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

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Abstract

This paper studies wildfires in California from 2000 to 2018 using comprehensive merged data on fires, mortgage and property characteristics, and weather. We find a significant increase in mortgage delinquency and foreclosure after a fire, but these effects *decrease* in the size of the fire, which we argue results from coordination externalities afforded by large fires. Recent large losses, combined with regulatory distortions, cast doubt on the continued ability of insurance companies to absorb fire-related losses. This paper provides central banks and insurance regulators with a framework for evaluating proposed banking and insurance-company models, similar to bank stress-testing.

Key words: Mortgages, climate-change risk, moral hazard.

JEL codes: G21

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1 Introduction

Climate change is expected to lead to significant increases in both the frequency and severity of destructive weather events globally,[1] with wildfires representing a particular problem. 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 was 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 PG&E shut down parts of its network to avoid causing additional fires. The area burned each year in California has increased 5-fold since 1972 (Williams, Abatzoglou, Gershunov, Guzman-Morales, Bishop, Balch, and Lettenmaier, 2019) — almost entirely due to high temperatures — and 15 of the largest 20 fires ever recorded in California have occurred since 2000 (Rogers, 2019). Less economically costly but on a much larger scale, the 2019–20 Australian bushfire season burnt an estimated 18.6 million hectares (46 million acres) across the country, destroyed over 5,900 buildings — including 2,779 homes — and killed at least 34 people.[2] Air quality in Sydney was among the worst anywhere on the planet,[3] and on Dec. 29, 2019, authorities ordered the evacuation of East Gippsland, an area half the size of Belgium.[4]

In the United States, wildfire risk is exacerbated by decades of poorly thought-out and implemented fire-management policies (North, Stephens, Collins, Agee, Aplet, Franklin, and Fulé, 2015; Smith and Gilless, 2011) and by increased development — both historical and ongoing — in the high-risk areas adjacent to wildland areas, the "wildland-urban interface" (WUI). This development is encouraged by the fact that firefighting in the forests and grasslands of the western US is the responsibility of state or federal agencies, and not of either homeowners or local decision-makers such as cities and counties.[5]

Most of the properties in fire-prone areas are purchased using mortgages, so wildfires pose risk not only to individual home-owners, but also to lenders and insurance companies. So far, insurance companies have been able to absorb fire losses in California, protecting homeowners and mortgage lenders from most of the associated costs. However, the increasing frequency and size of recent

[1] See Flannigan, Krawchuk, de Groot, Wotton, and Gowman (2009); Moritz, Parisien, Batllori, Krawchuk, Dorn, Ganz, and Hayhoe (2012); Wotton, Nock, and Flannigan (2010).

[2] See Jesinta Burton, "It was a line of fire coming at us: Firefighters return home," Busselton-Dunsborough Mail, Feb. 7, 2020, https://www.sbs.com.au/news/the-numbers-behind-australia-s-catastrophic-bushfire-season.

[3] See Peter Dockrill, "Fires in Australia Just Pushed Sydney's Air Quality 12 Times Above 'Hazardous' Levels," ScienceAlert, Dec. 11, 2019, https://www.sciencealert.com/sydney-air-soars-to-12-times-hazardous-levels-under-toxic-blanket-of-bushfire-smoke.

[4] "Thousands told to evacuate vast east Gippsland fire threat zone," https://www.theguardian.com/australia-news/2019/dec/29/victoria-bushfires-australia-thousands-evacuate-vast-east-gippsland-fire-threat-zone.

[5] See Baylis and Boomhower (2019); Davis (1995); Gude, Jones, Rasker, and Greenwood (2013); Gude, Rasker, and van den Noort (2008); Guerin (2018); Hammer, Stewart, and Radeloff (2009); Loomis (2004); Lueck and Yoder (2016); Mann, Berck, Moritz, Batllori, Baldwin, Gately, and Cameron (2014); Martinuzzi, Stewart, Helmers, Mockrin, Hammer, and Radeloff (2015); Radeloff, Hammer, Stewart, Fried, Holcomb, and McKeefry (2005); Radeloff, Helmers, Kramer, Mockrin, Alexandre, Bar-Massada, Butsic, Hawbaker, Martinuzzi, Syphard, and Stewart (2018); Simon (2017); Stetler, Venn, and Calkin (2010); Wibbenmeyer (2017).

wildfires cast significant doubt on their ability to continue to provide such protection. Potential risks to both homeowners and mortgage lenders are also increasing. Fire insurance rates in California are skyrocketing and many companies are refusing to write new policies on homes in particularly risky areas, such as canyons.[6] Moreover, according to the California Insurance Commissioner, over 340,000 rural homeowners with existing policies were dropped by their insurance companies over the last four years.[7]

A growing literature considers the effects of climate change on the health of the U.S. financial system.[8] Many of these papers 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, Mullins, and Hill, 2019; Giglio, Maggiori, Rao, Stroebel, and Weber, 2019; Keenan, Hill, and Gumber, 2018; Murfin and Spiegel, 2020; Ouazad and Kahn, 2019). 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 et al., 2019) or the effects of low flood insurance subscription rates on the incentives of banks to securitize (see Ouazad and Kahn, 2019).[9] Only one empirical paper explicitly models the ex post default outcomes of mortgages on homes damaged by flooding (see Billings, Gallagher, and Ricketts, 2020).

No existing papers focus on the relationship between wildfires, ex post house price dynamics, and mortgage performance risk. There are also no studies of the accuracy of the fire-risk maps used for casualty-insurance pricing. While flood insurance is required only for mortgages on homes in flood zones, fire insurance is required for *all* residential mortgages. In addition, fire insurance is bundled as a secondary risk within the typical homeowner policy, and thus its pricing is not as directly observable to consumers as that of flood insurance. Finally, 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.

In this paper, we study wildfires in California from 2000 to 2018 using a comprehensive data set of houses and mortgages in California. The locations and magnitudes of these fires are shown in Figure 1. We merge data on all California fire events reported by the California Department of Forestry and Fire Protection; loan-level mortgage characteristic and performance data from Black Knight McDash; house-characteristic data from ATTOM; and weather data from the National Climatic Data Center (NCDC) of the U.S. National Oceanic and Atmospheric Administration (NOAA).

Using a difference-in-differences approach, confirmed via panel regression, we compare mortgage performance in fire zones (the treatment group) with that in 1- and 2-mile rings around the fire

[6]See David Lazarus, "California fires will result in higher insurance rates for homeowners," LA Times, October 31, 2019, https://www.latimes.com/business/story/2019-10-31/fire-insurance-david-lazarus-column.

[7]See Autumn Payne, "Insurers dropped nearly 350,000 California homeowners with wildfire risk," Sacramento Bee, August 20, 2019, https://www.sacbee.com/news/politics-government/capitol-alert/article234161407.html.

[8]See Bernstein, Gustafson, and Lewis (2019); Ouazad and Kahn (2019) and a recent special issue of the *Review of Financial Studies*

[9]Ouazad and Kahn (2019) base their analysis on the forward looking expectations of default for *newly* originated mortgages rather than the current stock of houses and loans.

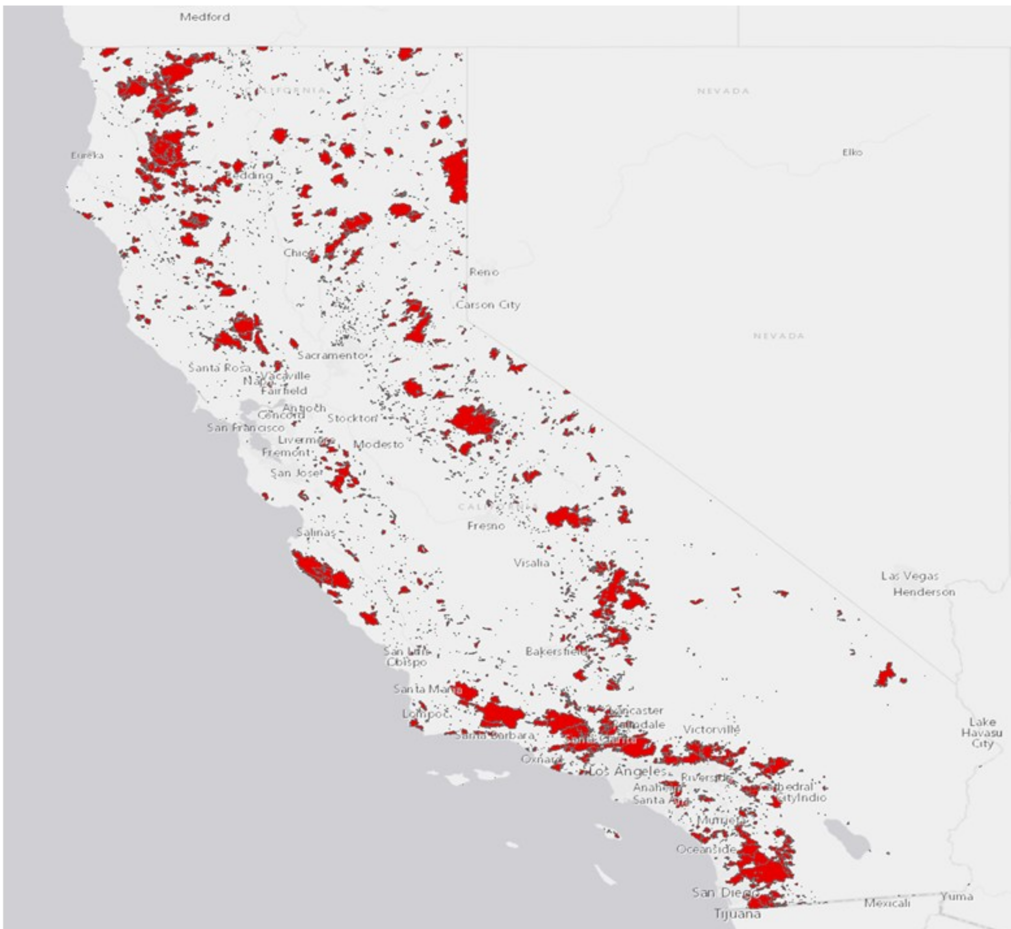


Figure 1: **Wildfires in California from 2000 to 2018**

zone (the control group). 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 probability of delinquency increases by 0.50% in the control group and 1.03% in the treatment 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 increase in the probability of delinquency is 21.3% lower in the treatment group than in the ring from the fire-zone edge to 1 mile outside the fire zone. Moreover, the increase in delinquency is 68% lower for big than for small fires. 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.

This mechanism, of course, only works to mitigate the risk of mortgage market losses if there exists a well-functioning casualty-insurance market. The extent of fire losses in recent years puts this in some doubt. According to a recent Rand study, "underwriting profits in the Homeowners Multiple Peril and Fire lines totaled $12.1 billion from 2001 through 2016 combined, and were almost completely wiped out by the results for 2017" (Dixon, Tsang, and Fitts, 2019, p. 55) due to WUI fire losses. 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, Yerkes, Moore, Calgianao, and Turakhia, 2019) and were broken again in 2019. The soundness of the California insurance market is further threatened by some significant regulatory distortions that are the subject of much current debate (we discuss these in more detail in Section 6):

1. The California Department of Insurance (CDI) prohibits the use of probabilistic wildfire models.
2. 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.
3. The CDI does not allow insurers to include the reinsurance margin as an expense in the rate-approval process.

The technology introduced in this paper could be used by the CDI and other insurance regulators to address all of these issues by establishing methods to build benchmark probabilistic models to evaluate proposed insurance-company models, much like the stress-testing carried out by the Federal Reserve System to evaluate banks' capital models.

2 Case Study: The Tunnel Fire

In 2018, California experienced 1,823,153 acres burned in wildland and wildland-urban-interface (WUI) fires, more than any other state in the country.[10] The 2018 fire season in California also

[10] 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.

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. The estimated cost of recovery for this fire is $9.3 billion (see Jeffrey et al., 2019).

Prior to the Camp Fire, the most deadly California fire in terms of loss of life and economic destruction was the Tunnel Fire. This fire occurred in 1991 within a densely populated WUI area in Oakland and Berkeley. It burned 1,540 acres; destroyed 3,354 single-family residential houses, 437 apartment units, and 2,000 vehicles; killed 25 people and seriously injured 150 others; and left 10,000 people without homes. The cost of recovery was about $3 billion in 1991 dollars.[11]

The 1991 Tunnel Fire area exhibited all of the key historical, meteorological, and geographical antecedents of WUI fires in California. The Tunnel Fire also provides important historical evidence concerning the economics of California WUI fires and the recovery process from such fires. A systematic consideration of these antecedents can inform the economic modeling of residential and mortgage risk exposure from such fires, as well as providing a clearer understanding of the economic forces that bear on homeowner choices about reconstruction and mortgage default after fire-related losses.

Table 1 reports the historical incidence of serious WUI fires in Alameda County from 1923 to 2015. As shown, the Tunnel Fire was located in a rapidly urbanizing residential area, where prior fires had destroyed homes and burned substantial acreage: one in 1940 on Buckingham Blvd. and one in 1970 on Buckingham Blvd. (the 1991 fire also started on Buckingham Blvd.). Similar fires occurred in the nearby Oakland Hills areas between 1923 and 1991. More recently, WUI fires have occurred in rapidly urbanizing areas of Western Alameda County, and again there is the same pattern of some streets experiencing multiple serious fires between 2006 and 2015. Several of the Alameda County fires started as grass fires associated with automobile accidents, including the 1960 Leona Fire and the 2015 Corral Hollow Rd. fire (caused by a Tesla battery fire).

A second feature evident in Table 1 is that the temperature is often quite elevated on fire-ignition days. Most of the fires occur in the late summer and early fall in the Eastern part of Alameda County and in early to mid-summer in the Western rain-shadowed slopes of the county. Although not reported in the table, these fires are also usually associated with a change in the direction of the winds, called Diablo winds in Northern California and Santa Ana winds in Southern California, which blow from the arid center of the state or the lee side of the mountain barriers toward the coast, rather the more typical moisture-laden wind pattern from the Pacific Ocean inland.

Figure 2 presents the important geographic and topographic antecedents of the Tunnel Fire. WUI areas are usually 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, often with naturally formed swales that become wind and fire chimneys that rapidly propagate fires once they are started; 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). As shown in Figure 2, the

[11] U.S. Fire Administration, Technical Report, The East Bay Hills Fire, Oakland-Berkeley, California, USFA TR 060, October 1991, https://www.usfa.fema.gov/downloads/pdf/publications/tr-060.pdf.

Table 1: **Large Wildland-Urban-Interface Fires in Alameda County (1923–2015).** This table reports the largest fires in the wildland-urban-interface areas of Alameda County (1923–2015). Sources: Alameda County Fire Department, Standards of Coverage Review, Technical Report, Volume 2, September 1, 2017, http://www2.oaklandnet.com/oakca1/groups/fire/documents/; http://www2.oaklandnet.com/oakca1/groups/fire/documents/.

