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

Paulo Issler[†] Richard Stanton[‡] Carles Vergara-Alert[§]
Nancy Wallace[¶]

April 23, 2020

Abstract

Climate change is leading to significant increases in destructive weather events, especially wildfires. In this paper, we study wildfires in California from 2000 to 2018 using a comprehensive data set of houses and mortgages in California that merges data on fires, mortgages, property characteristics, and weather. Using a difference-in-differences approach, confirmed via panel regression, we find a significant increase in mortgage delinquency and foreclosure after a fire event. More surprisingly, we find that default and foreclosure *decrease* in the size of the fire. We argue that this second result arises from the coordination externalities afforded by large fires, whereby county requirements to rebuild to current building codes and insurance-covered losses work together to ensure that rebuilt homes will be more valuable than they were pre-fire. This is true only as long as there exists a well-functioning insurance market; the size of recent losses, combined with regulatory distortions in the market, casts 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 building benchmark models to evaluate proposed banking and insurance-company models, much like the bank stress-testing carried out by the Federal Reserve System.

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

JEL codes: G21

[*]We are grateful for financial support from the Fisher Center for Real Estate and Urban Economics.

[†]Haas School of Business, U.C. Berkeley, 545 Student Services Building, Berkeley, CA 94720-1900. Email: paulo_issler@haas.berkeley.edu.

[‡]Haas School of Business, U.C. Berkeley, 545 Student Services Building, Berkeley, CA 94720-1900. Email: rhstanton@berkeley.edu.

[§]IESE Business School, Av. Pearson 21, 08034 Barcelona, Spain. Email: cvergara@iese.edu.

[¶]Haas School of Business, U.C. Berkeley, 545 Student Services Building, Berkeley, CA 94720-1900. Email: newallace@berkeley.edu.

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, unprecedented wildfires started in Australia in August 2019 and have so far burnt over 3,000,000 hectares — 7,413,150 acres — across the country (Zhou, 2019). Air quality in Sydney has been among the worst anywhere on the planet,[2] and on Dec. 29, 2019, authorities ordered the evacuation of East Gippsland, an area half the size of Belgium.[3]

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.[4]

While there has been little study of the effects of climate change on the health of the U.S.

[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 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.

[3] "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.

[4] 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).

financial system,[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 wildfires casts significant doubt on their ability to continue to provide such protection. The dollar amount of the losses caused by recent wildfires is too large for any single company to sustain, raising the specter of insurance-company failures in the event of a really large fire, potentially with huge systemic consequences.[6] 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.[7] 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.[8]

To understand the growing impact of fire risk, 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. Moreover, the event of a fire may increase the perceived likelihood of further fires in future. However, to obtain a mortgage, borrowers are required to take out fire insurance, which typically pays to rebuild a home not just as it was prior to the fire, but in conformance with *current* building codes. Moreover, there is much discussion of the idea that a natural disaster might, for certain neighborhoods, act as a coordinating mechanism that allows rapid gentrification of the affected area.[9]

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

[5]Notable recent exceptions include Bernstein, Gustafson, and Lewis (2019); Ouazad and Kahn (2019); and a recent special issue of the *Review of Financial Studies* (see Addoum, Ng, and Ortiz-Bobea, 2020; Alok, Kumar, and Wermers, 2020; Baldauf, Garlappi, and Yannelis, 2020; Bansal, Kiku, and Ochoa, 2016; Barnett, Brock, and Hansen, 2020; Choi, Gao, and Jiang, 2020; Engle, Giglio, Kelly, Lee, and Stroebel, 2020; Forster and Shive, 2020; Hong, Karolyi, and Scheinkman, 2020; Hong, Li, and Xu, 2019; Krueger, Sautner, and Starks, 2020; Murfin and Spiegel, 2020).

[6]An insurance company, AIG, was at the center of the last financial crisis (though its problems stemmed from providing financial rather than property insurance).

[7]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.

[8]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.

[9]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).

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).

