects of wildfire on household wealth 5 years after a wildfire. The results are similar to those in Table 7. There is a positive and significant effect in wealth 5 years after wildfires. Specifically, the results show that a wildfire causes an extra 2.14% wealth increase in the treatment (*Fire*) compared to the control group (*Control1*), even when using multiple controls and fixed effects (see column [4]). Columns [5] and [6] show the results of the

Table 7: **The long-run effects on household income.** The dependent variable is the logarithm of household income, $\log(i_t)$ for columns [1] and [2] and the difference between the logarithm of the household income 5 years after the fire, $\log(i_{t_0+5})$, minus the logarithm of the household income before the fire, $\log(i_{t_0})$ for columns [3]–[7]. *Fire* is a dummy variable that takes the value 1 if the property is inside the fire area (i.e., the treatment group). *Control1* is a dummy variable that takes the value 1 if the property is inside the ring defined by the edge of the fire area and 1 mile distance outside this limit (i.e., the control group). *Control1to2* is a dummy variable that takes the value 1 if the property is inside the ring between 1 and 2 mile distance outside the limit of the fire area (i.e., ring outside the *Control1* ring). All specifications except for the one in column [3] include controls for house characteristics, area characteristics, and size of the wildfire. Specifications using the panel SA approach also control for initial income, $\log(i_{t_0})$. Specifications in [2], [5], and [7] include year and zip code fixed effects. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Approach:	DID	DID	Panel SA	Panel SA	Panel SA	Panel SA	Panel SA
Treatment group:	Fire	Fire	Fire	Fire	Fire	Fire	Fire
Control group:	Control1	Control1	Control1	Control1	Control1	Control1to2	Control1to2
Dep. variable:	$\log(i)$	$\log(i)$	$\Delta \log(i)$	$\Delta \log(i)$	$\Delta \log(i)$	$\Delta \log(i)$	$\Delta \log(i)$
	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Fire × Afterfire	0.0404*	0.0550**					
	(0.02289)	(0.02335)					
Fire	-0.0468**	-0.0682***	0.1311***	0.1272***	0.0525**	0.2101***	0.1240***
	(0.01953)	(0.01988)	(0.02110)	(0.02091)	(0.02131)	(0.02082)	(0.02080)
Afterfire	0.3783***	0.4012***					
	(0.00651)	(0.00621)					
Control1						0.0749***	0.0696***
						(0.00779)	(0.00741)
Controls	Yes	Yes	No	Yes	Yes	Yes	Yes
Fixed effects	No	Yes	No	No	Yes	No	Yes
Observations	36,610	36,610	10,818	10,818	10,818	24,108	24,108

Table 8: **The long-run effects on household wealth.** This table shows the estimates of the DID and panel SA analyses in house sizes before *versus* after a wildfire. The dependent variable is the change in the logarithm of the household wealth 5 years after the fire, $\log(w_{t_0+5})$, minus the logarithm of the household wealth the year before the fire, $\log(w_{t_0})$. *Fire* is a dummy variable that takes the value 1 if the property is inside the fire area (i.e., the treatment group). *Control1* is a dummy variable that takes the value 1 if the property is inside the ring defined by the edge of the fire area and 1 mile distance outside this limit (i.e., the control group). *Control1to2* is a dummy variable that takes the value 1 if the property is inside the ring between 1 and 2 mile distance outside the limit of the fire area (i.e., ring outside the *Control1* ring). All specifications except for the one in column [3] include controls for house characteristics, area characteristics, and size of the wildfire. Specifications using the panel SA approach also control for initial wealth, $\log(w_{t_0})$. Specifications in [2], [5], and [7] include year and zip code fixed effects. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Approach:	DID	DID	Panel SA	Panel SA	Panel SA	Panel SA	Panel SA
Treatment group:	Fire	Fire	Fire	Fire	Fire	Fire	Fire
Control group:	Control1	Control1	Control1	Control1	Control1	Control1to2	Control1to2
Dep. variable:	$\log(w)$	$\log(w)$	$\Delta \log(w)$	$\Delta \log(w)$	$\Delta \log(w)$	$\Delta \log(w)$	$\Delta \log(w)$
	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Fire × Afterfire	0.0754***	0.0565**					
	(0.01501)	(0.02721)					
Fire	-0.0111	-0.0155	0.0506***	0.0519***	0.0214*	0.0740***	0.0433***
	(0.01268)	(0.01999)	(0.01061)	(0.01071)	(0.01120)	(0.01072)	(0.01081)
Afterfire	-0.3176***	0.0182					
	(0.00331)	(0.01670)					
Control1						0.0216***	0.02370***
						(0.00395)	(0.00387)
Controls	Yes	Yes	No	Yes	Yes	Yes	Yes
Fixed effects	No	Yes	No	No	Yes	No	Yes
Observations	51,129	51,129	10,818	10,818	10,818	24,108	24,108

equivalent DID approach to study the neighborhood effects on wealth in the same way as columns [5] and [6] in Table 7. These results show that the wealth increase is 2.37% higher in the *Control1* than in the *Control1to2*.

As a robustness of the causal inference, we analyze the trends of the logarithms of house sizes, house values, income, and wealth from 5 years before the fire to the year previous to the fire and from 5 to 9 years after the fire. The most critical assumption in DID analyses is related to "parallel trends", that is, pre-intervention trends in outcomes are the same between the treatment and control groups. Figure 5 exhibits the results of this analysis. Overall, the graphs in this figure show that the pre-intervention parallel trends assumption hold for house size, house prices, income, and wealth. Therefore, we can conclude that, in the absence of treatment (i.e., before the wildfire), the difference between the *Fire* and *Control1* groups is constant over time.