	Fire Name	Acres Burned	Temperature
Sep-23	North Berkeley	584	91
Nov-31	Leona Dr./Oakland Hills	1,800	87
Nov-33	Joaquin Miller/Oakland Hills	1,000	82
Sep-37	Broadway Terrace/Oakland Hills	700	90
Sep-40	Buckingham Blvd./Oakland Hills	1,000	70
Oct-60	Leona Dr./Oakland Hills	1,200	84
Nov-61	Tilden Park/Oakland Hills	400	67
Oct-68	Navel Hospital/Oakland Hills	400	80
Sep-70	Buckingham Blvd./Oakland Hills	204	80
Oct-90	Leona Dr./Oakland Hills	200	83
Oct-91	**Buckingham Blvd./Oakland Hills/Tunnel Fire**	**1,700**	**90**
Jul-06	Midway Rd./Tracy	6,400	88
Aug-09	Corral Hollow Rd./Tracy	12,500	92
Jun-11	Flynn Rd./Altamont Pass	917	
Jun-13	Vasco Rd./Livermore	240	
May-14	Christensen Rd./Livermore	242	
Aug-15	Corral Hollow Rd./Livermore	2,700	91

Tunnel Fire area, shown in red on the map, exhibits all of these topographic features. The primary burn area lies on the western- and southern-facing hillsides of the Coastal range, with pronounced swales all along these slopes. Although not shown, the Tunnel Fire area was heavily wooded, with large stands of non-native Monterey pines and eucalyptus trees interspersed with large areas of undeveloped grassland. The fire started just north of the intersection of Highways 24 (Grove-Shafter Freeway) and 13 (Warren Freeway) on a narrow and steeply sloped road, Buckingham Boulevard. The temperature was 90 degrees Fahrenheit and there was a strong and very dry northeasterly downslope wind that descended from the lee side of the coastal mountain barrier called a Diablo wind, more technically a foehn wind.[12]

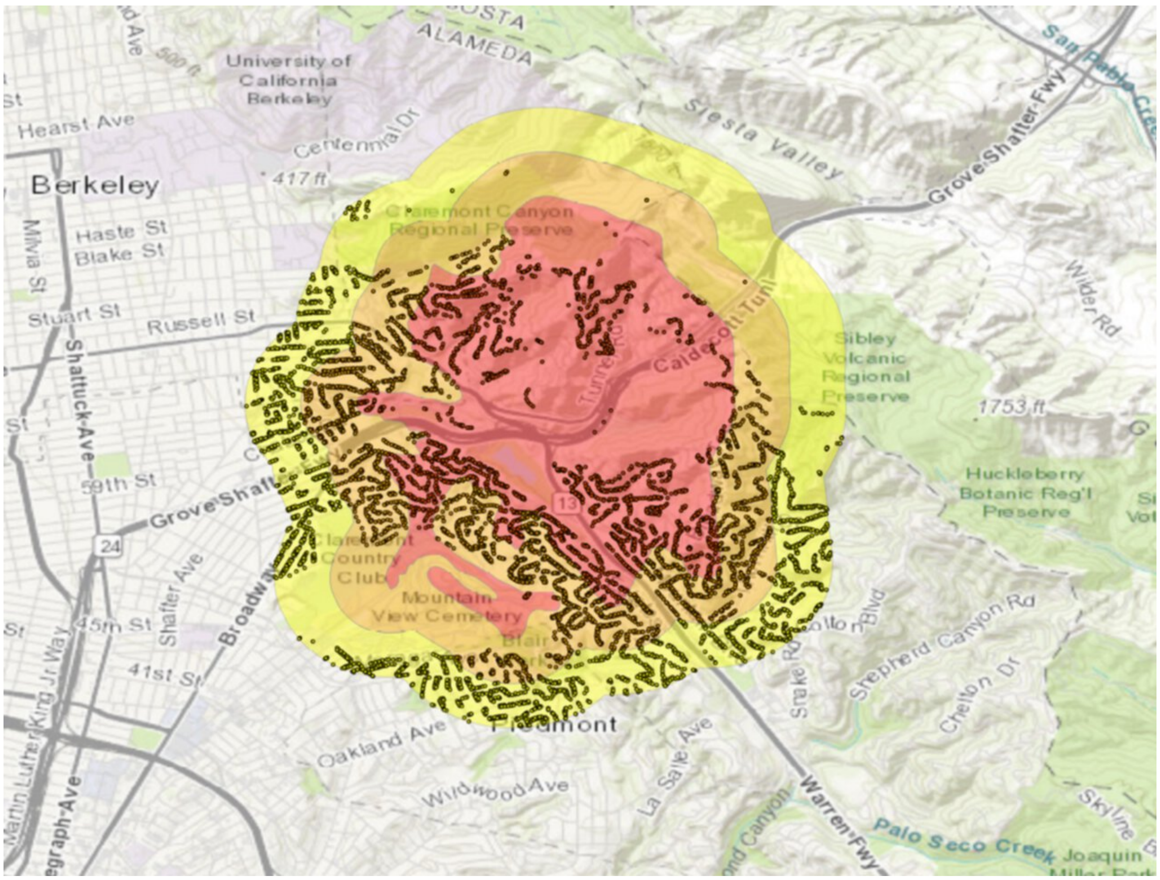


Figure 2: **Tunnel Fire, .25- and .50-mile peripheral rings.** This figure shows the geographic location of the burned and re-built transactions in the Tunnel Fire area (red), the transactions in the .25-mile peripheral ring (light orange), and the transactions in the .50-mile peripheral ring (yellow) in 1991.

The other feature of the Tunnel Fire geography is that in 1991 the area was, and remains, heavily urbanized. Figure 2 presents the plat maps (geographic demarcations for the legal boundaries of urban lots), shown in black, for the developed residential parcels that were located throughout

[12]A foehn is a type of warm, dry, down-slope wind that occurs in the lee of a mountain range.

the Tunnel Fire and peripheral areas. The Tunnel Fire burn area is shown in red in Figure 2, a .25-mile periphery area is shown in light orange, and a .50-mile periphery area is shown in yellow. All three areas include densely populated single- and multi-family residential development. Nearly all of the properties within the red Tunnel fire area were total losses, with only a few exceptions at the extreme periphery. The properties within the .25-mile periphery did not burn, but were often visually exposed to the remains of the fire and to the .50-mile area, which had neither visual nor actual exposure to the fire.

These three areas also provide a means to quantify the different responses to the fire for households within each area. First, based on a lot-by-lot count using aerial Google Maps, we find that the rebuilding rate for houses within the burn area was more than 95%. Thus, it appears that households within the burn area viewed building a new house on their existing lot, after the total loss of the original house, as a positive-NPV decision. Table 2 presents summary statistics for the realized house price growth rates for the three areas, measured as average annual returns per square foot, for a sample of repeat-sale transactions between 1988 and 2016. The repeat sales within the Tunnel Fire area includes properties that were sold pre-fire, burned, and were then sold again as re-built homes in the post-fire period; the .25-mile peripheral zone includes repeat sales in the pre- and post-fire periods for properties that did not burn; and the .5-mile peripheral zone includes repeat sales in the pre- and post-fire periods for properties that did not burn. As shown in Table 2, the average annual return is highest in the Tunnel Fire Area, at 8.9%, compared with 7.9% in the .25-mile peripheral area and 6.3% in the .5-mile peripheral area.

Table 2: **Summary Statistics for annual returns per square foot (1988–2016) for the Tunnel Fire and peripheral rings.** This table presents the summary statistics for the annual returns per square foot for a sample of repeat sale transactions from 1988–2016. The repeat sales within the Tunnel Fire area includes properties that were sold pre-fire, burned and then were sold again as re-built homes in the post-fire period; the .25-mile peripheral zone includes repeat sales in the pre- and post-fire periods for properties that did not burn; and the .5-mile peripheral zone includes repeat sales in the pre- and post-fire periods for properties that did not burn. These data are from ATTOM's assessor records.

	Annual Returns per Square Foot		
	Mean %	Standard dev. %	Number of observations
.50-mile peripheral ring	6.3	4.8	246
.25-mile peripheral ring	7.9	11.1	220
Tunnel Fire Area	8.9	7.8	182

Another important feature of the Tunnel Fire was its impact on the default performance of residential single-family mortgages in the three fire areas. From 1989 to 2017, more than $20 billion of loans were either newly originated for home purchases or refinanced on the 8,500 single-family detached homes within the three areas. Figure 3 presents the default rates by mortgage-origination vintage within the Tunnel Fire area and peripheral areas over the post-fire period

between November of 1991 and December 2001. The default rates are measured as the percentage of the stock of mortgages by vintage that foreclosed or became Real Estate Owned (bank-held defaults). As shown in Figure 3, the mortgage default rates for the 0.25-mile peripheral area exceeded those of the Tunnel Fire area for the 1989 and pre-fire 1991 vintages. The mortgage performance within the 0.50-mile peripheral area were slightly lower that the Tunnel Fire Area for the pre-fire 1991 vintage loans and 1990 vintage loans, however, they exceed them for the 1989 vintage loans. The 1990 vintage mortgages had nearly comparable default rates over the post-fire period at 3.8% in the Fire Area, 3.2% in the 0.25-mile peripheral area, and 3.2% in the 0.50-mile peripheral area. Although the ten-year post-fire mortgage foreclosure performance is slightly higher for the Tunnel Fire area relative to the other two areas for the 1990 vintage mortgages, given the fact that more than 3,000 houses experienced a catastrophic loss in the 1991 fire — many taking more than five years to rebuild — the three-year average mortgage default rate of 2.1% for the Tunnel Area was low compared to the 3.3% default rate for the 0.25 peripheral area and the 1.8% default rate in the 0.50 peripheral.

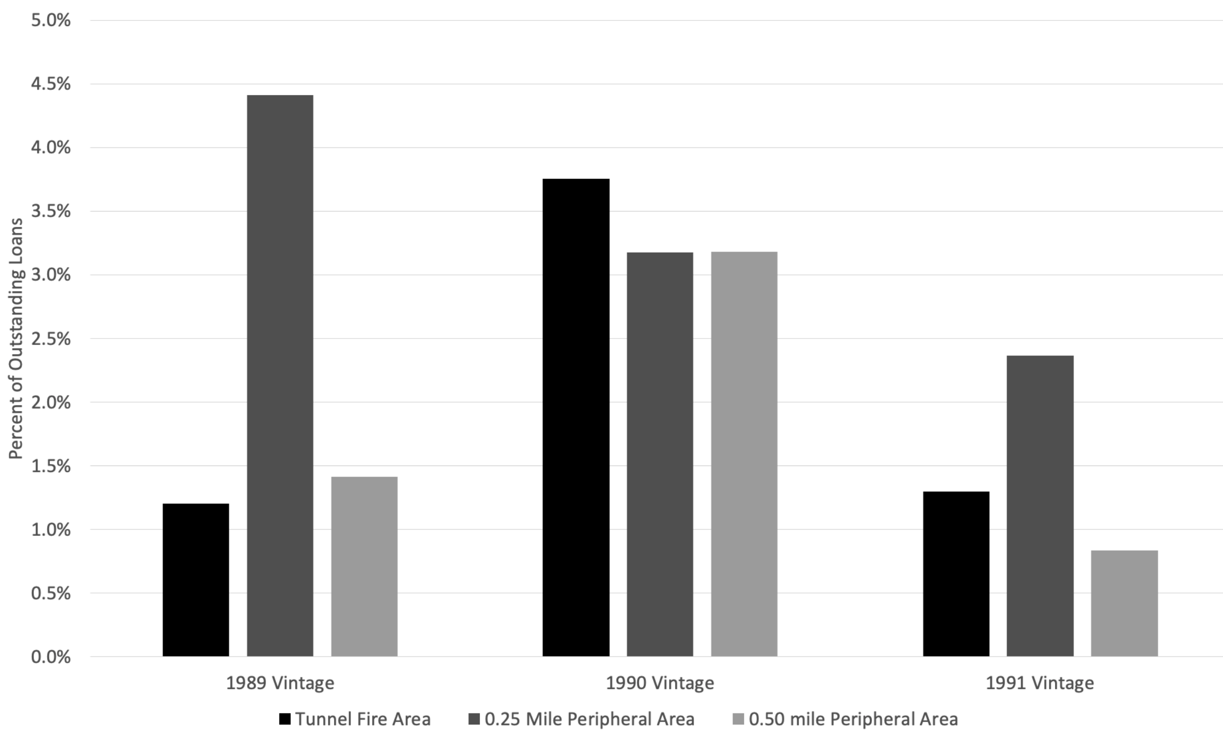


Figure 3: **Default probabilities over the post-fire period (November, 1991 through December, 2001) by the loan-origination vintage of mortgages located in the Tunnel Fire Area, 0.25-mile peripheral area, and 0.5-mile peripheral area.** This figure plots the default rates (foreclosure and Real Estate Owned — bank held default) over the post-fire period (November 1991–December 2001) for mortgages originated in three vintages prior to the Tunnel Fire; 1989, 1990, and pre-fire 1991. The rates are reported as the percentage of the outstanding mortgages by vintage that defaulted over the post-fire period in the Tunnel Fire Area, the 0.25-mile peripheral area, and the 0.50-mile peripheral are. These data are from ATTOM assessor's records.

Overall, the Tunnel Fire case study suggests that important elements of fires such as the terrain, slope aspect, temperature, and wind lead to elevated probabilities of fire for identifiable property locations. A very large fire such as the Tunnel Fire, in a densely urbanized area, also leads to surprisingly large coordination externalities by sweeping away vast tracts of homes that must be replaced — following local building code requirements — with modernized structures that meet *current* codes. Casualty insurance policies afford homeowners coverage for these added costs if homeowners purchase the needed riders; however, homeowners must cover the additional costs regardless. Since the newly upgraded homes within these large fire-devastated areas are likely to be more valuable once they are reconstructed, due to the coordinating effects of the building codes, mortgage holders in large fire-devastated areas have a strong incentive not to default, since their property value (and that of most surrounding properties) would be expected to rise in the post-fire period.

In summary, there are four main conclusions from this case study. First, coordination externalities were in place after this large wildfire event, that is, large tracts of homes were replaced with modernized structures due to build-to-code requirements. Second, more than 95% of the properties in the burn area were rebuilt. Third, mortgage borrowers in the devastated area had relatively low mortgage-default rates. Fourth, the disincentives for mortgage default lasted a long time.

3 Hypothesis Development

In this section, we formalize the conclusions of the case study using a simple theoretical framework based on: (i) the dynamics of house prices, taking into account direct and indirect effects of possible wildfires; (ii) frictions in the insurance markets; and (iii) the household's mortgage-default decisions.

3.1 The Effect of Insurance on Households' Mortgage Decisions

In a frictionless world, after paying for house insurance, households might be indifferent to wildfires, because if their house is damaged or destroyed, the insurance company will reimburse their entire loss. Therefore, wildfires should not have any effect on households' mortgage decisions. However, there are frictions among households, lenders, and insurance companies that affect mortgage defaults.

To understand the impact of fire risk on the mortgage markets, it is important to understand how borrowers respond to wildfire risk, both before and after the event. The size, and even the direction, of the effect of a wildfire on mortgage performance is not a priori clear. 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. The typical homeowner policy required by mortgage lenders includes *replacement cost value* (RCV) coverage for the dwelling (usually covering 16 perils, including fire), personal property coverage (usually 50%–70% of the dwelling coverage amount), liability coverage, and coverage for additional living

expenses.[13] 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.[14] For that reason, many, though not all, lenders require an additional endorsement, *Extended and Guaranteed Replacement Cost*, to cover build-to-code requirements.[15]

After a covered fire-related loss occurs, a borrower's insurance company will issue a claim check that identifies the borrower and the mortgage lender, or servicer, as the payee. However, since the lender/servicer's debt position is always first in priority, the lender/servicer effectively controls the disbursement of the insurance proceeds to the borrower. Despite the disbursement position of the lender, it is the borrower who directly negotiates the insurance settlement with the insurance adjusters.[16] As discussed further in Appendix A, borrowers faced with catastrophic losses face important frictions associated with ambiguity in the language of the California Insurance code defining loss coverage under both RVC and *Extended Guaranteed Replacement Cost*. In addition, if the borrower becomes ninety days or more delinquent on the loan payments, the lender may elect to satisfy the debt either by payment from the insurer or by foreclosing on the property (Hoberock and Griebel, 2018). More generally, the frictions faced by borrowers in exercising their state-regulated rights under their insurance policies, especially in large impact areas, may explain recent findings that natural disasters might, for certain neighborhoods, act as a coordinating mechanism that allows rapid gentrification of the affected area.[17]

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.[18] 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 increase mortgage defaults after a wildfire, especially since the liquidity position of the

[13]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/).

[14]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).

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

[16]For wildfire losses in areas with U.S. Presidential designations as national disaster areas, borrowers may also have access to low-interest disaster loans administered by the Small Business Administration under FEMA; however, by law this assistance cannot duplicate insurance coverage (see https://www.fema.gov/individual-disaster-assistance).

[17]See Contardo, Boano, and Wirsching (2018); Florida (2019); Freeman (2005); Lee (2017); Olshansky, Johnson, Horne, and Nee (2008); van Holm and Wyczalkowski (2019); Weber and Lichtenstein (2015).

[18]See Appendix A for a detailed discussion.

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. Hypothesis 1 formalizes this mechanism.