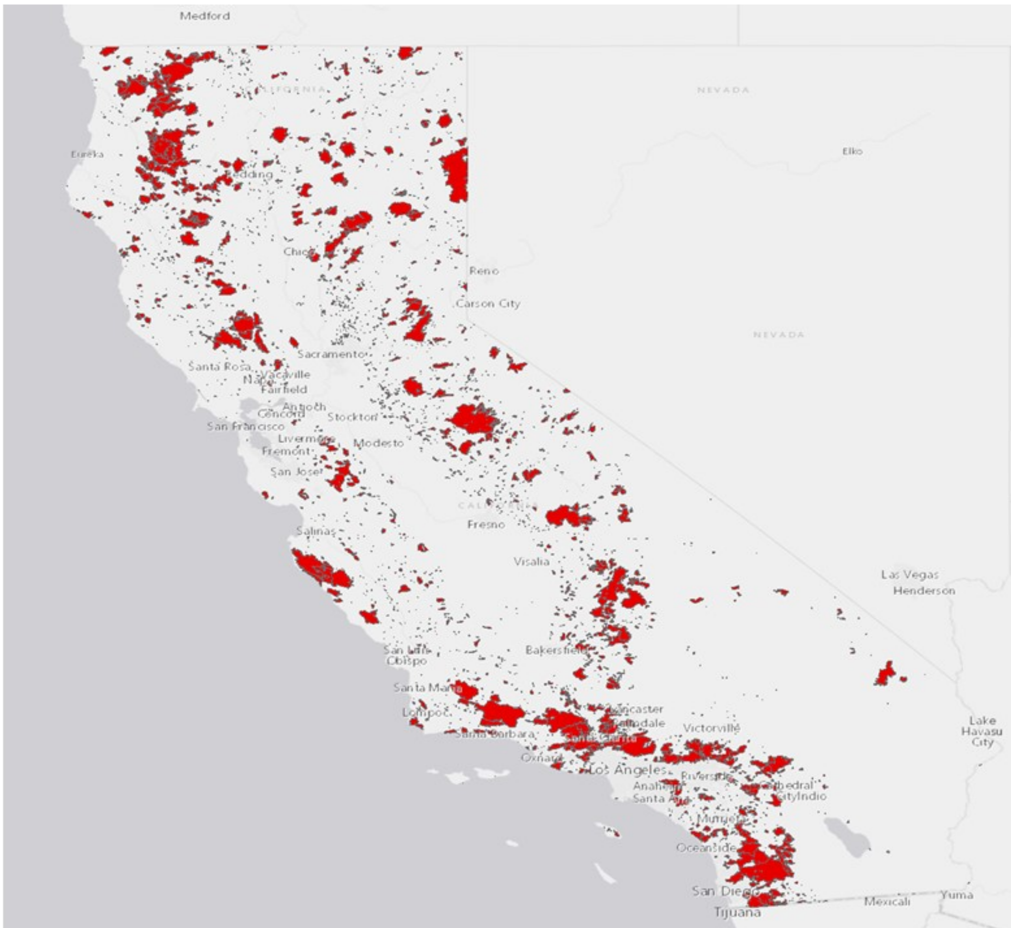


Figure 1: **Wildfires in California from 2000 to 2018**

Using a difference-in-differences approach, confirmed via panel regression, we compare mortgage performance in fire zones (treatment group) with that in a 0.25-mile and 0.5-mile ring around the fire zone (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 probability of delinquency is 0.61% lower in the treatment group than in the ring from the fire-zone edge to 1 mile outside the fire zone, and 0.11% lower than in the ring from 1 to 2 miles outside the fire zone. We argue that this second result arises 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 marked the occurrence of the then-most-disastrous single fire incident in

[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

the state's history, 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). This disastrous fire was then exceeded one year later by two wildfires in Southern California that cost an estimated $25 billion, although with no loss of life.

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 fire incidents 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. Interestingly, 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 explosion).

A second feature evident in Table 1 is that the temperature is often quite elevated on fire-ignition days and 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 or 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

[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.

pattern from the Pacific Ocean inland.

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

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 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 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.