5.3 Wildfire effects on mortgage default and foreclosure

In this subsection, we study the effects of wildfire events on mortgage default and foreclosure. We use the dummy variable change in delinquency within 6 months after the fire event as the dependent variable in our DID specification. We define *delinquency* as a status of more than 90 days delinquency of the mortgage. Equivalently, we use the dummy variable change in foreclosure within 6 months after the fire event as the dependent variable and we define *foreclosure* as a status of foreclosure pre-sale, foreclosure post-sale, or Real Estate Owned (REO).[31]

Table 9 shows the results of this analysis. The positive and significant coefficients for the treatment group (*Fire*) in columns [1]–[2] and [3]–[4] show that there is an increase in delinquency and foreclosure, respectively, within the 6 months after a fire event. This analysis includes mortgage controls. As expected, we obtain a positive effect of interest rates, term, loan amount, and GSE mortgage on both delinquency and foreclosure, and a negative effect from property value, credit score, LTV, and mortgage age.

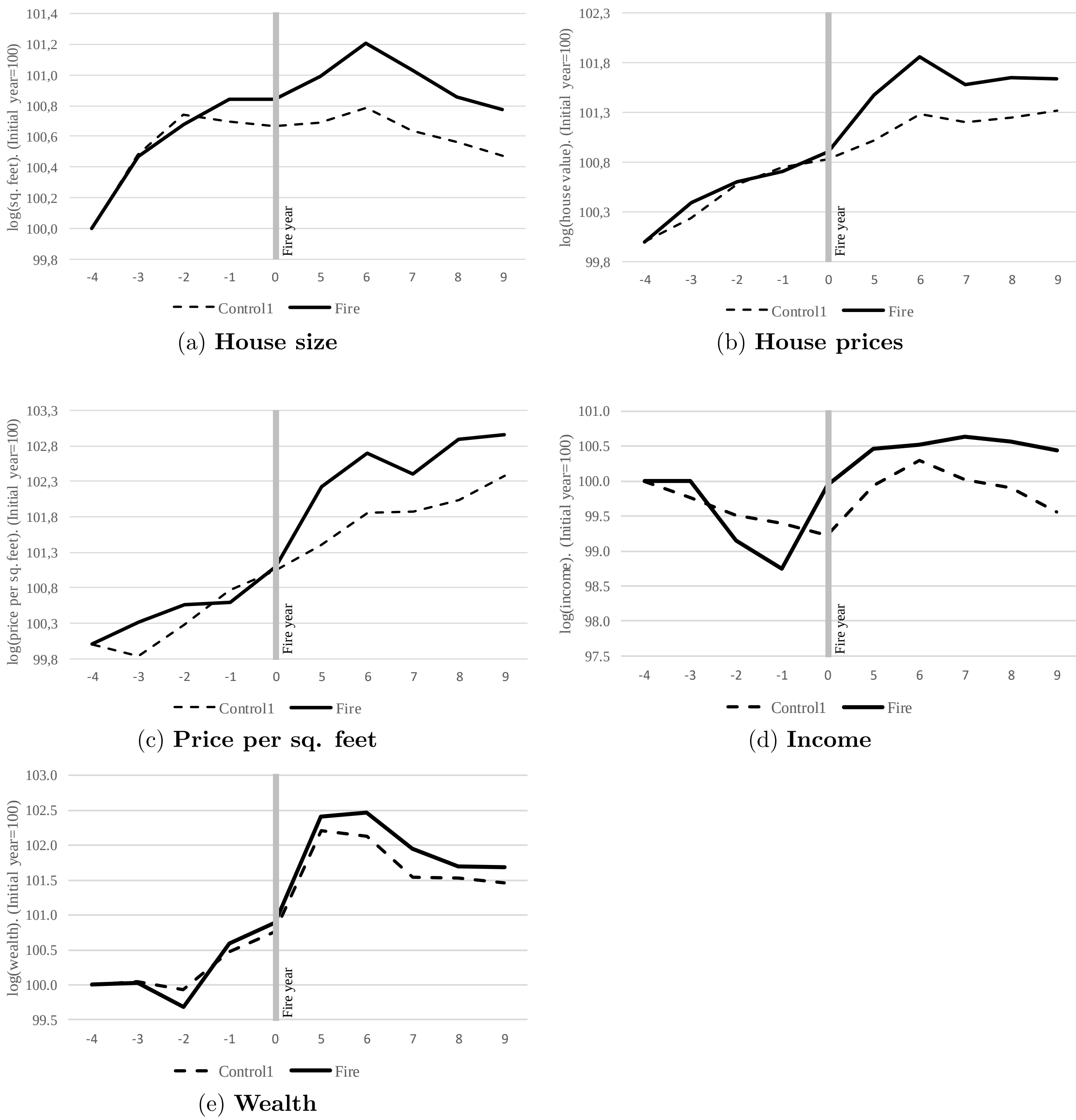
5.4 Impact of the size of wildfire events

A very interesting finding in our empirical analysis, is that results change when we take into account the size of the climate event. We use two measures of *BigFire*: i) columns [1] and [3] of Table 10 define *BigFire* as the number of acres in the burn area; ii) columns [2] and [4] of Table 10 define *BigFire* as a dummy variable that takes the value 1 if the mortgage is affected by a fire at or above the average wildfire in terms of burned area.[32]

We run equivalent regressions to the ones that we used in the previous subsections, but including the interaction between *Fire* and *BigFire*. Table 10 shows the results of this analysis. The negative and significant coefficients for the interaction of the treatment groups *Fire* and *BigFire* in all the columns show that there are fewer delinquencies and foreclosures after a large wildfire. The positive

[31] Our results are robust to using alternative periods from 3 to 12 months.

[32] Our results are robust to different definitions of this dummy variable, such as being one standard deviation above the average or using the number of mortgages affected to create the dummy (instead of the burned area).