Hypothesis 1: *The probability of mortgage default conditional on a wildfire in the treatment group is higher than the probability of default in the control group.*

3.2 A Simple Model of House Prices with Wildfires

Figure 4 shows a simple model of house prices, taking into account the possibility of wildfires and homeowners' responses to such fires.[19] Let H_t denote the value of the house. At each time t, there

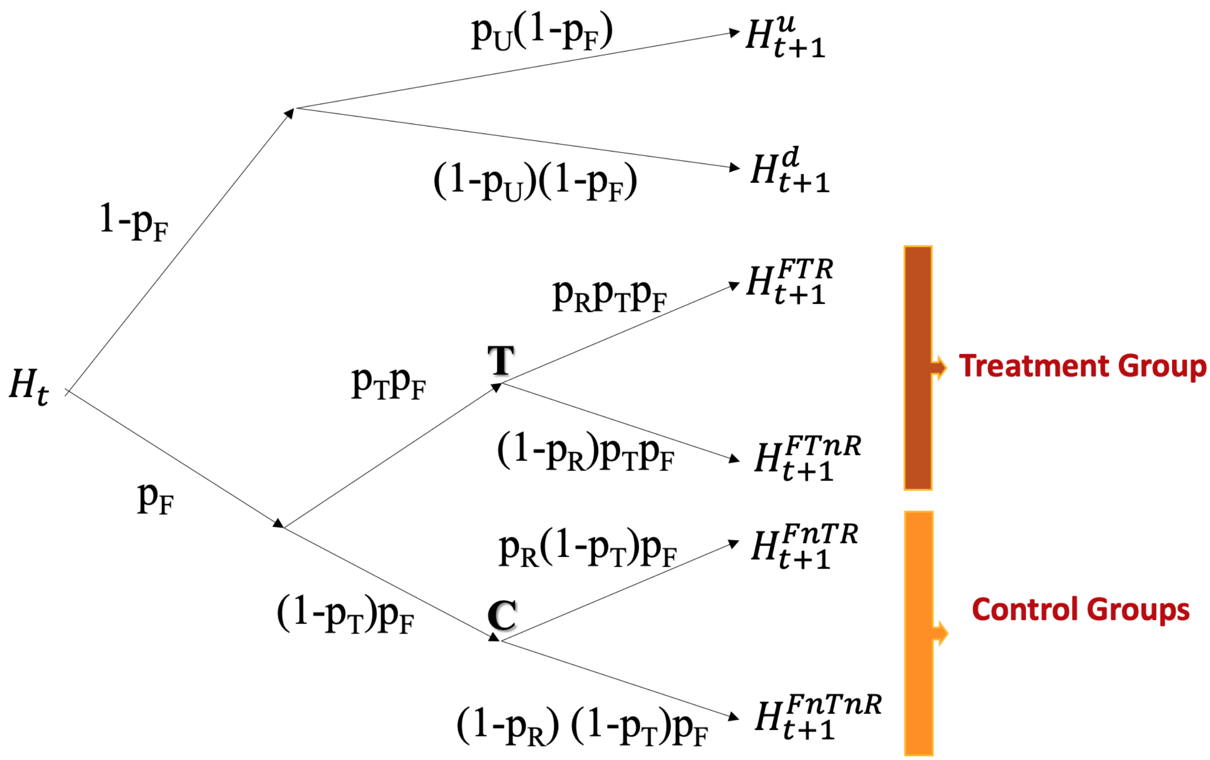


Figure 4: **House-price tree**. This figure plots the dynamics of house prices in a theoretical framework with fire risk (i.e., with fire probability p_F), probability of being in the treatment (i.e., the house is burnt), p_T or on the control group (i.e., the house is near the fire area), and probability of rebuilding of the area, p_R.

is a a probability p_F of a large, exogenous wildfire. If there is no fire, then the house price can exogenously move up to H_{t+1}^u with risk-neutral probability p_U or down to H_{t+1}^d with risk-neutral probability $1 - p_U$. In the case of a fire, there is a risk-neutral probability p_T that the house falls in a treatment group (i.e., the house is affected by the fire) and a risk-neutral probability $1 - p_T$

[19] Appendix B shows additional details.

that the house falls in a non-treatment group (i.e., the house is near the fire area but remains unaffected).

However, there are at least two issues that could make the household potentially *better* off in the case of an event. First, all new and replacement structures must conform to current building codes. Therefore, most households that experience a fire will end up owning a house of higher quality after reconstruction. The second issue relates to externalities in the neighborhood's investments and the coordination problem they induce. In the case of an event, there is a "forced" coordination in investing and upgrading the quality of the neighborhood. In equilibrium, this coordination will affect the value of the households' mortgage prepayment and default options.

Consequently, we assume that the area affected by a wildfire is rebuilt (up to code) with probability p_R. In such a case, the house price becomes H_{t+1}^{FTR} (i.e., **F**ire/**T**reatment/**R**ebuilt) or H_{t+1}^{FnTR} (i.e., Fire/non-Treatment/Rebuilt) if the house is in the treatment or control group, respectively. If there is no rebuilding, the house price decreases to H_{t+1}^{FTnR} or H_{t+1}^{FnTnR}, respectively.

Figure 4 shows a sketch of these dynamics. We are particularly interested in the study of mortgage defaults conditional on a wildfire, that is, in points T and C of the tree in figure 4. In the case of a fire, expected house prices in both the treatment (T) and control (C) groups increase with the probability of rebuilding of the neighborhood or area, p_R; the house prices conditional on rebuilding, H_{t+1}^{FTR} and H_{t+1}^{FnTR}, respectively; and the house price conditional on non-rebuilding, H_{t+1}^{FTnR} and H_{t+1}^{FnTnR}, respectively. Moreover, the coordination externalities after large wildfires lead to large tracts of homes being replaced with new structures due to build-to-code requirements. As a result, expected house prices in both the treatment and control groups increase with the size of the fire, leading to lower probabilities of default in both the treatment and control groups. Hypothesis 2 formalizes this conjecture.

Hypothesis 2: *The probability of mortgage default conditional on a wildfire for a house in both the treatment and control groups decreases with: (i) the probability of rebuilding; (ii) the house price conditional on rebuilding; (iii) the house price conditional on non-rebuilding; and (iv) the size of the fire.*

To test hypothesis 1, we develop a difference-in-differences (DID) analysis based on the following reduced-form model:

$$default_{i,f} = treatment_{i,f} * afterfire_{i,f} + afterfire_{i,f} + treatment_{i,f} + \bar{X}_{i,f} + \varepsilon_{i,f}, \qquad (1)$$

where $default_{i,f}$ denotes delinquency (first set of results) or foreclosure (second set of results) of mortgage i during the 6-month period after the event of fire f; $treatment_{i,f}$ is a dummy that takes the value of one if mortgage i is within the fire f zone and zero if mortgage i is within the ring of 1.0 miles outside the fire f zone; and $afterfire_{i,f}$ is a dummy that takes the value of one after the fire f event, and zero before the fire f event. Let $\bar{X}_{i,f}$ denote a set of mortgage controls, and let $\varepsilon_{i,f}$ be the error term.

For example, consider the Witch wildfire, which occurred in San Diego in October 2007. There

are 5,508 properties (from ATTOM) and 1,446 mortgages (from Black Knight McDash) in our database within the fire zone (the treatment group). There are over 22,000 properties and 6,570 mortgages within the ring that goes from 0 to 1 mile from the border of the fire zone (the control group). Figure 5 shows the mortgages affected in the treatment group and within rings 1 and 2 miles from the fire perimeter.

Note that we only include mortgages directly affected (treatment group) or indirectly affected (control group) and right before and right after the fire event ($afterfire$ dummy) in our DID analysis. We do not include mortgages further than a few miles from the perimeter of the wildfire, or mortgage performance years before or after the fire event. In the empirical analysis, we also use all the available mortgages in our data from January 2000 to April 2018 in a panel-data approach.

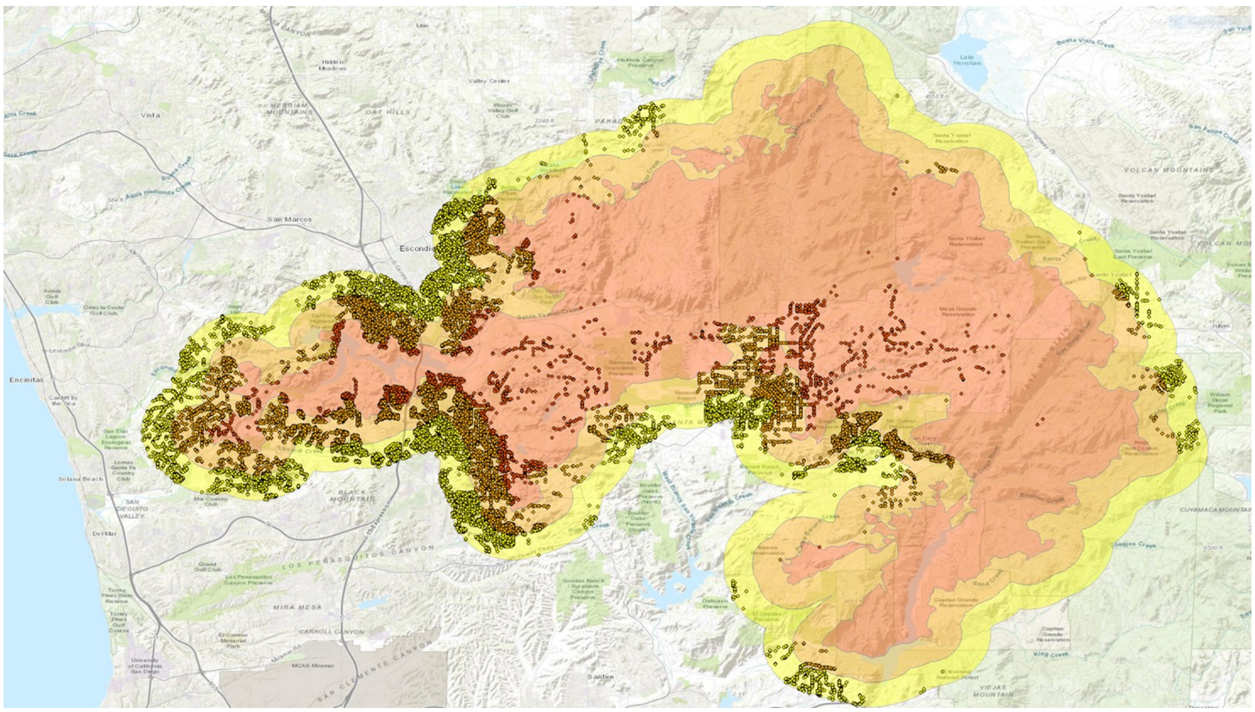


Figure 5: **Witch wildfire and mortgages affected.** This figure shows a map of the location of the properties with mortgages affected by the Witch wildfire. It shows the treatment group area in red, the *Ring 0–1* area in orange, and the *Ring 1–2* area in yellow.

We build upon the DID analysis in equation (1) to test hypothesis 2:

$$\begin{aligned} default_{i,f} = & treatment_{i,f} * bigfire_f * afterfire_{i,f} + treatment_{i,f} * afterfire_{i,f} + \\ & treatment_{i,f} * bigfire_f + bigfire_f * afterfire_{i,f} + \\ & afterfire_{i,f} + treatment_{i,f} + bigfire_f + \bar{X}_{i,f} + \varepsilon_{i,f}, \end{aligned} \tag{2}$$

where $default_{i,f}$, $treatment_{i,f}$, $afterfire_{i,f}$, $\bar{X}_{i,f}$, and $\varepsilon_{i,f}$ are defined as in the previous analysis.

We use the variable $bigfire_f$ to capture the size of the wildfire.[20] We provide empirical results

[20]Note that we use $bigfire_f$ because we cannot observe the probability of rebuilding a property after a fire event

using two definitions for this variable. First, we define $bigfire_f$ as a dummy variable that takes the value of one if the fire f is large and zero if the fire is small. We consider big fires those that affect a large number of mortgages, which we define as a number at least one standard deviation above the mean number of mortgages affected by all fires.[21] Second, we also define $bigfire_f$ as the number of mortgages affected by fire f.

4 Data

Our analyses focus on the state of California from 2000 to 2018. We use detailed data on mortgage characteristics and performance, housing data at the property level, accurate data on individual wildfire events, and weather data.

4.1 Wildfire events

We use data of all the fire events reported by the California Department of Forestry and Fire Protection from January 2000 to April 2018. Data include the exact location of the fire event, date, number of acres burnt, and type of fire event. We use only wildfire events. Table 3 describes the 20 largest wildfires in California during this period.

4.2 Mortgage characteristics and performance

We use 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. This data set includes 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.

Table 4 shows the top 5 wildfires in terms of number of mortgages affected. Notice that most of the largest fires listed in Table 3 are not the ones that have the largest impact in the mortgage markets. This is due to the fact that most of the large fires happen in rural low-density areas. This table shows that a single wildfire can have an impact on thousands of mortgages. For example, the Cedar and Witch fires that occurred in San Diego County directly affected 1,542 and 1,446

and the conditional distribution of future prices for each property. Moreover, there is no available survey to infer them. Therefore, we use measures of the fire size in terms of number of mortgages affected as a proxy for these variables. The intuition goes as follows. The larger the fire, the higher the probability of rebuilding the area and the higher the house prices in the future. The Tunnel Fire case study above provides the details behind this mechanism.

[21]The mean number of mortgages in the treatment and both control groups for all fires is 2,302 with a standard deviation of 3,621, so the mean plus one standard deviation is 5,923 mortgages.

Table 3: **Largest wildfires in California.** This table describes the 20 largest wildfires (in terms of km^2 burnt) in California for our period of analysis (Jan. 2000–Apr. 2018). Note that some individual fires that originate in different places merged into a large fire and they are grouped into a unique *complex fire* in the records. Sometimes they do not. Ex. Klamath Theater Complex in Siskiyou County burnt 777.2 km^2 in 2008 but it is a merge of smaller individual fires. Let (*) denote complex fire. It does not include the wildfires that occurred after April 2018 (e.g., Mendocino, Carr, Camp Fire, Woolsey, and Ferguson). Source: California Department of Forestry and Fire Protection.

	Fire name	County	Start date	Contained data	km^2
1	Thomas	Ventura, Santa Barbara	4-Dec-17	12-Jan-18	1,140.8
2	Cedar	San Diego	25-Oct-03	5-Nov-03	1,105.8
3	Rush	Lassen	12-Aug-12	22-Oct-12	1,100.4
4	Rim	Tuolumne	17-Aug-13	24-Oct-13	1,041.3
5	Zaca	Santa Barbara	4-Jul-07	2-Sep-07	972.1
6	Witch	San Diego	21-Oct-07	31-Oct-07	801.2
7	Klamath Theater (*)	Siskiyou	21-Jun-08	30-Sep-08	777.2
8	Basin (*)	Monterey	21-Jun-08	27-Jul-08	658.9
9	Day	Ventura	4-Sep-06	30-Oct-06	658.4
10	Station	Los Angeles	26-Aug-09	22-Sep-09	649.8
11	Rough	Fresno	31-Jul-15	6-Nov-15	613.6
12	McNally	Tulare	21-Jul-02	28-Aug-02	609.8
13	Happy Camp (*)	Siskiyou	14-Aug-14	31-Oct-14	542.5
14	Soberanes	Monterey	22-Jul-16	13-Oct-16	534.6
15	Manter	Tulare	22-Jul-00	6-Sep-00	490.0
16	Simi Fire	Ventura	25-Oct-03	5-Dec-03	437.9
17	Bake-Oven	Trinity	23-Jul-06	30-Nov-06	406.4
18	King	El Dorado Ventura	13-Sep-14	10-Oct-14	395.4
19	Storrie	Plumas	17-Aug-00	27-Sep-00	387.5
20	Old	San Bernardino	25-Oct-03	15-Nov-03	369.4

mortgages in the fire zone, and indirectly affected 7,089 and 6,570 mortgages in the perimeter within 1 mile outside of the wildfire, respectively.

Table 4: **Wildfires with the largest impact on the mortgage markets.** This table shows the 5 top wildfires in terms of number of mortgages within the fire zones in our data (Fire). It also exhibits the number of mortgages located in the ring of 1.0 miles right outside the fire zones (Ring 0.0–1.0) and the control group are the areas within the ring from 1.0 to 2.0 miles outside the fire zones (Ring 1.0–2.0) in our data. (*) denotes complex fire.