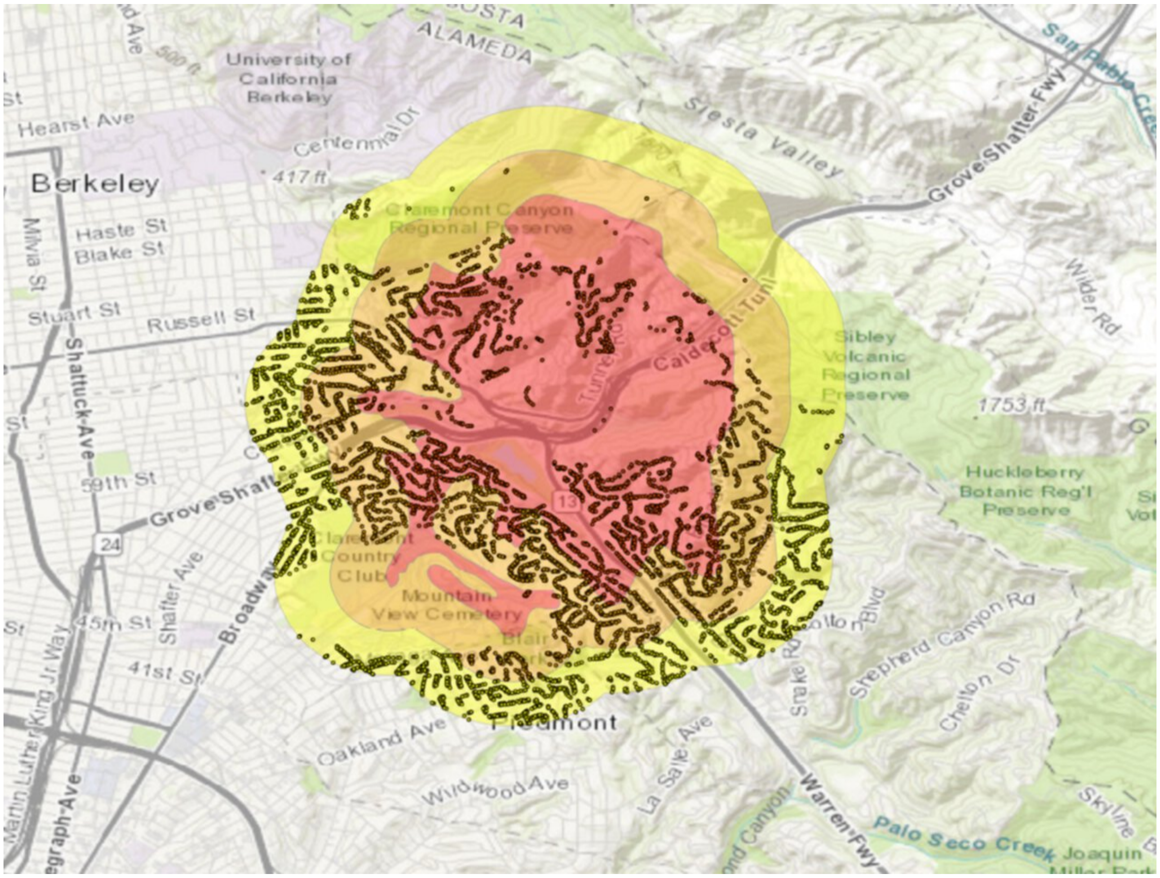


Figure 2: **Tunnel Fire, .25- and .50-mile peripheral rings.** This figure shows the geographic location of the burned and re-built transactions in the Tunnel Fire area (red), the transactions in the .25-mile peripheral ring (light orange), and the transactions in the .50-mile peripheral ring (yellow) 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 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 burned, 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 differential responses to the fire for households within each area by comparing the semi-annual change in price per square foot for residential single family homes that were purchased in the pre-fire period (1988–1991) and then sold in the post fire period (1992–2016). Table 2 presents the summary statistics for the repeat sales transactions within the three areas. 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 unconditional growth rate over the sample period is highest in the Tunnel Fire Area, with an annual average percentage price change of 8.9%. The .25-mile peripheral area has an annual unconditional average percentage price change of 7.9% and the .5-mile peripheral area has an annual unconditional average percentage price change of 6.3%.

Table 2: **Summary Statistics for semi-annual house price growth rates (1988–2016) for the Tunnel Fire and peripheral rings.** This table presents the summary statistics for the semi-annual percentage changes per square foot for a sample of repeat sale transactions between the pre-fire (1988–1991) and post-fire (1992–2016) periods. 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.