(a) **House size**

(b) **House prices**

(c) **Price per sq. feet**

(d) **Income**

(e) **Wealth**

Figure 5: **Parallel trends analysis.** Logarithm of house sizes (panel a), house prices (panel b), house prices per squared feet (panel c), households' income (panel d), and households' wealth (panel e) in the *Fire* treatment area in dashed line and the *Control1* area in solid line. The x-axis displays the year to the fire from 5 years before the fire (-4) to the year previous to the fire (0) and from 5 years after the fire (+5) to 9 years after the fire (+9).

Table 9: **The effect of wildfires on mortgage delinquency and foreclosure.** This table shows the results of the difference-in-differences analyses of the effect of wildfires on mortgage delinquency and foreclosure. The dependant variable for columns [1]–[2] is the change in delinquency (i.e., changing to 90 days or more) during the 6 months after the fire event. The dependant variable for [3]–[4] is the change to foreclosure status (i.e., changing to foreclosure presale, foreclosure post sale, or REO) 6 months after the fire event. Mortgage controls include interest rate, term of the mortgage, loan amount, property value, credit score, and LTV, as well as the mortgage age, and dummy for GSE mortgages. Columns [2] and [4] include month, and the interaction between year and zip code fixed effects. Robust standard errors clustered at the year and tract level are shown in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	ΔDelinquency	ΔDelinquency	ΔForeclosure	ΔForeclosure
Treatment group:	Fire	Fire	Fire	Fire
Control group:	Control1	Control1	Control1	Control1
	[1]	[2]	[3]	[4]
Fire	0.00418***	0.00398***	0.00303***	0.00298***
	(0.000490)	(0.000492)	(0.000380)	(0.000382)
Interest rate (original)	1.799***	1.798***	1.041***	1.041***
	(0.00864)	(0.00864)	(0.00677)	(0.00677)
Term (original)	0.000158***	0.000157***	0.000107***	0.000107***
	(2.12e-06)	(2.12e-06)	(1.53e-06)	(1.52e-06)
Loan amount (original)	8.47e-08***	8.48e-08***	5.23e-08***	5.23e-08***
	(2.45e-09)	(2.45e-09)	(1.49e-09)	(1.49e-09)
Property value (original)	-2.91e-08***	-2.91e-08***	-1.73e-08***	-1.73e-08***
	(1.64e-09)	(1.63e-09)	(9.75e-10)	(9.74e-10)
Credit score (original)	-0.000363***	-0.000363***	-0.000185***	-0.000185***
	(1.95e-06)	(1.95e-06)	(1.43e-06)	(1.43e-06)
LTV (original)	-0.000995***	-0.000994***	-0.000541***	-0.000539***
	(6.50e-05)	(6.49e-05)	(4.16e-05)	(4.16e-05)
GSE dummy	0.0827***	0.0826***	0.0625***	0.0625***
	(0.00125)	(0.00125)	(0.00108)	(0.00108)
Mortgage age	-0.00375***	-0.00379***	-0.00224***	-0.00225***
	(5.33e-05)	(5.42e-05)	(3.80e-05)	(3.87e-05)
Controls	No	Yes	No	Yes
Fixed effects	Yes	Yes	Yes	Yes
Observations	3,911,416	3,911,416	3,911,416	3,911,416
R-squared	0.079	0.079	0.048	0.048

coefficients for *Fire* confirm that delinquency and foreclosure increase on average after a wildfire, but less so inside the wildfire areas (treatment group) for big fires.

For large fires, the decrease in the probability of delinquency is 87.1% higher in the treatment group than in the ring from the fire-zone edge to 1 mile outside the fire zone.[33] Nevertheless, the decrease in delinquency is more than 6 times lower for big than for small fires.[34] We obtain these magnitudes by evaluating the results in column [1] for a fire of 2554.55 acres, the average wildfire in our sample; larger wildfires produce larger estimates.

We also use the definition of *BigFire* as a dummy variable that takes the value 1 if the mortgage is affected by a fire at above the average wildfire in terms of the burned area (column [2]). Interestingly, if we evaluate the total effect by adding up the coefficients in the treatment *Fire* (0.0089), *BigFire* (-0.0110), and their interaction (-0.0119), we obtain a total negative effect of -1.4%. These results show that delinquency actually decreases in the treatment areas within 6 months after a big fire. The results that we obtain for foreclosure in columns [3] and [4] are similar to those for delinquency in columns [1] and [2], respectively. Overall, we conclude that although delinquency and foreclosure generally increase after a wildfire, these effects decrease with the size of the event, and importantly both delinquency and foreclosure *decrease* for large enough events.

6 Expected losses due to California Wildfire events

The logistic regression estimates reported in Section 2 allow us to compute property-specific measures of wildfire risk that are similar to measures of expected loss commonly used in the mortgage market. Our initial focus is on loss exposure for houses with mortgages, because these properties must carry fire and casualty insurance, so we know that they are insured. Our expected loss estimate is computed by: i) estimating the probability of wildfire for each geographic grid; ii) computing the October 2015 value for each mortgaged house within the grid using a local house price index; and iii) computing the current balance of the mortgage. The expected loss per property (loan), is computed as the 2015 value of the property (loan balance) times the probability of wildfire for the grid in the month of October.[35]

The results reported in Table 11 indicate several important regularities. First, CDI hazard code 0 involves the bulk of the aggregate risk to the housing stock from wildfires, since our estimated probability of wildfire for this hazard zone is not zero and there are large numbers of single family homes with mortgages that are located in this zone. Higher property values are found in the riskier hazard codes 1 through 3, where the probability of wildfire is higher.[36] The highest priced properties, representing about 3% of the single family residential housing stock with mortgages,

[33] For big fires (i.e., fires of the size of the average fire of 2554.55 acres), the decrease in delinquency in the treatment group is -5.8% ($-1.51e-05*1*2554.55+0.0111*1-1.20e-05*2554.55$), which is 87.1% higher than the decrease of -3.1% ($-1.20e-05*2554.55$) in the control group.