	Fire name	Fire Obs.	Ring 0.0–1.0 Obs.	Ring 1.0–2.0 Obs.	Start date	Contained data	km^2
1	Cedar	1,542	7,089	6,784	25-Oct-03	5-Nov-03	1,105.8
2	Witch	1,446	6,570	7,289	21-Oct-07	31-Oct-07	801.2
3	Fireway (*)	1,388	9,751	9,950	15-Nov-08	18-Nov-08	178.5
4	Old	520	5,200	3,434	25-Oct-03	15-Nov-03	369.4
5	Buckweed	348	4,856	4,027	21-Oct-07	21-Oct-07	229.1

Table 5 shows information on the number of times that a single mortgage is affected by a wildfire. We find that 95.78% of the mortgages in our sample have never been affected by a fire. A mortgage affected by fire means that it is located in the treatment group (mortgages within the fire zones, Fire) or any of the 2 control groups (i.e., areas within the ring of 1.0 miles outside the fire zones, Ring 0.0–1.0, or areas within the ring from 1.0 to 2.0 miles outside the fire zones, Ring 1.0–2.0). In other words, 95.78% of the mortgages have never been within a wildfire zone or within 2.0 miles from the perimeter of a fire. It also shows that 0.30% and 0.04% of the mortgages have been affected by a wildfire two and three times, respectively.

4.3 Mortgage geolocation and property characteristics

We geolocate the Black Knight McDash loan-level mortgage data by merging it with the ATTOM property data. ATTOM includes not only the latitude and longitude coordinates of each property, but also specific characteristics of the houses collateralizing the mortgages. Table 6 exhibits the statistics of the main variables that define the mortgages at origination and the characteristics of the collateral properties.

4.4 Weather

We obtain detailed weather data from the National Climatic Data Center (NCDC) of the U.S. National Oceanic and Atmospheric Administration (NOAA). Its "Local Climatological Data" (LCD) data tool contains comprehensive hourly, daily, and monthly data from nearly 2,400 locations within the U.S., surrounding territories, and other selected areas. We limit our analysis to the monthly measurements between January 2001 and December 2018 obtained from the 94 weather stations in California. We link each census tract to the closest weather station.

Table 5: **Mortgages and wildfires.** This table shows the number of mortgages affected by wildfires. Panel A shows the number of times (as number of observations and as a percentage of total) that a mortgage is affected by a wildfire. In this panel, mortgage affected by fire means that it is located in the treatment group (mortgages within the fire zones, Fire) or any of the 2 control groups (i.e., areas within the ring of 1.0 miles outside the fire zones, Ring 0.0–1.0, or areas within the ring from 1.0 to 2.0 miles outside the fire zones, Ring 1.0–2.0). Panel B shows the number of mortgages in the treatment group, the control group Ring 0.0–1.0, and the control group Ring 1.0–2.0. Notice that some mortgages could be in different groups at different times (e.g., a mortgage can be in the treatment group in July 2010 and in the control group Ring 1.0–2.0 in September 2013).

Panel A. Times that mortgages are affected by wildfires

	Obs.	% of total
Never affected by fire	6,759,547	95.78%
One time affected by fire	268,911	3.81%
Two times affected by fire	26,031	0.30%
Three times affected by fire	2,614	0.04%
Four times affected by fire	170	0.00%
Total	7,057,273	100.00%

Panel B. Mortgages in fire zones (burnt) or in control zones (nearby)

	Obs.	% of total
Mortgages in fire zones (treatment group):		
Affected once	8,629	0.12%
Affected twice	31	0.00%
Total number of unique mortgages affected	8,660	0.12%
Total number of mortgage-fire observations	8,691	0.12%
Mortgages in control group 0 to 1.0 miles:		
Affected once	124,857	1.77%
Affected twice	6,178	0.09%
Affected three times	196	0.00%
Affected four times	6	0.00%
Total number of unique mortgages affected	131,237	1.86%
Total number of mortgage-fire observations	137,825	1.95%
Mortgages in control group 1.0 to 2.0 miles:		
Affected once	164,661	2.33%
Affected twice	8,775	0.12%
Affected three times	252	0.00%
Affected four times	3	0.00%
Total number of unique mortgages affected	173,691	2.46%
Total number of mortgage-fire observations	182,979	2.59%

Table 6: **Characteristics of the mortgages and collateral properties.** This table shows the mean and standard deviation of the mortgage characteristics and the collateral properties in our data for the entire monthly mortgage-level panel data set.

	All mortgages	
	Mean	Standard dev.
Mortgage factors:		
Original interest rate	5.42%	1.83%
Original term	338.0	70.1
Original loan amount	327,749	255,415
Original credit score	700.1	69.5
Original LTV	0.7289	0.2189
Property attributes:		
Sq. feet	1,902.6	4,858.1
Num. of rooms	4.7	4.2
Num. of bedrooms	3.4	3.1

LCD data includes surface observations from both manual and automated (AWOS, ASOS) stations with source data taken from the National Centers for the Environmental Information's Integrated Surface Data (ISD). Geographic availability includes thousands of locations worldwide. Climate variables include hourly, daily, and monthly measurements of temperature, dew point, humidity, winds, sky condition, weather type, atmospheric pressure, and more.

Let *Max.Temperature* and *Average Temperature* denote the maximum and average temperature of the day, respectively. Let *Days with* > 0.01 and *Days with* > 0.1 denote the days with precipitation greater than 0.01 inches and 0.1 inches, respectively.

5 Empirical Results

In this section we study the causal relationship between mortgage performance (delinquency and foreclosure) and climate-change-driven events (wildfires). We define *delinquency* as a status of more than 90 days delinquency of the mortgage and *foreclosure* as a status of foreclosure presale, foreclosure post-sale, or Real Estate Owned (REO). First, we implement the difference-in-differences (DID) approach that we described in the previous section. Second, we use panel data and an instrument based on weather data to provide further empirical results and address potential endogeneity concerns.

5.1 Difference-in-differences approach

We use a time frame of 6 months before and after a fire event.[22] We geolocalize all the mortgages in our database, as well as the shapes of the wildfires, which we obtain from the California Department

[22] Our results are robust to using alternative periods of analysis from 3 to 12 months.

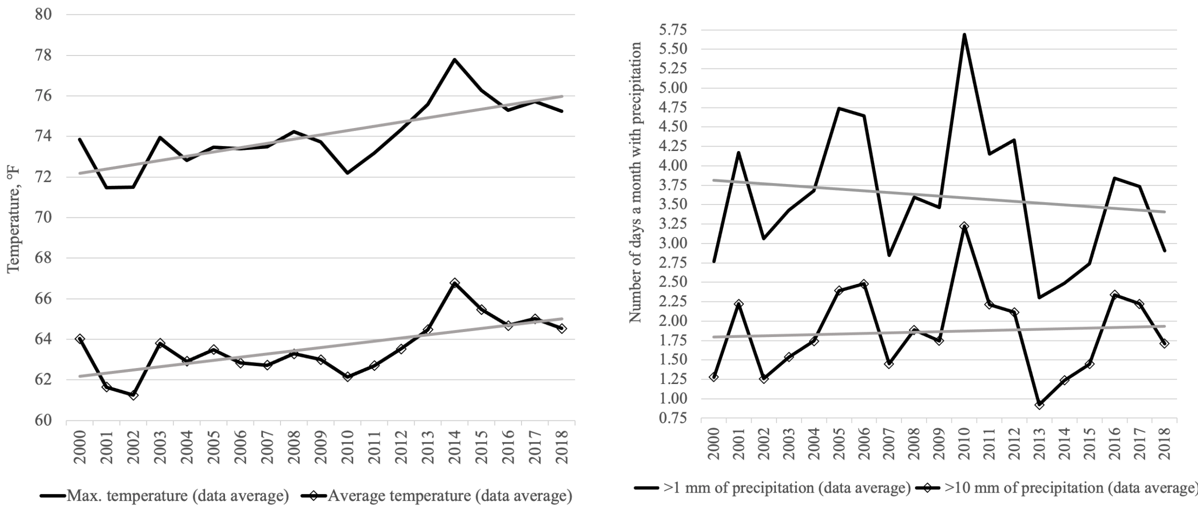


Figure 6: **Weather data over the period of analysis.** This figure shows the dynamics of the monthly mean of four weather-related variables in all the U.S census tracts in California. Panel A displays the mean of the maximum temperature of the month and the mean of the average temperature of the month. Panel B displays the mean of the days with at least 1 mm. and 10 mm. of precipitation per month. Both panels show the average linear trend of these variables.

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 (i.e, $Fire$). We define the dummy variable $treatment$, which takes the value 1 if the active mortgage falls inside the wildfire zone and 0 otherwise. We consider a ring 1 mile around the perimeter of the wildfire zone, *Ring 0–1*. The set of mortgages that fall in *Ring 0–1* conform the control group. We define the dummy variable $afterfire$, which takes the value 1 after the fire if the mortgage has been involved in a fire event (either as part of the treatment or control group), and 0 before the fire event. Columns [1] and [2] in Table 7 show that there is a significant increase in delinquency after a fire event. However, there is no significantly different effect in the treatment and control zones.

Our results change when we take into account the size of the fire. In column [3], we define $bigfire$ as a dummy variable that takes the value of 1 if the mortgage is affected by a fire at least 1 standard deviation above the average wildfire in terms of mortgages affected.[23] The coefficients in this column show that delinquency increase on average after a wildfire, but it increases less inside the wildfire zone (treatment group) for big fires. For big fires, the increase in the probability of delinquency is 21.3% lower in the treatment group than in the ring from the fire-zone edge to 1 mile outside the fire zone.[24] Nevertheless, the increase in delinquency is 68% lower for big than for small fires.[25]

[23] Our results are robust to different definitions of this dummy variable, such as being above the average (instead of being 1 standard deviation above the average) or using the number of acres burnt to create the dummy (instead of the number of mortgages affected).

[24] For big fires, the increase in delinquency in the treatment group is 0.33% ($-0.00614+0.00525+0.00502-0.00084$), which is 21.3% lower than the increase of 0.42% ($0.00502-0.00084$) in the control group.

[25] The increase in delinquency for big fires is 0.33% ($-0.00614+0.00525+0.00502-0.00084$), which is 68.0% lower

Table 7: **The effect of wildfires on mortgage delinquency.** This table shows the whole table for the difference-in-differences analysis about the effect of wildfires on mortgage delinquency. Delinquency is defined as a delinquency (i.e., 90 days or more), 6 months before or after the fire event. For columns [1]–[3], the treatment group contains the mortgages within the fire zones (fire=1) and the control group is the areas within the ring 1.0 miles outside the fire zones (control10=1). For columns [4]–[5], the treatment group contains the mortgages in the areas within the ring of 1.0 miles outside the fire zones (control10=1) and the control group are the areas within the ring from 1.0 to 2.0 miles outside the fire zones (control10to20=1). Mortgage controls include interest rate, term of the mortgage, loan amount, credit score, and LTV at origination. Robust standard errors in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Treatment group:	Fire	Fire	Fire	Ring 0–1	Ring 0–1
Control group:	Ring 0–1	Ring 0–1	Ring 0–1	Ring 1–2	Ring 1–2
bigfire:	—	—	Dummy	—	—
	[1]	[2]	[3]	[4]	[5]
treatment*bigfire*afterfire			-0.00614**		
			(0.00252)		
treatment*afterfire	0.00134	0.00143	0.00525**	-0.00120***	-0.00108***
	(0.00105)	(0.00115)	(0.00226)	(0.00037)	(0.00040)
treatment*bigfire			-0.00126		
			(0.00094)		
bigfire*afterfire			-0.00094		
			(0.00061)		
afterfire	0.00459***	0.00479***	0.00502***	0.00579***	0.00587***
	(0.00026)	(0.00029)	(0.00034)	(0.00026)	(0.00028)
treatment	6.83e-05	-0.00031	0.00067	0.00012	0.00031**
	(0.00038)	(0.000423)	(0.00088)	(0.00013)	(0.00015)
bigfire			-0.00084***		
			(0.00022)		
Mortgage controls	No	Yes	Yes	No	Yes
Observations	208,422	177,532	177,532	412,604	350,590
R-squared	0.002	0.011	0.011	0.002	0.012

We also study the neighborhood effects of climate-change-driven events. Columns [4] and [5] show the results of the equivalent DID approach to columns [1] and [2], but using *Ring 0–1* as a treatment group and the ring located from 1 to 2 miles outside the border of the wildfire, *Ring 1–2*, as the control group. These results show that there is a significant decrease in mortgage delinquency in the 6-month period after a wildfire event in mortgages of houses located within a mile of the wildfire border, compared with mortgages of houses located between 1 and 2 miles away. Overall, these results show that there are neighborhood effects driven by the positive externalities from the potential rebuilding. Table 8 provides equivalent results for foreclosures.

Table 8: **The effect of wildfires on foreclosures.** This table shows the whole table for the difference-in-differences analysis about the effect of wildfires on mortgage foreclosures. Foreclosure is defined as foreclosure presale, foreclosure post sale, or REO, 6 months before or after the fire event. For columns [1]–[3], the treatment group contains the mortgages within the fire zones (fire=1) and the control group is the areas within the ring 1.0 miles outside the fire zones (control10=1). For columns [4]–[5], the treatment group contains the mortgages in the areas within the ring of 1.0 miles outside the fire zones (control10=1) and the control group is the areas within the ring from 1.0 to 2.0 miles outside the fire zones (control10to20=1). Mortgage controls include interest rate, term of the mortgage, loan amount, credit score, and LTV at origination. Robust standard errors in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Treatment group: Control group: bigfire:	Fire Ring 0–1 —	Fire Ring 0–1 —	Fire Ring 0–1 Dummy	Ring 0–1 Ring 1–2 —	Ring 0–1 Ring 1–2 —
	[1]	[2]	[3]	[4]	[5]
treatment*bigfire*afterfire			-0.00605***		
			(0.00198)		
treatment*afterfire	0.00105	0.00116	0.00463**	-0.00076***	-0.00052*
	(0.00081)	(0.00088)	(0.00184)	(0.00027)	(0.00030)
treatment*bigfire			-0.00079		
			(0.00064)		
bigfire*afterfire			-6.10e-05		
			(0.00047)		
afterfire	0.00270***	0.00279***	0.00280***	0.00345***	0.00331***
	(0.00019)	(0.00021)	(0.00025)	(0.00020)	(0.00021)
treatment	7.04e-05	-0.00021	0.00036	6.34e-05	0.00013
	(0.00027)	(0.00027)	(0.00062)	(9.00e-05)	(0.00010)
bigfire			-0.00041***		
			(0.00015)		
Mortgage controls	No	Yes	Yes	No	Yes
Observations	208,422	177,532	177,532	412,604	350,590
R-squared	0.001	0.007	0.007	0.001	0.008

than the increase of 1.03% $(0.00525 + 0.00502)$ for small fires.

Table 9 shows the summary statistics of the variables that we use in the DID approach (panel A). Importantly, panel B shows the t-tests of the difference of the means of the variables of interest, *delinquency* and *foreclosure*, during the 6 months prior to the fire event. These results show that the average *delinquency* and *foreclosure* is not different between the treatment and control groups in our DID analyses.

Table 9: **Summary statistics and t-tests.** This table shows the summary statistics of the variables that we use in the difference-in-differences analysis (Panel A) and the t-tests for the difference of the means of these variables before the fire (Panel B). Note that the mean of the variables delinquency and foreclosure are not statistically different for the control and treatment groups before fire events, which supports the validity of our DID analysis.

Panel A. Summary statistics of the data for the DID analysis

	Mean	St. Dev.	p25	p50	p75	Obs.
delinquency	0.00351	0.05910	0	0	0	522,954
foreclosure	0.00193	0.04393	0	0	0	522,954
interest rate	0.05663	0.01322	0.05250	0.05750	0.06250	522,938
term	335.8	71.2	360.0	360.0	360.0	522,832
loan amount	329,570	223,141	190,000	284,000	416,000	522,954
credit score	719.3	61.6	682.0	727.0	768.0	446,778
LTV	0.662	0.811	0.526	0.684	0.794	519,474
Num. of mortgages per wildfire	440.5	586.1	38.0	96.0	520.0	522,954
bigfire (dummy)	0.2431	0.4289	0	0	0	522,954

Panel B. t-Tests of the difference of the means of variables before the fire

	Control	Treatment	Mean control	Mean treatment	Diff.	t-stat	H_0: Diff.=0
delinquency	Ring 0–1	Fire	0.00096	0.00103	-0.00007	-0.19	Not rejected
			(0.03104)	(0.03212)			
foreclosure	Ring 0–1	Fire	0.00045	0.00052	-0.00007	-0.28	Not rejected
			(0.02111)	(0.02272)			
delinquency	Ring 1–2	Ring 0-1	0.00085	0.00096	-0.00090	-0.89	Not rejected
			(0.02909)	(0.03104)			
foreclosure	Ring 1–2	Ring 0-1	0.00038	0.00045	-0.00006	-0.71	Not rejected
			(0.01955)	(0.02111)			

5.2 Instrumental variable approach

We implement a panel data approach for two reasons. First, the IV approach provides a robustness check for the effect of big fires on mortgage default that we find in our main difference-in-differences. Second, the first stage of the IV approach provides property-level estimates for the probability of large fires. These estimates are important as a test for whether probabilistic fire estimates can improve on the purely deterministic fire map assignments that are currently used to price fire

casualty insurance in California. To make this comparison, we embed the fire codes into the first stage specification along with measurements for each property's exposure to monthly maximum temperatures and census tract fixed effects.