[34] The decrease in delinquency for big fires is -5.8% (see previous footnote), which is 627% lower than the increase of 1.1% ($0.0111*1$) for small fires.

[35] Note that this value ignores any reimbursement from insurance companies, because the goal of this variable is to estimate the expected loss in a wildfire before taking into consideration insurance payments.

[36] Though, as shown in Table 1, codes 1 and 2 do not represent very different levels of risk.

Table 10: **The impact of the size of climate events on mortgages.** This table shows the results of an analyses of the size of a wildfire on mortgage delinquency and foreclosure. The dependant variable for columns [1]–[2] is the change in delinquency (i.e., changing to 90 days or more) during the 6 months after the fire event. The dependant variable for [3]–[4] is the change to foreclosure status (i.e., changing to foreclosure presale, foreclosure post sale, or REO) 6 months after the fire event. Mortgage controls include interest rate, term of the mortgage, loan amount, property value, credit score, and LTV, as well as the mortgage age, and dummy for GSE mortgages. *BigFire* is defined as the number of acres in each wildfire in columns [1] and [3], and it is defined as a dummy variable that takes the value one if the wildfire that affects each mortgage is larger than the mean of the burned areas of all wildfires in California. All specifications include month, and the interaction between year and zip code fixed effects. Robust standard errors clustered at the year and tract level are shown in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable: BigFire:	ΔDelinquency Num. acres [1]	ΔDelinquency Dummy acres [2]	ΔForeclosure Num. acres [3]	ΔForeclosure Dummy acres [4]
Fire × BigFire	-1.51e-05***	-0.0119***	-1.15e-05***	-0.0111***
	(8.97e-07)	(0.000978)	(6.97e-07)	(0.000755)
Fire	0.0111***	0.00890***	0.00859***	0.00795***
	(0.000737)	(0.000729)	(0.000580)	(0.000576)
BigFire	-1.20e-05***	-0.0110***	-6.70e-06***	-0.00575***
	(4.01e-07)	(0.000380)	(2.97e-07)	(0.000286)
Interest rate (original)	1.849***	1.849***	1.079***	1.079***
	(0.00883)	(0.00883)	(0.00685)	(0.00685)
Term (original)	0.000207***	0.000207***	0.000134***	0.000134***
	(2.18e-06)	(2.18e-06)	(1.56e-06)	(1.56e-06)
Loan amount (original)	1.02e-07***	1.02e-07***	6.17e-08***	6.19e-08***
	(2.52e-09)	(2.52e-09)	(1.52e-09)	(1.52e-09)
Property value (original)	-3.06e-08***	-3.06e-08***	-1.80e-08***	-1.80e-08***
	(1.68e-09)	(1.68e-09)	(9.93e-10)	(9.93e-10)
Credit score (original)	-0.000348***	-0.000349***	-0.000177***	-0.000177***
	(1.97e-06)	(1.97e-06)	(1.43e-06)	(1.43e-06)
LTV (original)	-0.000784***	-0.000783***	-0.000435***	-0.000434***
	(6.55e-05)	(6.55e-05)	(4.15e-05)	(4.14e-05)
GSE dummy	0.0866***	0.0862***	0.0649***	0.0647***
	(0.00131)	(0.00131)	(0.00111)	(0.00111)
Mortgage age	0.00208***	0.00208***	0.000574***	0.000576***
	(2.72e-05)	(2.72e-05)	(1.89e-05)	(1.90e-05)
Fixed effects	Yes	Yes	Yes	Yes
Observations	3,911,416	3,911,416	3,911,416	3,911,416
R-squared	0.043	0.043	0.025	0.025

Table 11: **Estimated Losses for Homes and Mortgages in Peak Fire Season (In Sample for October)** This table compares the October average monthly probability of wildfire estimates for grids with single family residential houses and mortgages within each of the CDI hazard code assignment for the grid.

CDI	Properties	Total Prop. Value $ Billion	Total Loan Value $ Billion	Mean Prop. Value $ Thousand	Mean Loan Value $ Thousand	October Prop. Loss $ Billion	October Loan Loss $ Billion
0	716,051	421	290	594	405	7.94	5.42
1	14,408	9	6	615	430	0.28	0.20
2	14,231	9	7	672	459	0.36	0.25
3	22,811	16	11	709	471	1.05	0.72
Total	767,501	455	314	593	409	9.63	6.59

are located in geographic areas rated as hazard code 3 by the CDI; these homes represent 11% of the expected total loss of property and mortgage balances.

To measure the expected risk to the overall California residential housing stock (single family residential, duplexes, triplexes, and quadruplexes), we link the estimated probabilities of wildfire from Table 1 to the estimated long-run effects of wildfire on rebuilt homes from Table 6 to carry out a back-of-the-envelope risk-assessment exercise. In the 2020 geo-processed ATTOM Assessor data for California, the total number of residential housing units is 7,687,975, of which 7% (539,509) are located in CDI hazard codes 1 through 3. As a lower bound on the value of these properties, the total 2020 assessed value for all California housing units is $3.6 trillion, and for housing units located in the three more hazardous zones the total assessed value is $265.6 billion. At the end of 2019, the balances of securitized residential mortgages (GSE, GNMA, and private label) was $1.42 trillion.

Assuming stable estimates for the probability of wildfires, we first calculate the marginal effects of changes in maximum temperature, wind speed, and relative humidity for an October day in the peak fire season in California. In the first four rows of Table 12, we report the ceteris paribus estimates for one- and two-standard-deviation shocks to maximum temperature, wind speed, and relative humidity, repectively, using our Table 1 results. In the last two rows of Table 12, we report the total effect of a one- and two-standard-=deviation shock to maximum temperature accounting for the historical correlations between maximum temperature, wind speed, and relative humidity, again for an October day. For these estimates, we are assuming the status quo for California's fire casualty insurance coverage (i.e., no acceleration in policy cancellations), the status quo for payouts for large wildfires (i.e., coverage levels stay the same), and static pricing for fire casualty insurance.

As shown in Table 12, shocks to maximum temperature for a day in October have the largest incremental effect on wildfire risk, both ceteris paribus and accounting for correlations across the meteorological features. One- and two-standard-deviation shocks to the maximum temperature lead to an overall change in the daily probability of wildfire of 0.16%–0.32%. Similarly, the estimated incremental number of houses burned on an October day due to these overall marginal shocks is between 12,464 and 24,293.

Of course, meteorological shocks also have implications for expected wildfire related losses to housing assessed values as well as for long-run assessed value gains arising from the replacement of the "older" burned housing stock with "new" modernized (and, given the results of Table 5, often larger) structures. As shown in the second to last column of Table 12, the marginal effect on the daily expected assessed value losses from one- to two-standard-deviation shocks to the overall weather factors in October are between \$5.846 and \$11.396 billion. The effects on the post-fire rebuilt assessed value of housing units is computed using estimates from Table 6 that indicated a 3.44% increase in house values five years after wildfire treatment events. As shown in Table 12, estimates for one- and two-standard-deviation weather shocks lead to between \$6.048 and \$11.788 billion additional assessed value within five years for housing units that have been rebuilt in burned areas. Clearly, these expected one-day expected loss exposures are very substantial, and a reasonable concern is that such loss levels cannot be supported without insurance industry responses in the form of more reliance on probabilistic models, consideration of reinsurance pricing in the rates, possible rate hikes, increases in policy cancellations, or reductions in fire-related loss coverage.

Table 12: **Marginal Effects of Meteorological Changes on California Wildfire Outcomes.** This table evaluates the effects of 1x and 2x standard deviation shocks to daily maximum temperature, relative humidity, and wind speed assuming the status quo in insurance coverage for wildfire loss coverage and rebuilding policies with a 5-year post-fire horizon.

	Wildfire Probability (% Change)	Incremental Property Counts (Number)	Increment of Assessed Value to Wildfire Losses (\$ Billion)	Increment of Assessed Value to Gentrification Gains (\$ Billion)
One std. dev. shock to max. temperature	0.0013	10,377	4.867	5.035
Two std. dev. shock to max. temperature	0.0022	16,848	7.902	8.174
One std dev. shock to relative humidity	0.0011	8,243	3.866	4.000
Two std dev. shock to relative humidity	0.0014	10,633	4.987	5.159
One std dev. shock to wind speed	0.0012	9,508	4.459	4.612
Two std dev. shock to wind speed	0.0018	14,138	6,632	6.861
Total effect one std. dev.	0.0016	12,464	5.846	6.048
Total effect two std. dev.	0.0032	24,293	11.396	11.788

Overall, these results suggest that probabilistic models of big fire risks are tractable and informative. Additionally, the static, four-level deterministic Hazard Zone maps used by the California Department of Insurance, especially the zero risk areas, do not appear to accurately match likely fire incidence estimates. Part of the problem appears to be that the four-level grid is not fine enough to accurately represent the interplay of temperature and topography in defining wildfire risk. A second problem, given the magnitude of the California wildfire risks, is the growing pressure on California casualty insurers to implement and price reinsurance strategies that treat California wildfires as primary perils such as hurricane, tsunami, and earthquake risk.[37] Prior realized losses in the 2018 and 2019 California fire season, wildfire risk in the re-insurance market had been considered a secondary peril without the potential for the level of significant losses that are typically associated with primary peril events. Given the CDI prohibitions on incorporating these re-insurance costs into the rate schedules, and recent estimates that wildfire reinsurance costs are expected to increase by twenty to seventy percent (Manku, 2020), there appears to be an important disconnect between insurance regulatory policies and the actuarial pricing of wildfire risk in the state of California.[38]

7 Conclusions and policy implications

We study the effects of climate-driven events on the housing and real estate markets. We quantify these effects using a quasi-natural experimental approach provided by California wildfires and a comprehensive data set of houses and mortgages in California between 2000 and 2018. We find that there is a **rebuilding** in devastated areas with increases in home sizes, house prices, income, and wealth. Specifically, we empirically document that wildfires cause an extra 1.46% and 4.2% increase in square footage and house price, respectively, in the treatment (*Fire* areas) compared to the control groups (*Control1* or 1-mile wide rings outside the edge of the fire areas) in 5 years after the wildfire. Furthermore, we find that wildfires cause **gentrification**: There is an extra 5.25% and 2.14% increase in income and wealth, respectively, in the treatment (*Fire* areas) compared to the control groups (*Control1*).

We also analyze the **neighborhood effects** of climate-driven events. Firstly, we discover that the positive effects on the house prices affect nearby areas that have not burned by the wildfire. Specifically, we find that the increase in house prices after the wildfire event is, on average, 2.1% higher in the rings outside the fire areas (*Control1*) than in a second ring with houses located between 1 and 2 miles away from the fire edges (*Control1to2*). Secondly, we document that there is a 5-year higher increase in income and wealth of 6.96% and a 2.37%, respectively, in the *Control1* areas than in the *Control1to2* areas.

Moreover, we find, unsurprisingly, that mortgage default and foreclosure increase in the event of a climate-related event. The probability of delinquency and foreclosure are 0.40% and 0.30%, respectively, higher in the treatment than in the control group within the 6 months after the wildfire. However, we also find a rather more surprising result: default and foreclosure *decrease* in the **size of the climate-driven event**. We argue that this result arises from the **coordination externalities** afforded by large catastrophic events, whereby requirements to rebuild to current

[37] In the catastrophic re-insurance risk markets primary perils are defined as events that affect all.