For the IV regression approach, we create a panel with all the available monthly mortgage-level data for the period 2000–2018. We run OLS and IV regressions with two measures of default and foreclosure as dependent variables. We define $\text{default}_{i,t}$ for each mortgage i at each month t as a dummy variable that takes the value 1 if the mortgage is delinquent (i.e., 90 days or more) in the following 6 months, and 0 otherwise. We define $\text{foreclosure}_{i,t}$ for each mortgage i at each month t as a dummy variable that takes the value of 1 if the mortgage gets into foreclosure presale, foreclosure post sale, or REO in the following 6 months, and 0 otherwise.

To address potential endogeneity and measurement-error concerns, we provide a valid instrumental variable (IV) for our measure of fires and big fires. We use the maximum temperature of the month in the location of the property that is used as collateral for the mortgage as an IV for the measure of fires and big fires. The reasoning for using this type of weather-related data goes as follows. When the maximum temperature increases, the probability of starting a large fire increases. Moreover, the exclusion restriction holds, that is, there is no straight relationship between months with high values of maximum temperature and the levels of mortgage delinquency or foreclosure.

The first stage of our IV approach is a linear regression of our two measures for fire size: the number of mortgages affected and our indicator variable for big fires. The baseline specification for our analysis uses the following variables: maximum temperature of the month in the location of the property that is used as collateral for the mortgage (Max. temp.); indicator variables for the deterministic hazard codes that are assigned to the location by the California Department of Insurance; and fixed effects.

Table 10 shows the panel data prediction of fire events at a property level. We measure fire events as a dummy variable for big fires. The fire hazard code is a variable that takes integer values from 0 to 3 (i.e., a property with hazard code of 0 is located in the group of lowest fire hazardous areas and a property with hazard code of 3 is located in the group of highest fire hazardous areas according to the California Fire Department).

The results from the first stage analysis show that there is a positive and significant relationship between the maximum temperature of the month and the probability of a big fire event at the property level. The maximum-temperature effect is statistically significant even with the controls for the hazard map assignments for the property (which also have positive relationships with big fire events).

To better interpret the results in Table 10, we plot maps for the deterministic assignments for properties in Northern and Southern California in Figure 7. As shown in the maps, 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

Table 10: **Forecast of wildfires: First stage regressions — panel data analysis.** This table shows the panel data analysis of the prediction of wildfires at the property level using weather data and the fire hazard code of the property. We use the panel of data at the mortgage-month level. We use the maximum temperature of the month of the closest weather station and the hazard code of the property, which is a variable that takes integer values from 0 to 3 (i.e., a property with hazard code 0 is located in an area with the lowest fire hazard, while a property with hazard code 3 is located in an area with the highest fire hazard according to the California Fire Department). We use the dummy variable for big fire as dependent variable. Robust standard errors in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	[1]	[2]	[3]	[4]
Max. temp.	5.93e-05***		7.99e-05***	7.95e-05***
	(7.01e-06)		(8.13e-06)	(7.95e-06)
haz_code		0.00797***	0.00822***	
		(8.92e-05)	(9.78e-05)	
D. hazard=1				0.00777***
				(0.000153)
D. hazard=2				0.00553***
				(5.37e-05)
D. hazard=3				0.0285***
				(0.000373)
Constant	-0.00234***	0.00119***	-0.00473***	-0.00465***
	(0.000521)	(9.56e-06)	(0.000608)	(0.000594)
Fixed effects:	Yes	Yes	Yes	Yes
Observations	184,958,421	194,499,073	184,958,210	184,958,421
R-squared	0.002	0.008	0.008	0.010

of the lee 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. Interestingly, the deterministic codes do not provide a very wide range of pricing differentiation since there are only three different codes.

In Figure 8 and Figure 9, we present the big fire probability estimates from the first stage regression for Northern and Southern California for each of four months in 2017. As shown, there appears to be broader range of risks than are not apparent in the deterministic maps. The code-3 hazard zones, remain important but clearly the maximum temperate effects by location, as the maps move from Winter and Spring to Summer and Fall, are particularly evident with our estimates. Although not shown, since these maximum temperatures are gradually rising over time these maps also change over the panel not just over the seasons. As shown, in the probability scales over the eight submaps, the monthly probabilities of big fires range from essentially zero to more than 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.

In the second stage of our IV approach, we study the effect of big fire events on mortgage delinquency and foreclosure. Table 11 shows the panel data results for mortgage delinquency, which is defined as dummy variable that takes the value of 1 if the mortgage is 90 days or more delinquent in the following 6 months of the fire event, and zero otherwise. Both OLS and IV regressions show that there is a negative effect between big wildfires and the default of mortgages with collateral in areas affected. Therefore, the size of the fire has an effect on delinquency: The larger the wildfire, the lower the level of mortgage delinquency. This effect is causal, as shown in the IV specification in column [3].

Finally, Table 12 shows the equivalent panel data results for mortgage foreclosure. The sign and significance of the coefficients for mortgage foreclosure are similar to the results for mortgage default. However, the magnitude of the coefficients for mortgage foreclosure are smaller, which indicates that foreclosure is less likely to occur than delinquency.

Overall, these panel data results show the robustness of our main two empirical results. First, mortgage default and foreclosure increase in the event of a wildfire. Second, the level of mortgage default and foreclosure decreases in the size of the wildfire, that is, large wildfires lead to a lower level of defaults and foreclosures.

5.3 Expected big-fire losses

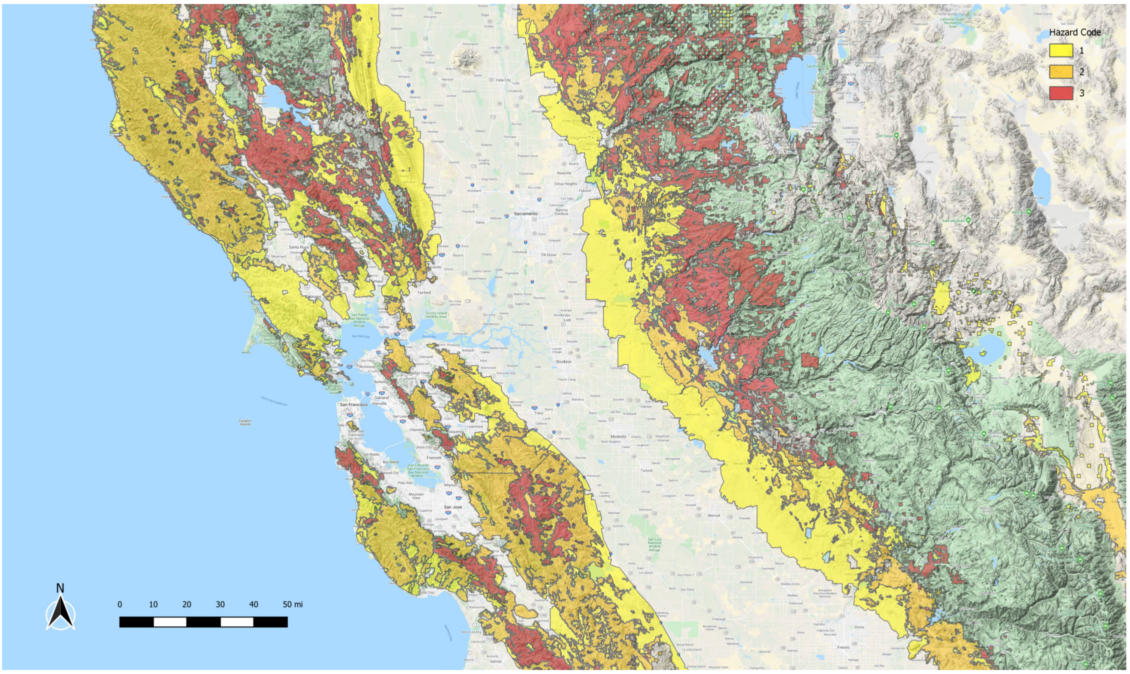
As discussed above in Section 5.2, a second important set of results from the first stage of the IV strategy includes property-level estimates of the probability of large fires. These estimates allow us to compute a new property-specific measure of risk, similar to the measure of expected loss commonly applied in the mortgage market, which we call "expected big-fire loss" (EBFL). EBFL is computed by first estimating the value of each property for each month using the value of the house at the date of mortgage origination and then updating that observed value with a local house price

Table 11: **The effect of wildfires on mortgage delinquency. Panel data analysis.** This table shows the panel data analysis about the effect of wildfires on mortgage delinquency. We use the panel of data at the mortgage-month level. We define delinquency$_{i,t}$ for each mortgage i at each month t as a dummy variable that takes the value of 1 if the mortgage is delinquent (i.e., 90 days or more) in the following 6 months, and 0 otherwise. Columns [1] and [2] use OLS with fixed effects. Column [3] uses an IV approach that instruments the variables big fire using the maximum temperature of the month at the house location. Let LTV denote the dynamic loan-to-value for each mortgage at each month. Let coupon-interest rate diff. denote the dynamic difference between the interest rate coupon of the mortgage and the 10-year Treasury yield for each mortgage at each month. Mortgage controls include interest rate, term of the mortgage, loan amount, credit score, and LTV at origination. Robust standard errors in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

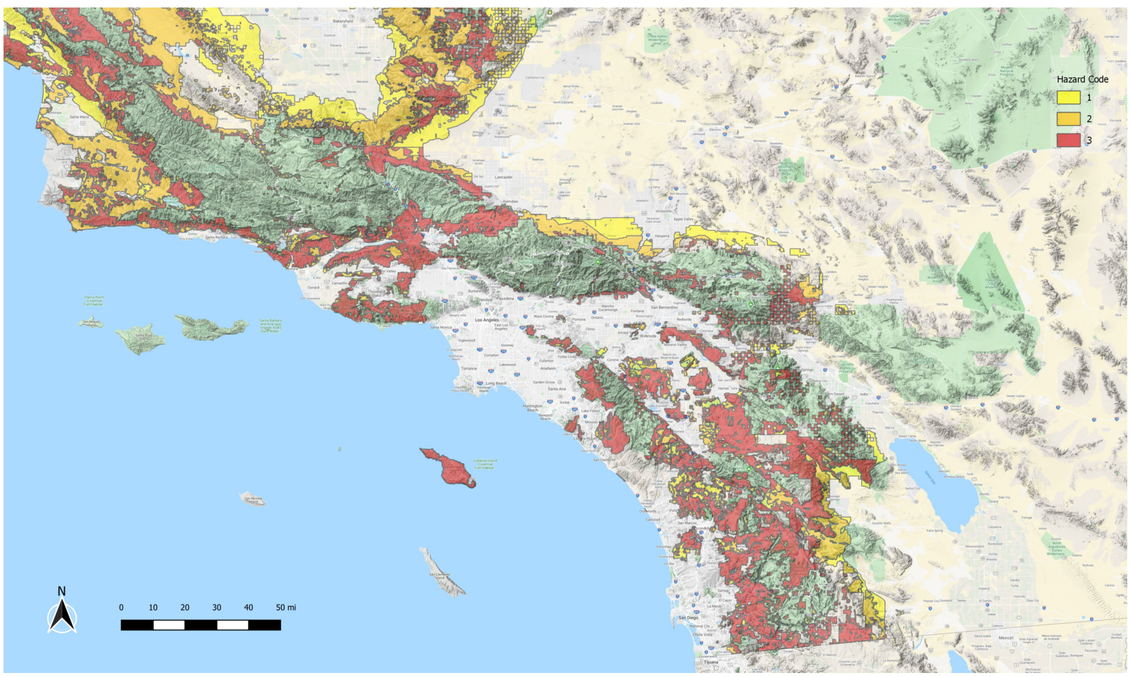
	OLS Num. of mortgages per wildfire [1]	OLS Dummy [2]	IV Dummy [3]
Big fire	-1.42e-07**	-0.0116**	-0.05794**
	(6.33e-08)	(0.00512)	(0.02664)
LTV	2.72e-09	2.78e-09	-8.37e-08
	(2.92e-08)	(2.93e-08)	(3.60e-06)
coupon-interest rate diff.	-2.211*	-2.210*	-0.375
	(1.146)	(1.145)	(1.050)
Month max. temperature			-0.375
	(1.146)	(1.145)	(1.050)
Mortgage controls:	Yes	Yes	Yes
Fixed effects:	Yes	Yes	Yes
Observations	90,368,381	90,368,381	86,303,137
R-squared	0.089	0.089	—

Table 12: **The effect of wildfires on mortgage default. Panel data analysis.** This table shows the panel data analysis about the effect of wildfires on mortgage foreclosures. We define foreclosure$_{i,t}$ for each mortgage i at each month t as a dummy variable that takes the value of 1 if the mortgage gets into foreclosure presale, foreclosure post sale, or REO in the following 6 months, and 0 otherwise. Columns [1] and [2] use OLS with fixed effects. Column [3] uses an IV approach that instruments the variables big fire using the maximum temperature of the month at the house location. Let LTV denote the dynamic loan-to-value for each mortgage at each month. Let coupon-interest rate diff. denote the dynamic difference between the interest rate coupon of the mortgage and the 10-year Treasury yield for each mortgage at each month. Mortgage controls include interest rate, term of the mortgage, loan amount, credit score, and LTV at origination. Robust standard errors in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	OLS Num. of mortgages per wildfire [1]	OLS Dummy [2]	IV Dummy [3]
Big fire	-1.31e-07**	-0.0104**	-0.033258**
	(5.17e-08)	(0.00415)	(0.01498)
LTV	8.14e-09	8.19e-09	-4.02e-08
	(1.39e-08)	(1.39e-08)	(2.03e-06)
coupon-interest rate diff.	-1.497	-1.498	-0.412
	(0.911)	(0.912)	(0.591)
Mortgage controls:	Yes	Yes	Yes
Fixed effects:	Yes	Yes	Yes
Observations	90,368,381	90,368,381	86,303,137
R-squared	0.072	0.072	—

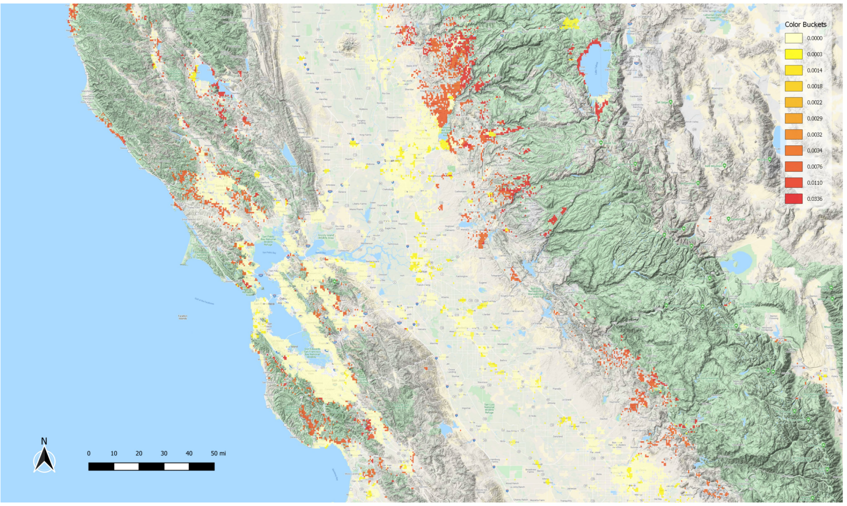


(a) Northern California

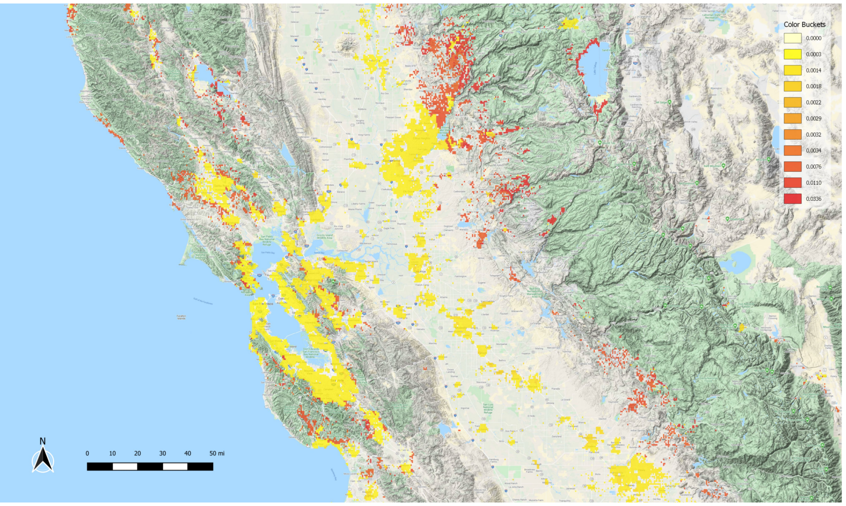


(b) Southern California

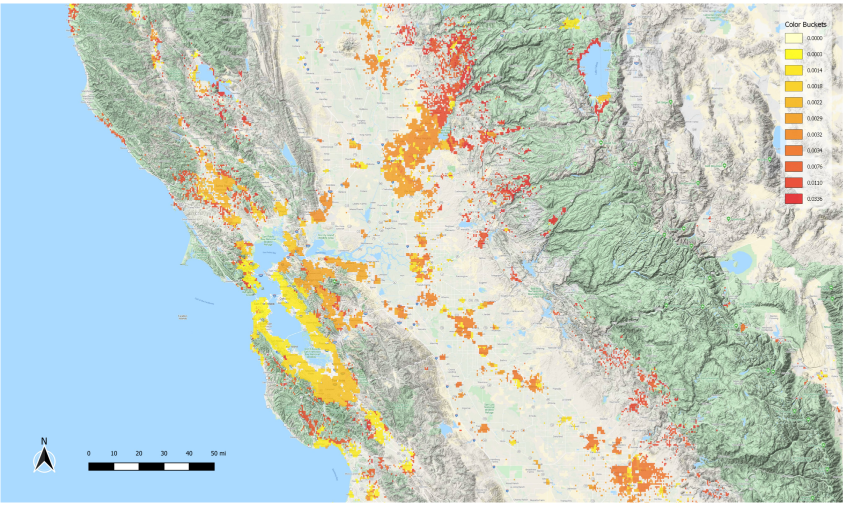
Figure 7: Northern and Southern California deterministic fire codes (see https://osfm.fire.ca.gov/divisions/wildfire-planning-engineering/wildland-hazards-building-codes/fire-hazard-severity-zones-maps/)



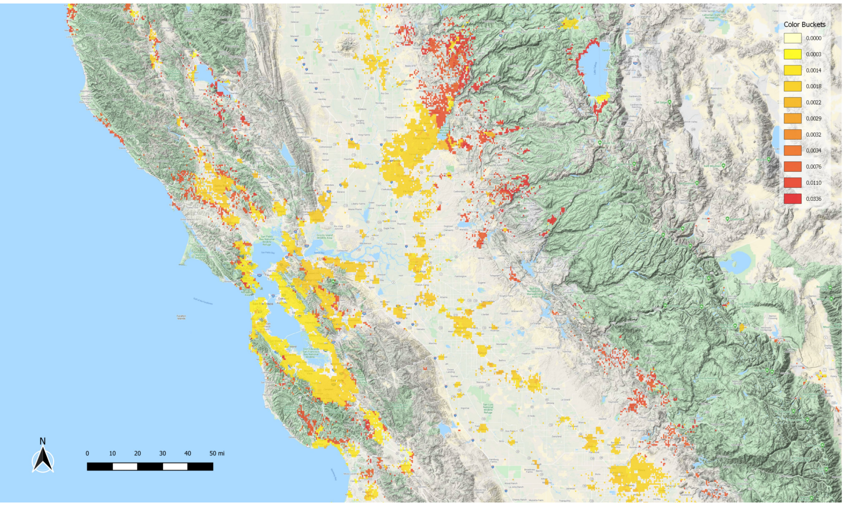
(a) January



(b) April

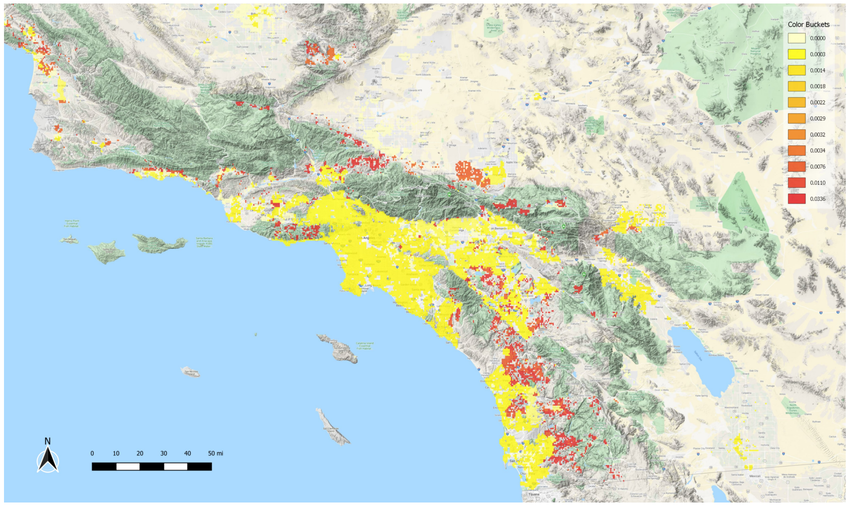


(c) July

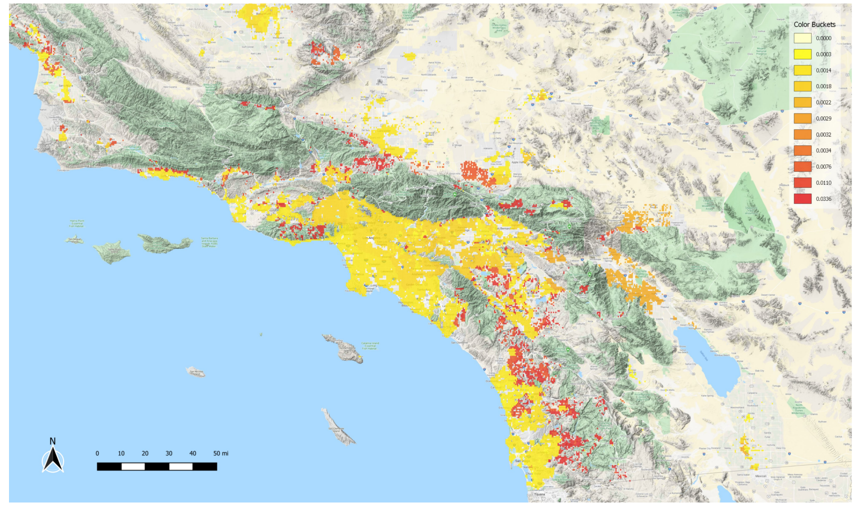


(d) October

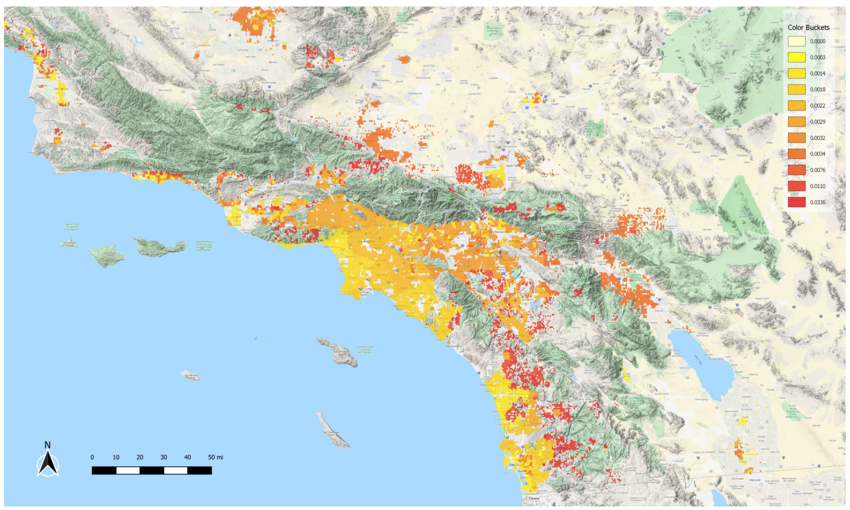
Figure 8: Northern California probabilistic fire estimates, 2017



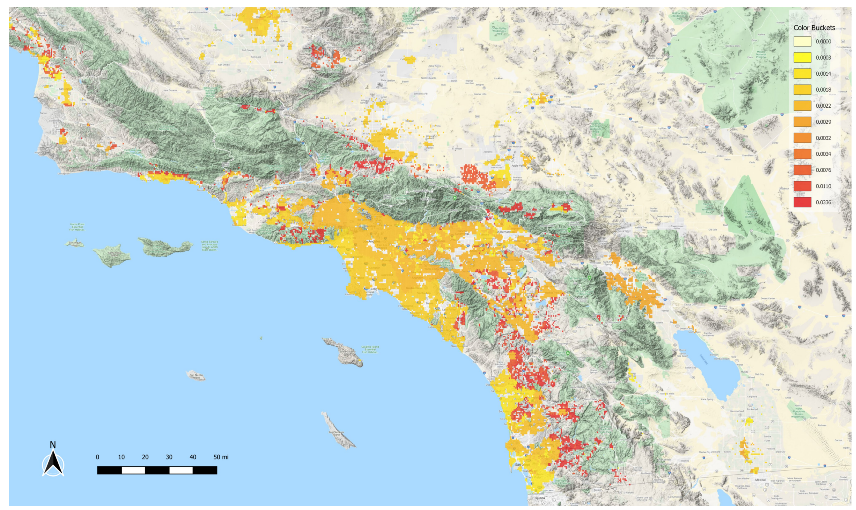
(a) January



(b) April



(c) July



(d) October

Figure 9: Southern California probabilistic fire estimates, 2017

index. Next, we estimate the probability of a big fire for each month by evaluating the property-level probability estimates using the first stage of the panel regression reported in Column [4] of Table 10. Finally, we compute EBFL per property as as the time-specific value of each property multiplied by the probability of a big fire for the property at that time (assuming that the value of each property is zero after a fire has occurred).[26]

Panel A of Table 13 present forecasts for expected big-fire losses per property by hazard code; *Panel B* presents the probabilities of big fires by hazard codes; and *Panel C* presents the aggregate expected monthly and annual big-fire losses for California, in millions of dollars.

The results reported in Table 13 indicate several important regularities. First, as shown in *Panel A*, the magnitude of EBFL, which is based on probabilities of big fires using the first stage of the IV, Column [4] of Table 10, incorporates information on each property's monthly maximum temperate, its hazard zone, as well as the value of the property, does not accurately track the hazard zone rankings from most risky (Zone 3) to least risky (Zone 1). Instead Hazard Zone 1 has a higher EBFL than Hazard Zone 2. In addition, Hazard Zone 3 is shown to have an annual mean EBFL of $20,000 for properties with mortgages, indicating that the risks of Hazard Zone 3 are more than an order of magnitude larger than the other two zones. The same lack of monotonicity over the Hazard Zone assignments is found in *Panel B*, where again the estimated probability of big fires is higher for Hazard Zone 1 than Hazard zone 2, which is currently treated as riskier by the California Department of Insurance. Here again, the risks of Hazard Zone 3 are evident given the reported 3% average probability of a big fire over a year.

Seasonal time series variations in EBFL are also reported in Table 13, *Panel C*. As expected, EBFL is lower in the winter months and then rises to more than a billion dollars per month in the mid summer to late fall months (July through October), which together are considered to be "fire season" in California. Disturbingly, the aggregate annual exposure for these property-specific losses given the probability of big fires is $14.98 billion dollars per year. As noted in Manku (2020), a recent industry report by a reinsurance specialist at S&P Global, magnitudes such as these have led the reinsurance industry to re-evaluate California wildfires and "increase the risk from secondary perils" to primary casualty perils with direct rather than wrapped pricing.[27]

Overall, these results suggest that probabilistic models of big fire risks are tractable and informative. Additionally, the static, deterministic Hazard Zone maps do not accurately order risk. Part of the problem appears to be that the three-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. Given

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

[27]Primary perils are defined by the re-insurance industry as those that have the highest loss potentials, are well-monitored, are separately priced, and usually are covered by catastrophe models. Secondary perils are defined as small- to mid-sized events or the secondary effects of a primary peril. These perils often are not modeled, their pricing is often bundled across risks, and they receive little monitoring by the industry, despite their potential for severity (Howard, 2019).

Table 13: **Forecasts for expected big-fire losses. Panel A: Expected dollar losses per property by hazard codes; Panel B: Probabilities of big fires by hazard code; and Panel C: Expected aggregate California property losses, in millions of dollars.** This table shows forecasts for expected big-fire losses at the property level, the probability of big fires by hazard level, and the aggregate property-level loss in California by month. Forecasts are computed by first estimating the value of each property for each month using the value of the house at the mortgage origination date and updating it using the local house-price index; second, by estimating the probability of big fires for each month by evaluating at the property level the results from the first stage of the panel regression; and third, computing EBFL = (value of each property) $\times$ (probability of a big fire), assuming that the value of each property is zero after a fire.

Panel A: Expected loss given big fires (EBFL) at the property level by hazard code						
Variable	Hazard Code	Obs	Mean ($)	Std. Dev. ($)	Min ($)	Max ($)
Expected Big-Fire Loss (EBFL)	All	182,282,517	1,227	5,196	0	2,399,582
Expected Big-Fire Loss (EBFL)	3	4,030,442	20,189	27,323	0	2,399,582
Expected Big-Fire Loss (EBFL)	2	2,132,588	4,722	5,916	0	1,031,230
Expected Big-Fire Loss (EBFL)	1	2,525,164	6,376	6,346	0	438,871
Expected Big-Fire Loss (EBFL)	0	173,594,311	669	897	0	327,357
Panel B: Probability of big fires by hazard code						
Variable	Hazard Code	Obs	Mean	Std. Dev.		
Probability of Big Fires	All	184,958,430	0.21%	0.44%		
Probability of Big Fires	3	4,090,977	2.97%	0.09%		
Probability of Big Fires	2	2,185,065	0.67%	0.09%		
Probability of Big Fires	1	2,550,770	0.90%	0.09%		
Probability of Big Fires	0	176,131,398	0.13%	0.09%		
Panel C: Aggregate expected big-fire loss (EBFL) for California						
Variable	Month	Obs	Mean ($ Mil.)	Std. Dev. ($ Mil.)		
EBFL month total	1	16,359,769	840	224		
EBFL month total	2	16,354,840	883	281		
EBFL month total	3	16,391,968	1,030	333		
EBFL month total	4	16,492,916	1,150	325		
EBFL month total	5	15,881,505	1,310	378		
EBFL month total	6	15,953,899	1,550	498		
EBFL month total	7	16,030,242	1,720	538		
EBFL month total	8	16,091,320	1,710	468		
EBFL month total	9	16,160,246	1,690	439		
EBFL month total	10	16,201,560	1,430	404		
EBFL month total	11	16,274,959	1,110	343		
EBFL month total	12	16,305,849	559	416		
Variable	Total Months	Obs	Total ($ Mil.)	Std. Dev. ($ Mil.)		
EBFL Annual Total	12	194,499,425	14,982	4,647		

the CDI prohibitions on incorporating these costs into the rate schedules, and recent estimates that wildfire reinsurance costs may be expected to increase by 30% to 70% in 2020 (Manku, 2020), there appears to be an important disconnect between insurance policy and the actuarial pricing of wildfire risk in the state of California.

6 Conclusions and Policy Implications

Using a comprehensive data set of houses and mortgages in California between 2000 and 2018, we find, unsurprisingly, that mortgage default and foreclosure increase in the event of a wildfire. However, we also find a rather more surprising result: default and foreclosure *decrease* in the size of the wildfire. We argue that this second result arises from the coordination externalities afforded by large fires, whereby county requirements to rebuild to current building codes work with casualty-insurance-covered losses to ensure that the rebuilt homes will be modernized, and hence more valuable than the pre-fire stock of homes.

This mechanism, of course, only works to mitigate the risk of mortgage market losses if there exists a well-functioning casualty insurance markets in WUI areas (and in the State of California generally). However, the risk associated to the fire insurance markets is increasing. 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 risk.[28] 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.[29]

Our results provide a tractable framework to quantify the risks of fire on housing and mortgage markets in California given changing weather patterns, with 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.