[38] Sen and Tenekedjieva (2021) document empirically that the California property and casualty insurance market has some of the highest regulatory frictions in the country.

building codes work with casualty-insurance-covered losses to ensure that the rebuilt homes will be modernized, and hence more valuable than the pre-event stock of homes.

This mechanism, of course, only works to mitigate the risk of housing and mortgage market losses if there exists a well-functioning casualty insurance market. However, the risk associated with the climate event insurance markets such as fire or flood insurance is increasing in many regions worldwide, including in the State of California. In the case of wildfires, currently there are 2.6 to 4.5 million homes in the WUI of California, of which 1 million are in areas rated high or very high fire risk.[39] Although the 2017 wildfires dwarfed previous records for both the size and amount of destruction, these records were in turn dwarfed by the fires in 2018 (Jeffrey et al., 2019) and were broken again in 2019 by the Kincade fire, with an estimated cost of $10.6 billion, and the Tick, Getty and Saddle Ridge blazes, which could cost $14.8 billion, for a combined total of $25.4 billion.[40]

Our results provide a tractable framework to quantify the risks of climate-related catastrophes on housing and mortgage markets given changing weather patterns. For example, our estimates for our application to California wildfires has important implications for three key fire-related insurance regulatory debates in California. These three issues comprise an important segment of the Commission on Catastrophic Wildfire Cost and Recovery, June 2019 report and the RAND study (Dixon et al., 2019):

1. Probabilistic wildfire models: The CDI argues that the complexity and proprietary nature of probabilistic models make assessment of their accuracy difficult and potentially allows for manipulation and misuse. On the other hand the insurers argue that deterministic scoring models used by the CDI, such as those provided by Corelogic and Fireline, are based on periods that are too short and do not reflect the rapidly changing dynamics of wildfire risks in the state.
2. Variation of rates by wildfire risk: Although the CDI does allow for adjustment factors to increase rates for properties considered to be at high wildfire risk, these scaling factors must be approved by the CDI. Insurers claim that the the factor structure is too flat. Furthermore, insurers claim that the flat factor structure allows for cross-subsidization from low- to high-fire-risk areas in the state and provides incentives for homeowners to live in risky areas, while at the same time reducing the willingness of insurers to write policies in these areas.
3. Reinsurance costs: CDI regulations do not allow insurers to include the reinsurance margin as an expense in the rate-approval process, providing incentives for insurance companies to reduce the number of high-risk properties insured. In response, the insurers have claimed that the diversification benefits of the reinsurance market have been well established for other hazards, such as tsunamis and hurricanes among others, as a successful means to diversify

[39] See Cignarale et al. (2017) and Commission on Catastrophic Wildfire Cost and Recovery, Final Report, Governor's Office of Planning and Research, State of California, June 2019, http://opr.ca.gov/docs/20190618-Commission_on_Catastrophic_Wildfire_Report_FINAL_for_transmittal.pdf.

[40] See https://www.bloomberg.com/news/articles/2019-10-28/california-fire-damages-already-at-25-4-billion-and-counting.

> risk exposure and thus reduce the risk of losses that could bankrupt or financially impair companies or the industry as a whole. Although it is true that allowing the reinsurance margin to be included as an expense would cause average rates to rise, it would allow insurers to more aggressively underwrite higher-risk properties.

We can also evaluate the aggregate climate risk in the mortgage markets. For example, we evaluate the wildfire risk in the California mortgage market. We find that for the peak fire-season the expected daily wildfire risk exposure for the 539,509 residential housing units that are located in hazard zones 1 through 3 is about $411 million (a low estimate using 2020 assessed values), based on our Table 1 estimates. In fact, these estimates may be low because they do not include the risk to the 7.1 million residential units that are located in hazard zone 0, which increases the daily risk exposure by $2.4 billion. These estimates are reasonably comparable, if scaled by the number of days of that a wildfire typically burns, to the realized $25 billion of market value losses from just four wildfire events in Southern California in 2019 (these wildfires were outside of our wildfire analysis period). In addition, the expected increases in the reinsurance costs of California wildfire risk of 30% to 70% in 2020 appear to suggest that the prohibitions on including reinsurance costs into the rate schedules are unlikely to be sustainable.

Finally, the technology introduced in this paper offers a possible way forward to address policy issues by establishing methods to estimate granular climate-incidence probabilities and to introduce these into forecasting models of housing and mortgage performance at specific locations. Such a framework could be used to build benchmark models to evaluate proposed insurance-company probabilistic models, much like the stress-testing carried out by the Federal Reserve System to evaluation the banks' capital models (which are also all based on probabilistic models). The reinsurance evaluation technology is also probabilistic and more standardized for applications such as the reinsurance of the National Flood Insurance Program.

APPENDIX

A Fire insurance in California

The typical homeowner policy required by mortgage lenders in California includes *replacement cost value* (RCV) coverage for the dwelling (usually covering 16 perils, including fire), personal property coverage (usually about 50% of the dwelling coverage amount up to a policy limit), liability coverage, and coverage for additional living expenses for the loss of the use of the property.[41] RCV coverage includes the cost to rebuild the dwelling at the current price for labor and materials; however, it does not cover any increased costs associated with changes in local building codes and ordinances. In California, most counties and municipalities require that repaired or replacement structures for fire-damaged or destroyed dwellings must be built to code.[42] For that reason, many — though not all — lenders require an additional endorsement, *Extended and Guaranteed Replacement Cost*, to cover build-to-code requirements.[43]

Under California Insurance Code, determining the amount of money due as compensation — the "indemnity" — for an insured total loss of a home due to wildfire presents the homeowner/borrower with numerous challenges/frictions. Negotiating an insurance settlement with an insurance adjuster is both challenging and extremely time-consuming; many homeowners simply do not have the legal expertise, data access, or modelling skill to determine the monetary implications of key terminology. Hiring professional services to negotiate an insurance settlement can cost tens of thousands of dollars, and fair settlements usually require detailed accounting of the exact cost of replacing a destroyed property. Settlement negotiations, especially after large wildfires, often take place in highly dynamic factor markets characterized by significant demand surges. Not surprisingly, these frictions could increase mortgage defaults after a wildfire, especially since the liquidity position of the homeowner/borrower is: (i) subordinate to the mortgage lender in payment priority, and (ii) fragile due to the associated immediate wealth shock and the psychological stress of loss.

In California, the total possible amount of the indemnity is determined by the lesser of the maximum value of: i) the pre-fire value of the property minus the value of the land, ii) the actual realized costs of rebuilding the destroyed property at the original site including code upgrades under guaranteed replacement cost if applicable; iii) a value equivalent to the cost of rebuilding at the original site that can be used to buy or rebuild at another site; iv) the policy limit. In addition, the policy holder would receive: i) realized additional living expenses, often as an up-front payment, up to the policy limit; ii) payment at settlement for the value of the personal contents of the destroyed home based on an inventory produced by the insured, again up to the policy limit.[44] Thus, the

[41] Although there are eight types of homeowners insurance policies available in the U.S., most mortgage lenders require the HO3 - Special Form Policy (see https://www.thezebra.com/homeowners-insurance/policies/what-is-ho-3-insurance-policy/).

[42] For example, in San Diego County "buildings must be constructed according to current codes in effect at the time the permit is issued for the reconstruction" (see County of San Diego, Planning & Development Services, Firestorm Policy and Guidance Document, Building Division, http://www.sdcpds.org).

[43] http://www.insurance.ca.gov/01-consumers/105-type/95-guides/03-res/res-ins-guide.cfm.

[44] This provision does not limit the authority of an insurer to seek additional reasonable information from an insured

payout for total losses as the result of fire in California can exceed the depreciated value of the original property, due to the replacement of new for old, as well as the fungible payout for the personal contents which is *not* contingent upon actually replacing the contents and can be applied to additional costs of replacing the structure. Of course, homeowners can also suffer significant losses if their homeowners insurance is insufficient to cover all of these costs.

B Additional empirical long-run effects results

In this Appendix, we show additional empirical results and full tables that complement the main results shown in the main body of the paper. Table 13 shows empirical results that complement the ones exhibited in table 5. By comparing these two tables, we can conclude that the sign, magnitude, and significance of our estimates are robust to the inclusion of techniques to account for spatial autocorrelation.

Table 13: **The long-run effects on house size. Additional results.** This table complements table 5 and shows the estimates of the analysis for differences in house sizes before *versus* after a wildfire without implementing any spacial autocorrelation correction. The dependent variable is the change in the logarithm of the house size (in sq. feet) 5 years after the fire, $\log(size_{t_0+5})$, minus the logarithm of the house size the month before the fire, $\log(size_{t_0})$.

Treatment group: Control group:	Fire Control1 [1]	Fire Control1 [2]	Fire Control1 [3]	Fire Control1 [4]
Fire	0.0164***	0.0138***	0.0147***	0.0146***
	(0.00427)	(0.00429)	(0.00479)	(0.00481)
$\log(size_{t_0})$	-0.0643***	-0.0647***	-0.0764***	-0.0763***
	(0.00336)	(0.00337)	(0.00376)	(0.00375)
Controls	No	Yes	No	Yes
Fixed effects	No	No	Yes	Yes
Observations	20,483	20,483	20,483	20,483
R-squared	0.031	0.031	0.043	0.044

Tables 14, 16, and 17 show additional results to the ones displayed in table 6, 7, and 8. As in the analysis of the long-run effects on house size shown above, the estimates of the long-run effects on house prices, income, and wealth are robust to the inclusion of techniques to account for spatial autocorrelation. Additionally, table 15 shows the results using log house price per square foot instead of log house price (see table 6) as the dependent variable.

upon receipt of an inventory form submitted by an insured (CA Insurance Code, Section 2051, Article 2. Measure of Indemnity, 2061).

Table 14: **The long-run effects on house prices. Additional results.** This table complements table 6 and shows the estimates of the analysis for differences in house prices before *versus* after a wildfire without implementing any spacial autocorrelation correction. The dependent variable is the change in the logarithm of the house price 5 years after the fire, $\log(price_{t_0+5})$, minus the logarithm of the house price the month before the fire, $\log(price_{t_0})$.

Treatment group: Control group:	Fire Control1 [1]	Fire Control1 [2]	Fire Control1 [3]	Fire Control1 [4]	Fire Control1 [5]	Fire Control1to2 [6]	Fire Control1to2 [7]
Fire	0.0568***	0.0498***	0.0418***	0.0417***	0.0424***	0.0698***	0.0634***
	(0.00687)	(0.00927)	(0.00927)	(0.00953)	(0.00954)	(0.00859)	(0.00869)
$\log(price_{t_0})$	-0.1865***	-0.1883***	-0.1910***	-0.238***	-0.2378***	-0.1691***	-0.2185***
	(0.00595)	(0.00856)	(0.008587)	(0.0144)	(0.0144)	(0.00413)	(0.00611)
$\Delta \log(size_{t_0,t_0+5})$		0.2620***	0.2632***	0.245***	0.2460***	0.263***	0.2454***
		(0.0223)	(0.0222)	(0.0217)	(0.0217)	(0.0145)	(0.0139)
Control1						0.0251***	0.02148***
						(0.00381)	(0.00362)
Controls	No	No	Yes	No	Yes	Yes	Yes
Fixed effects	No	No	No	Yes	Yes	No	Yes
Observations	22,978	13,359	13,359	13,359	13,359	41,802	41,802
R-squared	0.101	0.123	0.129	0.236	0.237	0.100	0.213