[28] See Cignarale, Laucher, Allen, and Landsman-Smith (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.

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

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 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 also evaluate the wildfire risk in the California mortgage market. Our results suggest that the aggregate annual exposure for California property specific losses given the probability of wildfire fires is $14.98 billion dollars a year, based on models calibrated with data from 2000 to 2018. In fact, these estimates may be low given the $25 billion of losses from just two wildfire events in Southern California in 2019 (which is outside our 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 all three of these issues by establishing methods to estimate granular fire-incidence probabilities and to introduce these into forecasting models of mortgage performance at specific locations. Such a framework could be used by the CDI 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 outcome variables). The reinsurance evaluation technology is also probabilistic and more and more standardized for applications such as the reinsurance of the National Flood Insurance Program.

A California Fire Insurance Indemnity (1970–2018)

The California Insurance Code, Section 2051, codifies the measure of indemnity for the total loss of a home due to fire. In 1991, at the time of the Oakland Tunnel Fire, Section 2051 defined the indemnity as the "expense to the insured of replacing the thing lost or injured in its condition at the time of the injury, the expense being computed as of the time of the commencement of the fire."[30] However, after the passage of California Assembly Bill 2199 in 2005, Section 2051 was amended to the measure applicable to our study period (2005–2018), stating that the measure of indemnity is "the amount that it would cost the insured to repair, rebuild, or replace the thing lost or injured, without a deduction for physical depreciation, or the policy limit, whichever is less."[31]

This measure of indemnity is generally understood to be applicable to the *in situ* rebuild of a fire-destroyed property. AB 2199 also amended Section 2051.5 1(a) of the California Insurance Code, which states that "[I]f the policy requires the insured to repair, rebuild, or replace the damaged property in order to collect the full replacement cost, the insurer shall pay the actual cash value of the damaged property, as defined in Section 2051, until the damaged property is repaired, rebuilt, or replaced. Once the property is repaired, rebuilt, or replaced, the insurer shall pay the difference between the actual cash value payment made and the full replacement cost reasonably paid to replace the damaged property, up to the limits stated in the policy."[32] Furthermore, under Section 2051, the actual cash value of the destroyed property is defined as the fair market value of the property net of the value of the land at the time of the fire.[33]

Thus, a homeowner who rebuilds *in situ* would first be paid the pre-fire net-of-land market value of their home. Then, after they rebuild, they would receive an additional sum equal to the difference between the current replacement cost for the damages and the pre-fire net-of-land market value of the property (if this difference is positive). In addition, many homeowner policies include further endorsements — *Extended and Guaranteed Replacement Cost* — which cover additional expenses associated with the increased costs of meeting local build-to-code requirements, the cleanup of lot debris, and demand surges driving up the cost of materials and labor in the aftermath of a large wildfire. Thus, the final net indemnity payment to homeowners who rebuild and who have already received their actual cost value coverage would be the replacement cost value for the rebuild plus the coverage from the additional endorsements — if those are part of the policy — minus the pre-fire net-of-land market value of the home.

California Insurance Code, Section 2051.5 codifies two further conditions for the measurement of indemnity that do not involve *in situ* rebuilding of the destroyed property. The two conditions are: i) the homeowner does not re-build the totally destroyed property at all; ii) the homeowner seeks to rebuild or purchase a property at an alternative location. Under the wording of Section 2051.5

[30] See Assembly Bill 2199, Chapter 311, http://leginfo.legislature.ca.gov/faces/billTextClient.xhtml?bill_id=200320040AB2199.

[31] Ibid.

[32] See https://leginfo.legislature.ca.gov/faces/codes_displaySection.xhtml?lawCode=INS&sectionNum=2051.5..

[33] Ibid.

(1)(a) above, in the absence of contrary policy provisions, if the homeowner does not rebuild the property, the homeowner would receive the pre-fire net-of-land actual cash value of the destroyed property.

Alternatively, the conditions for the homeowner who chooses not to rebuild the destroyed property *in situ*, but instead chooses to rebuild or purchase a property at a location other than the insured premises, are codified in the California Insurance Code, Section 2051.5 (2)(c) as amended by California Assembly Bill 2199. This amended code states that, "In the event of a total loss of the insured structure, no policy issued or delivered in this state may contain a provision that limits or denies payment of the replacement cost in the event the insured decides to rebuild or replace the property at a location other than the insured premises. However, the measure of indemnity shall be based upon the replacement cost of the insured property and shall not be based upon the cost to repair, rebuild, or replace at a location other than the insured premises."[34]

As an example of the types of frictions that can arise for homeowners as the result of insurers' implementation of Sections 2051 and 2051.5, consider a homeowner who seeks not to rebuild a fire-destroyed home that had a pre-fire market value of $500,000. Assume that the replacement cost value for rebuilding the house is $600,000. Assume further that the homeowner wants to build a new property at another location for $500,000. Under the AB 2199 amended versions of Sections 2051 and 2051.5, the homeowner would only recover $500,000 to build the new home, which is the actual cash value, the pre-fire net-of-land market value, of the destroyed property. $500,000 is also the "the cost reasonably paid to replace the damaged property" as required in Section 2051.5(1)(a). Thus, as a result of not rebuilding *in situ*, the homeowner would forgo the additional $100,000 in cash from the replacement value that he/she would have received if he or she had rebuilt at the original location. In addition, just negotiating the $600,000 replacement cost value with the insurer could take the homeowner over a year to accomplish.

The homeowner's choice may also become more complicated if there is a mortgage on the destroyed property. The mortgage lender has a first lien position and would therefore require the mortgage balance to be paid directly from the $500,000 insurance settlement as required by the contractual language of both trust deeds and mortgages. The net proceeds to the borrower after the insurance payment is used to pay off the mortgage lender and after the fire-damaged land has been sold would determine the amount of leverage that would be required to acquire the land and build the new property. Combinations of these circumstances, the timing of these transactions, and their costs often lead homeowners to rebuild *in situ*. Under local building requirements, these properties would be built to current code.[35]

[34] Ibid.

[35] Although outside the scope of our study, Section 2051.5(2)(c) was again amended by Assembly Bill 1800 in 2019 so that code now prohibits fire insurance policies with "a provision that limits or denies, on the basis that the insured has decided to rebuild at a new location or to purchase an already built home at a new location, payment of the building code upgrade cost or the replacement cost, including any extended replacement cost coverage, to the extent those costs are otherwise covered by the terms of the policy or any policy endorsement (see Bill Text: CA AB1800, 2017–2018, Regular Session, https://legiscan.com/CA/text/AB1800/id/1820805).

B Theoretical Model

This appendix presents details of the simple theoretical model discussed in Section 3. Our model generalizes the classic models of households' mortgage decisions with default and prepayment options by including climate-change risk. In a frictionless world, after paying for house insurance, households will be indifferent to climate-change-driven events such as wildfires, because if their house is damaged or destroyed, the insurance company will reimburse their entire loss.

In general, the casualty loss and the uncertainty about the future value of the property would make the household *worse* off in the case of an event. However, there are at least two issues that make the household potentially *better* off in the case of an event. First, all new and replacement structures must conform to current building codes. Therefore, most insured households that experience a fire will end up owning a house of higher quality after reconstruction. The second issue is related to externalities in the neighborhood's investments and the coordination problem they induce. In the case of an event, there is a "forced" coordination in investing and upgrading the quality of the neighborhood. In equilibrium, these effects decrease the value of the households' prepayment and default options and increase the probability that they continue meeting their mortgage payments, even if the house has been damaged.

B.1 Model setup

We assume an economy with households that borrow using mortgages with their houses as collateral in a perfectly competitive market without transaction costs. At each point in time t, household i decides if it continues meeting the payments of its mortgage, if it defaults, or if it prepays. Therefore, default and prepayment are financial options that a household can exercise at each point in time. To simplify the notation, we omit any household sub-index i and focus our study on the behavior of a generic household and its mortgage.

House values and big wildfires. The value of the house, H_t, is one of the state variables of the model. At each time t, there is a a probability p_F of a large exogenous wildfire. Figure 4 in the body of the paper shows a sketch of the process for the value of the house. This process is defined as follows:

- If there is no fire, then the house price can exogenously move up to $H^u_{t+1} = H_t e^{\sigma\sqrt{\Delta t}}$ with risk-neutral probability p_U or down to $H^d_{t+1} = H_t e^{-\sigma\sqrt{\Delta t}}$ with risk-neutral probability $1-p_U$, where σ is the annualized house-price volatility and Δt is the length of each time step in the tree.
- In the case of a fire, there is a risk-neutral probability p_T that the house falls in a treatment group (i.e., the house is affected by the fire) and a risk-neutral probability $1-p_T$ that the house falls in a non-treatment group (i.e., the house is near the fire area but remains unaffected).
- In the case of a fire, with probability p_R, a large fraction of the houses in the treatment group rebuild up to code. In such a case, the house price becomes H^{FTR}_{t+1} (i.e., **F**ire/**T**reatment/**R**ebuilt)

or H_{t+1}^{FnTR} (i.e., Fire/non-Treatment/Rebuilt) if the house is in the treatment or control group, respectively.

- In the case of a fire, if there is no rebuilding in a large fraction of the houses in the treatment group, the house price decreases to H_{t+1}^{FTnR} or H_{t+1}^{FnTnR}, respectively.

Interest rates. Let r_t denote the one-period riskless interest rate. At time 0, the interest rate is r_0. At each period, it increases with conditional probability p_r or decreases with probability $1-p_r$.

Mortgages. There are mortgages available at a fixed rate r_M,[36] a fixed maturity T, and an initial loan-to-value ratio LTV_0. The value of the household's mortgage at time t, M_t, is determined in equilibrium and depends on the coupon rate, c; the interest rate, r_t; the house value H_t; the outstanding balance of the mortgage, B_t; the remaining number of periods of the mortgage, $T-t$; the probability of climate-change-driven events, p_F; the probability of being treated in case of an event, p_T; and the probability of rebuilding, p_R.

B.2 Equilibrium and numerical approach

There is no analytical solution for this model. In this subsection, we describe the backward-induction approach that we use to solve it numerically. The value of the mortgage at each point in time, the optimal prepayment and default strategies given the probability of climate-change-driven events, and the potential ex-post rebuilding of the area are determined simultaneously in equilibrium. The algorithm to solve the model has 4 steps.

Step 1: Generating interest-rate and house-price trees. We generate a tree of forward rates according to the Black, Derman, and Toy (1990) model and a tree of house prices according to Figure 4. The co-movement of interest rates and house prices is set to have a posterior joint probability of -0.4 to account for negative correlation. We combine both trees into one. As a result, we obtain twelve states of the world at $t+1$ from each single node at any time t. We assume that interest-rate and house-price trees tree cover 5 years. We recursively consider that a combined tree of interest-rates and house-prices start at each of the twelve nodes at $t+1$. We do this 5 times and, therefore, we end up with a combined tree of 2,985,984 nodes ($= 12^6$) that represents 30 years ($= 5 * 6$).

Step 2: Evaluating the mortgage-related optimal decisions. We construct a fixed-rate mortgage with fixed payments. We assume that the probabilities in the combined tree are *risk-neutral* rather than true probabilities. We evaluate the mortgage-related optimal decisions at each node of the tree and we move backwards through the tree. For each node we compute: (i) the value of the mortgage in that state as the periodic payment plus the probabilistic weighted average of

[36] In reality, the mortgage rate is set endogenously and depends on the value of the embedded options to prepay and default. In this simple example, we assume a fixed spread over r_0.

the values that the mortgage can take in the possible future states, discounted by the discount rate each specific node; (ii) the prepayment option value as the maximum between 0 and the difference between the mortgage value and the principal due at each specific node[37]; (iii) the default option value as the maximum between 0 and the difference between the mortgage principal and the house price at each specific node; the value of the "wait" option as the discounted *best* options (i.e., the maximum of the prepayment, default and wait options) in each state that can be reached in $t+1$ moving from the node considered.[38]

Step 3: Detecting the termination nodes. Given the new structure of the tree, end all the nodes that follow a termination (i.e., node with a prepayment or a default) with a label at will, so as to recognize that those nodes cannot be reached as they follow a termination.

Step 4: Calculating node probabilities. Assign to each node the probability it has to occur given that we are sitting in the node from which it stems. We compute unconditional probabilities by multiplying the conditional probability of each node by the probability of the node from which it stems. Finally, we fix a time period-vector t and add up the unconditional probabilities of a default or of prepayment occurring divided by the add up probability of all the possible nodes in time period t, which is the probability to have such an event at time t.

Table 14 shows the parameters of the model. We consider the initial house value, H_0, as the median California house price in 2017, \$504,000. The house prices process conditional on no wildfire follows a Bernoulli process with p=0.5. $K^u = 1.05$ and $K^d = 0.98$ are the factors by which by which H_t is multiplied when house prices go up or down, respectively. They are calibrated parameters to capture the dynamics of house prices in California using aggregate data from 2000 to 2018. The factors by which the house value H_t is multiplied in the different branches of the tree conditional on the event of a wildfire are chosen according to our estimations of the evolution of house prices in different areas (i.e., equivalent to burnt/treatment areas and control groups) using repeated-sales house price data for our case study. Therefore, the house value when the house in the fire area burns down or not is multiplied by the factor $K^T = 0.4$ and $K^{nT} = 0.95$, respectively. Similarly, the house value when the treated house in the fire area is rebuilt or not is multiplied by the factor $K^R = 7.5$ or $K^{nR} = 0.5$, respectively. The house value when the house in the control group is rebuilt or not is multiplied by the factor $K^{nTR} = 1.58$ and $K^{nTnR} = 0.94$, respectively. By applying these factors from the initial house value as a starting point, we obtain the different house values in Table 14.

We choose the mortgage amount of \$504,000 to obtain $LTV_0 = 80\%$. The probability of a fire — in each period in which such an event is possible — is set to 0.05, in line with the annual probability of fire in our data. The fixed mortgage rate r_M is set at 5.65%, the mean mortgage rate in our data set. Finally, interest rates are assumed to follow the Black, Derman, and Toy (1990)

[37]Equivalently, the prepayment option at each node is in the money when the net present value of the future payments at time t is greater than the principal due at the end of the time period before.

[38]Notice that this option will not be available to the agent in the last time period T.

Variable	Description	Value
H_0	Initial house value ($'000)	504
H^u	House price when house prices go up ($'000)	529
H^d	House price when house prices go down ($'000)	493
H^T	House price if house burns down ($'000)	560
H^{nT}	House price if house is not burnt down ($'000)	431
H^{TR}	House price if house burnt and rebuilt ($'000)	700
H^{TnR}	House price if house is burnt and not rebuilt ($'000)	351
H^{nTR}	House price in the control area if prices go up ($'000)	542
H^{nTnR}	House price in the control area if prices go down ($'000)	320
M_0	Initial mortgage amount ($'000)	400
r_M	Fixed rate of the mortgage	5.65%
p_F	Probability of fire occurrence	0.05
p_T	Probability of a house to burn down (treatment)	0.5
p_U	Probability of house prices going up	0.5
p_R	Probability of a house to get rebuilt conditional on being burnt	0.6
p_r^u	Probability of the interest rate going up	0.5

Table 14: **Baseline parameters of the model.** This table shows the parameters of the model. All the parameters related to probabilities describe Bernoulli random variables, as such we just report the probability of a positive realization of the event in the description and the probability of the opposite event follows.

model.

B.3 Numerical results and model predictions

By implementing the numerical approach described above, we obtain a set of results that we summarize in the 2 testable hypotheses that we developed in Section 3.

We first study the numerical results related to the probability of mortgage default as a function of the fire probability, p_F, and the probability of rebuilding after a fire event, p_R (see Figure 10). The first result that we obtain is that the probability of mortgage default increases with the probability of a fire event, p_F.

Although, in general, mortgage defaults increase with, p_F, we are interested in studying the differential default rates in the treatment and control groups. Figure 11 shows that default in the treatment group is only lower than in the control group for extremely low values of both p_R and the expected house price increases after rebuilding. Therefore, we hypothesize that the probability of default conditional on a wildfire in the treatment group is higher than the probability of default in the control group.[39] This hypothesis corresponds to Hypothesis 1 in Section 3.