Table 15: **The long-run effects on house prices per square foot.** This table complements table 6 and shows the estimates of the DID and panel SA analyses in house prices per square foot. The dependent variable is the logarithm of the house price per square foot, $\log(price_t/size_t)$ or $\log(psqf_t)$ for columns [1] and [2] and the difference between the logarithm of the house price per square foot 5 years after the fire, $\log(psqf_{t_0+5})$, minus the logarithm of the house price per square foot the month before the fire, $\log(psqf_{t_0})$ for columns [3]–[7]. *Fire* is a dummy variable that takes the value 1 if the property is inside the fire area (i.e., the treatment group). *Control1* is a dummy variable that takes the value 1 if the property is inside the ring defined by the edge of the fire area and 1 mile distance outside this limit (i.e., the control group). *Control1to2* is a dummy variable that takes the value 1 if the property is inside the ring between 1 and 2 mile distance outside the limit of the fire area (i.e., ring outside the *Control1* ring). *Afterfire* is a dummy variable that takes the value one 5 years after the fire event and zero before the fire event. We exclude the observations between 0 and 4 years after the fire event for the DID analysis. All specifications include controls for house characteristics and size of the wildfire in acres. Specifications in [2] and [4] include time and zip code fixed effects. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Approach:	DID	DID	Panel SA	Panel SA	Panel SA	Panel SA	Panel SA
Treatment group:	Fire	Fire	Fire	Fire	Fire	Fire	Fire
Control group:	Control1	Control1	Control1	Control1	Control1	Control1to2	Control1to2
Dep. variable:	$\log(psqf)$	$\log(psqf)$	$\Delta\log(psqf)$	$\Delta\log(psqf)$	$\Delta\log(psqf)$	$\Delta\log(psqf)$	$\Delta\log(psqf)$
	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Fire × Afterfire	0.0467***	0.0494*					
	(0.01174)	(0.02638)					
Fire	-0.0728***	-0.0662***	0.0498***	0.0418***	0.0391***	0.0567***	0.0492***
	(0.00911)	(0.02090)	(0.00970)	(0.00982)	(0.00970)	(0.00960)	(0.00927)
Afterfire	0.0499***	-0.0380					
	(0.00287)	(0.08255)					
$\log(psqf_{t_0})$			-0.1883***	-0.1910***	-0.1821***	-0.1699***	-0.1565***
			(0.00478)	(0.00477)	(0.00552)	(0.00276)	(0.00313)
$\Delta\log(size_{t_0,t_0+5})$			-0.7382***	-0.7371***	-0.7423***	-0.7360***	-0.7344***
			(0.0173)	(0.0172)	(0.0166)	(0.0102)	(0.0098)
Control1						0.0228***	0.0179***
						(0.00383)	(0.00369)
Controls	Yes	Yes	No	Yes	Yes	Yes	Yes
Fixed effects	No	Yes	No	No	Yes	No	Yes
Observations	118,337	118,337	13,359	13,359	13,359	41,802	41,802

Table 16: **The long-run effects on household income. Additional results.** This table complements table 7 and shows the estimates of the analysis for differences in household income before *versus* after a wildfire fire. The dependent variable is the change in the logarithm of the household income 5 years after the fire, $\log(income_{t_0+5})$, minus the logarithm of the house price the year before the fire, $\log(income_{t_0})$.

Treatment group:	Fire	Fire	Fire	Fire	Fire	Fire
Control group:	Control1	Control1	Control1	Control1	Control1to2	Control1to2
	[1]	[2]	[3]	[4]	[5]	[6]
Fire	0.131***	0.0487**	0.127***	0.0525**	0.210***	0.124***
	(0.0211)	(0.0214)	(0.0209)	(0.0213)	(0.0208)	(0.0208)
$\log(income_{t_0})$	-0.495***	-0.589***	-0.504***	-0.590***	-0.497***	-0.585***
	(0.00831)	(0.00826)	(0.00826)	(0.00825)	(0.00557)	(0.00558)
Control1					0.0749***	0.0696***
					(0.00779)	(0.00741)
Controls	No	No	Yes	Yes	Yes	Yes
Fixed effects	No	Yes	No	Yes	No	Yes
Observations	10,818	10,818	10,818	10,818	24,108	24,108
R-squared	0.309	0.411	0.315	0.413	0.301	0.404

Table 17: **The long-run effects on household wealth. Additional results.** This table complements table 8 and shows the estimates of analysis for differences in household wealth before *versus* after a wildfire. The dependent variable is the change in the logarithm of the household wealth 5 years after the fire, $\log(wealth_{t_0+5})$, minus the logarithm of the house price the year before the fire, $\log(wealth_{t_0})$.

Treatment group:	Fire	Fire	Fire	Fire	Fire	Fire
Control group:	Control1	Control1	Control1	Control1	Control1to2	Control1to2
	[1]	[2]	[3]	[4]	[5]	[6]
Fire	0.0506***	0.0206*	0.0519***	0.0214*	0.0740***	0.0433***
	(0.0106)	(0.0112)	(0.0107)	(0.0112)	(0.0107)	(0.0108)
$\log(wealth_{t_0})$	-0.211***	-0.260***	-0.198***	-0.262***	-0.178***	-0.236***
	(0.0101)	(0.0140)	(0.0106)	(0.0140)	(0.00683)	(0.00901)
Control1					0.0216***	0.0237***
					(0.00395)	(0.00387)
Controls	No	No	Yes	Yes	Yes	Yes
Fixed effects	No	Yes	No	Yes	No	Yes
Observations	10,818	10,818	10,818	10,818	24,108	24,108
R-squared	0.062	0.152	0.064	0.153	0.053	0.135

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