In the case of a fire, the expected house prices in both the treatment and control groups increase

[39]Notice also that this hypothesis is always true for the general cases with $H_{t+1}^{FTR} > H_{t+1}^{FnTR}$ and $H_{t+1}^{FTnR} \geqslant H_{t+1}^{FnTnR}$ or with $H_{t+1}^{FTR} \geqslant H_{t+1}^{FnTR}$ and $H_{t+1}^{FTnR} > H_{t+1}^{FnTnR}$. This is the case in which households expect that the house price in the treatment group will be at least as high as in the control group.

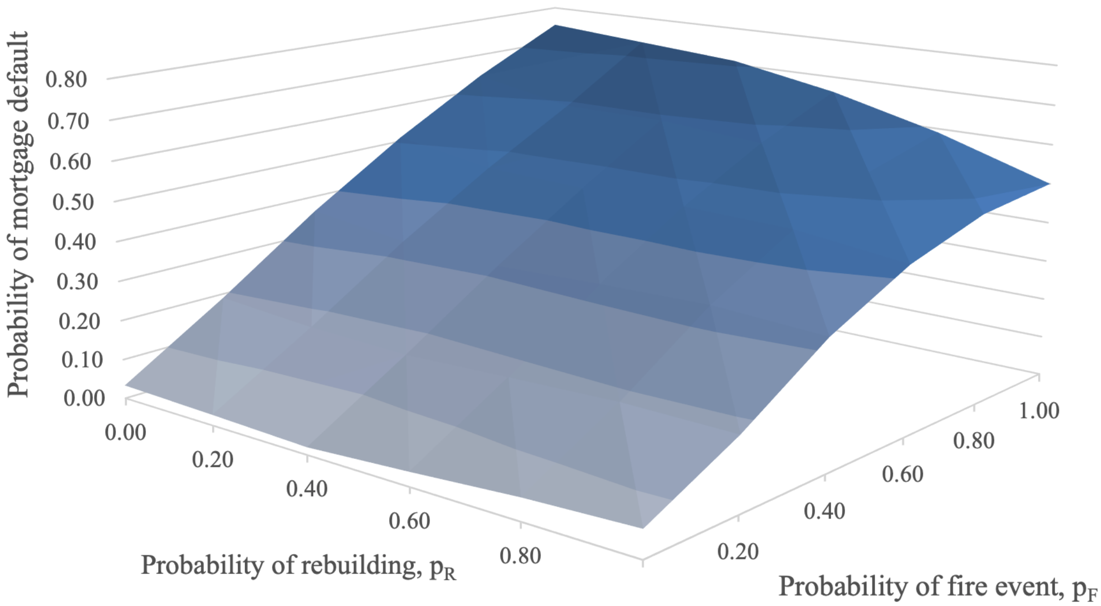


Figure 10: **Effect of fire risk on mortgage default.** This figure shows numerical results from the model for the baseline parameters in Table 14.

with the probability of rebuilding of the neighborhood or area, p_R; the house prices conditional on rebuilding, H_{t+1}^{FTR} and H_{t+1}^{FnTR}, respectively; and the house price conditional on non-rebuilding, H_{t+1}^{FTnR} and H_{t+1}^{FnTnR}, respectively. As previously discussed, insurance policies and coordination externalities after large wildfires lead to a large number of homes being replaced with new structures due to build-to-code requirements. As a result, the expected house prices in both the treatment and control groups increase with the size of the fire and, equivalently, to p_R. Figure 10 also shows that the probability of mortgage default decreases with the probability of rebuilding, p_R. This mechanism leads to a lower probabilities of default in both the treatment and control groups. In summary, the probability of mortgage default conditional on a wildfire for a house in both the treatment and control groups decreases with: (i) the probability of rebuilding p_R; (ii) the house price conditional on rebuilding, H_{t+1}^{FTR} (H_{t+1}^{FnTR}); (iii) the house price conditional on non-rebuilding, H_{t+1}^{FTnR} (H_{t+1}^{FnTnR}); and (iv) the size of the fire. This hypothesis corresponds to Hypothesis 2 in Section 3.

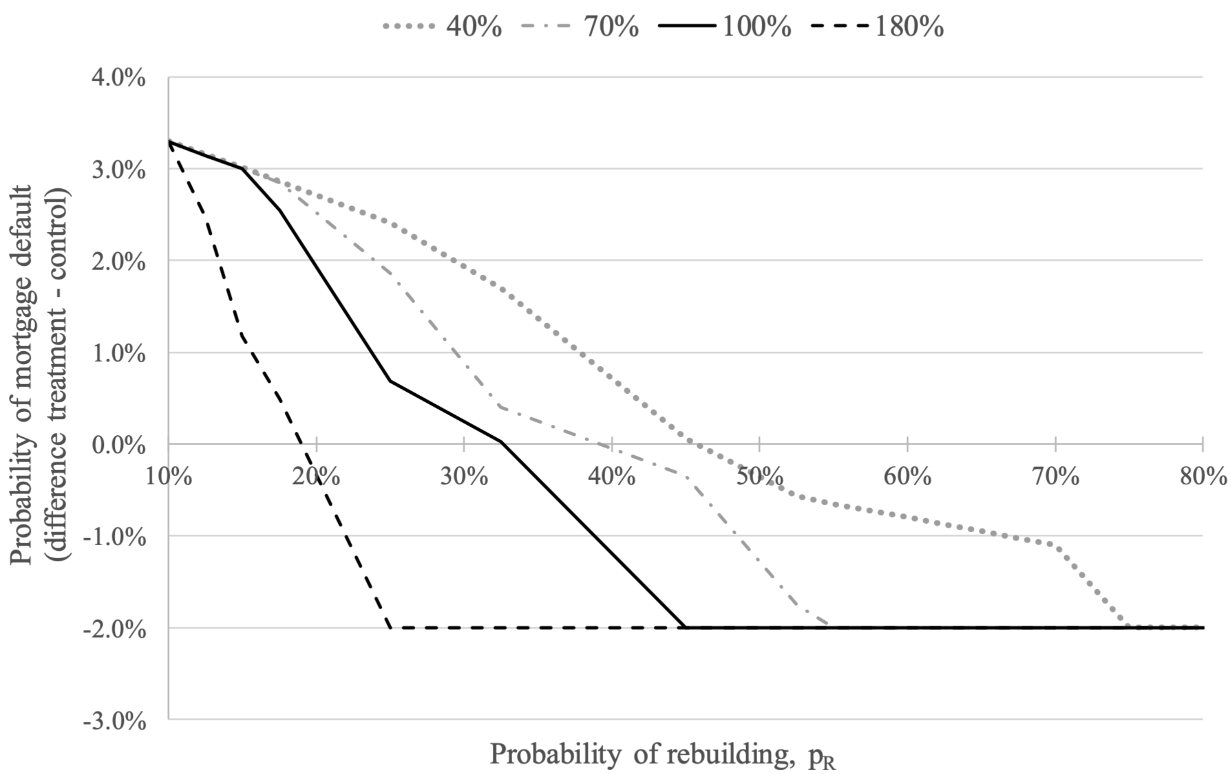


Figure 11: **Effect of the probability of rebuilding on mortgage default as a function of the expected increase in the house price after rebuilding.** This figure shows numerical results on the difference of the probability of mortgage default in the treatment minus control groups as a function of the probability of rebuilding, p_R and the expected house price increase after rebuilding compared to a baseline after rebuilding house price (i.e., when the rebuilt house price is 40%, 70%, 100%, or 180% of the baseline rebuilt value; 100% means that the rebuilt house price is equal to the baseline rebuilt house price). These results are obtained numerically from the model and the baseline parameters in Table 14.

References

Baldauf, M., L. Garlappi, and C. Yannelis. 2020. Does Climate Change Affect Real Estate Prices? Only if you Believe in it. *Review of Financial Studies* 33:1256–1295.

Baylis, P., and J. Boomhower. 2019. Moral Hazard, Wildfires, and the Economic Incidence of Natural Disasters. Working Paper 26550, NBER.

Bernstein, A., M. T. Gustafson, and R. Lewis. 2019. Disaster on the Horizon: The Price Effect of Sea Level Rise. *Journal of Financial Economics* 134:253–272.

Billings, S. B., E. A. Gallagher, and L. Ricketts. 2020. Let the Rich be Flooded: The Unequal Impact of Hurricane Harvey on Household Debt. Working paper, University of Colorado, Boulder.

Black, F., E. Derman, and W. Toy. 1990. A One-Factor Model of Interest Rates and its Application to Treasury Bond Options. *Financial Analysts Journal* 46:33–39.

Cignarale, T., J. Laucher, K. Allen, and L. Landsman-Smith. 2017. The Availability and Affordability of Coverage for Wildfire Loss in Residential Property Insurance in the Wildland-Urban-Interface and Other High Risk Areas of California. Technical report, California Department of Insurance.

Contardo, J. I., C. Boano, and C. Wirsching. 2018. Gentrification in (Re)construction: Talca's Neighbourhoods Post 2010 Earthquake. *International Journal of Disaster Resilience in the Built Environment* 9:170–183.

Davis, M. 1995. The Case for Letting Malibu Burn. *Environmental History Review* 19:1–36.

Dixon, L., F. Tsang, and G. Fitts. 2019. The Impact of Changing Wildfire Risk on California's Residential Insurance Market. Technical Report CCCA4-CNRA-2018-008, California Natural Resources Agency.

Flannigan, M. D., M. A. Krawchuk, W. J. de Groot, B. M. Wotton, and L. M. Gowman. 2009. Implications of Changing Climate for Global Wildland Fire. *International Journal of Wildland Fire* 18:483–507.

Florida, R. 2019. How Natural Disasters Can Spur Gentrification. https://www.citylab.com/environment/2019/02/gentrification-causes-new-orleans-natural-disasters-hurricane-katrina/582499/.

Freeman, L. 2005. Displacement or Succession? Residential Mobility in Gentrifying Neighborhoods. *Urban Affairs Review* 40:463–491.

Gibson, M., J. T. Mullins, and A. Hill. 2019. Climate Risk and Beliefs: Evidence From New York Floodplains. Working paper, Williams College.

Giglio, S., M. Maggiori, K. Rao, J. Stroebel, and A. Weber. 2019. Climate Change and Long-Run Discount Rates: Evidence from Real Estate. Working paper, Yale University.

Gude, P. H., K. Jones, R. Rasker, and M. C. Greenwood. 2013. Evidence for the Effect of Homes on Wildfire Suppression Costs. *International Journal of Wildland Fire* 22:537–548.

Gude, P. H., R. Rasker, and J. van den Noort. 2008. Potential for Future Development on Fire-Prone Lands. *Journal of Forestry* 106:198–205.

Guerin, E. 2018. Why do we Keep Building Houses in Places that Burn Down? https://laist.com/2018/09/24/why_do_we_keep_building_houses_in_places_that_burn_down.php.

Hammer, R. B., S. Stewart, and V. Radeloff. 2009. Demographic Trends, the Wildland-Urban Interface, and Wildfire Management. *Society and Natural Resources* 22:777–782.

Hoberock, M. A., and N. A. Griebel. 2018. Are Lenders Entitled to Insurance Proceeds when Foreclosing? *National Law Review* January.

Howard, L. S. 2019. Insurance Industry Must Wake Up to Costs of Secondary Catastrophe Perils. *Insurance Journal* April.

Jeffrey, T., S. Yerkes, D. Moore, F. Calgianao, and R. Turakhia. 2019. 2019 Wildfire Risk Report. Tech. rep., CoreLogic.

Keenan, J. M., T. Hill, and A. Gumber. 2018. Climate Gentrification: From Theory to Empiricism in Miami-Dade County Florida. *Environmental Research Letters* 13.

Kramer, K., and J. Ware. 2019. Counting the Cost 2019: A Year of Climate Breakdown. Technical report, Christian Aid.

Lee, D. 2017. Neighborhood Change Induced by Natural Hazards. *Journal of Planning Literature* 32:240–252.

Loomis, J. 2004. Do Nearby Forest Fires Cause a Reduction in Residential Property Values? *Journal of Forest Economics* 10:149–157.

Lueck, D., and J. Yoder. 2016. Clearing the Smoke from Wildfire Policy: An Economic Perspective. Policy Series 56, PERC.

Manku, H. 2020. Jolted By California Wildfires, Re/Insurers Recalibrate their Risk Appetite. Analyst report, S&P Global.

Mann, M. L., P. Berck, M. A. Moritz, E. Batllori, J. G. Baldwin, C. K. Gately, and D. R. Cameron. 2014. Modeling Residential Development in California from 2000 to 2050: Integrating Wildfire Risk, Wildland and Agricultural Encroachment. *Land Use Policy* 41:438–452.

Martinuzzi, S., S. Stewart, D. Helmers, M. Mockrin, R. Hammer, and V. Radeloff. 2015. The 2010 Wildland-Urban Interface of the Conterminous United States. Research Map NRS-8. U.S. Department of Agriculture, Forest Service, Northern Research Station.

Moritz, M. A., M.-A. Parisien, E. Batllori, M. A. Krawchuk, J. V. Dorn, D. J. Ganz, and K. Hayhoe. 2012. Climate Change and Disruptions to Global Fire Activity. *Ecosphere* 3:1–22.

Murfin, J., and M. Spiegel. 2020. Is the Risk of Sea Level Rise Capitalized in Residential Real Estate? *Review of Financial Studies* 33:1217–1255.

North, M. P., S. L. Stephens, B. M. Collins, J. K. Agee, G. Aplet, J. F. Franklin, and Z. Fulé. 2015. Reform Forest Fire Management: Agency Incentives Undermine Policy Effectiveness. *Science* 349.

Olshansky, R. B., L. A. Johnson, J. Horne, and B. Nee. 2008. Longer View: Planning for the Rebuilding of New Orleans. *Journal of the American Planning Association* 74:273–287.

Ouazad, A., and M. E. Kahn. 2019. Mortgage Finance in the Face of Rising Climate Risk. Working Paper 26322, NBER.

Querolo, N., and B. K. Sullivan. 2019. California Fire Damage Estimated at $25.4 Billion. https://www.bloomberg.com/news/articles/2019-10-28/california-fire-damages-already-at-25-4-billion-and-counting. Bloomberg.

Radeloff, V., R. Hammer, S. Stewart, J. Fried, S. Holcomb, and J. McKeefry. 2005. The Wildland-Urban Interface in the United States. *Ecological Applications* 15:799–805.

Radeloff, V. C., D. P. Helmers, H. A. Kramer, M. H. Mockrin, P. M. Alexandre, A. Bar-Massada, V. Butsic, T. J. Hawbaker, S. Martinuzzi, A. D. Syphard, and S. I. Stewart. 2018. Rapid Growth of the US Wildland-Urban Interface Raises Wildfire Risk. *Proceedings of the National Academy of Sciences* 115:3314–3319.

Rogers, P. 2019. List: The 20 Largest Wildfires in California History. https://www.mercurynews.com/2019/10/28/list-the-20-largest-wildfires-in-california-history/. The Mercury News.

Simon, G. L. 2017. *Flame and Fortune in the American West: Urban Development, Environmental Change, and the Great Oakland Hills Fire*. 1st ed. University of California Press.

Smith, R. C., and J. K. Gilless. 2011. Institutional Obstacles to Success in Implementing a Statewide Community-Based Fire Planning Mandate. *The California Journal of Politics & Policy* 3:1–8.

Stetler, K. M., T. J. Venn, and D. E. Calkin. 2010. The Effects of Wildfire and Environmental Amenities on Property Values in Northwest Montana, USA. *Ecological Economics* 69:2233–2243.

van Holm, E. J., and C. K. Wyczalkowski. 2019. Gentrification in the Wake of a Hurricane: New Orleans after Katrina. *Urban Studies* 56:2763–2778.

Weber, J., and B. Lichtenstein. 2015. Building Back: Stratified Recovery After an EF-4 Tornado in Tuscaloosa, Alabama. *City and Community* 14:186–205.

Wibbenmeyer, M. 2017. Burning Down the House: Wildfire and the Benefits of Natural Disaster Mitigation. Working paper, UC Santa Barbara.

Williams, A. P., J. T. Abatzoglou, A. Gershunov, J. Guzman-Morales, D. A. Bishop, J. K. Balch, and D. P. Lettenmaier. 2019. Observed Impacts of Anthropogenic Climate Change on Wildfire in California. *Earth's Future* 7:892–910.

Wotton, B. M., C. A. Nock, and M. D. Flannigan. 2010. Forest Fire Occurrence and Climate Change in Canada. *International Journal of Wildland Fire* 19:253–271.