	Percentage Annual Price Change		
	Mean %	Standard dev. %	Number of observations
.50-mile peripheral ring	6.3	4.7	246
.25-mile peripheral ring	7.9	11.1	220
Tunnel Fire Area	8.9	7.8	182

The final important feature of the Tunnel Fire was its impact on the default performance of residential single family mortgages in the three fire areas. From 1988 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 within the Tunnel Fire area both before and over the ten years after the fire. The default rates are measured as foreclosure and Real Estate Owned (bank-held defaults) and they are presented by default year in the three areas: the Tunnel Fire area, the .25-mile peripheral ring, and the .50-mile peripheral ring. The number of properties with mortgages in each of the areas is quite similar: 2,520 in the Tunnel Area, 3,096 in the .25-mile peripheral ring, and 2,884 in the .50-mile peripheral ring.

Despite the sluggish overall levels of economic, employment, and wage growth in the U.S. economy from 1990 to 1995, as shown, the mortgage default rates after the Tunnel fire were either below or comparable to the other two areas through 1995. They then rose in 1996 to 1.2%, considerably higher than the rate for the other two areas, but still substantially below the 1996 national average residential single family default rate of 2.24%.[12] The highest default rate in the .25-mile peripheral ring was .48%, also in 1996. The .5-mile peripheral ring experienced default rates that were comparable to the other two areas and never exceeded .40%. Although the long-term Tunnel Fire foreclosure rate is slightly elevated relative to the other two areas, 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 mortgage performance in the fire is surprisingly good.

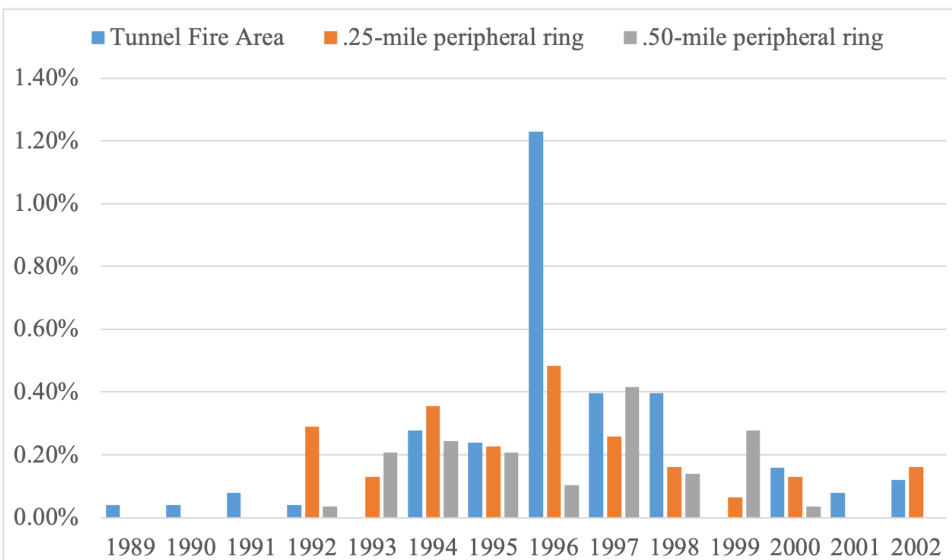


Figure 3: **Annual aggregate loan loss amounts for the Tunnel Fire Area, .25-mile peripheral ring, and .5-mile peripheral ring by year.** This figure plots the rates of foreclosure and Real Estate Owned (bank held default) by year. The rates are reported for the Tunnel Fire Area, the .25-mile peripheral ring, and the .5-mile peripheral ring. These data are from ATTOM.

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 identi-

[12]See https://fred.stlouisfed.org/series/DRSFRMACBS.

fiable property locations. As shown, 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.

3 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.

3.1 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.

3.2 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 dataset 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 dataset contains information of the monthly performance of the mortgage from origination to its final payment, prepayment, default, or 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

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

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 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.

3.3 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 collateral houses. Table 6 exhibits the statistics of the main variables that define the mortgages at origination and the characteristics of the collateral properties.

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 dataset.

	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

3.4 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 2400 locations within the U.S., surrounding territories, and other selected areas. We limit our analysis to the monthly measurements comprised between January 2001 and December 2018 obtained from the 94 weather stations located in California.

For our first set of analyses, we link each census tract to the closest weather station by applying the haversine formula, thus obtaining a panel of 94 stations for 179 months. This approach is a weighting average of all the weather stations with weights based on the population density of the different areas. For the latest set of empirical results, we do not link weather data to census tracts and we use geolocated weather data to forecast specific climate change events.

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.

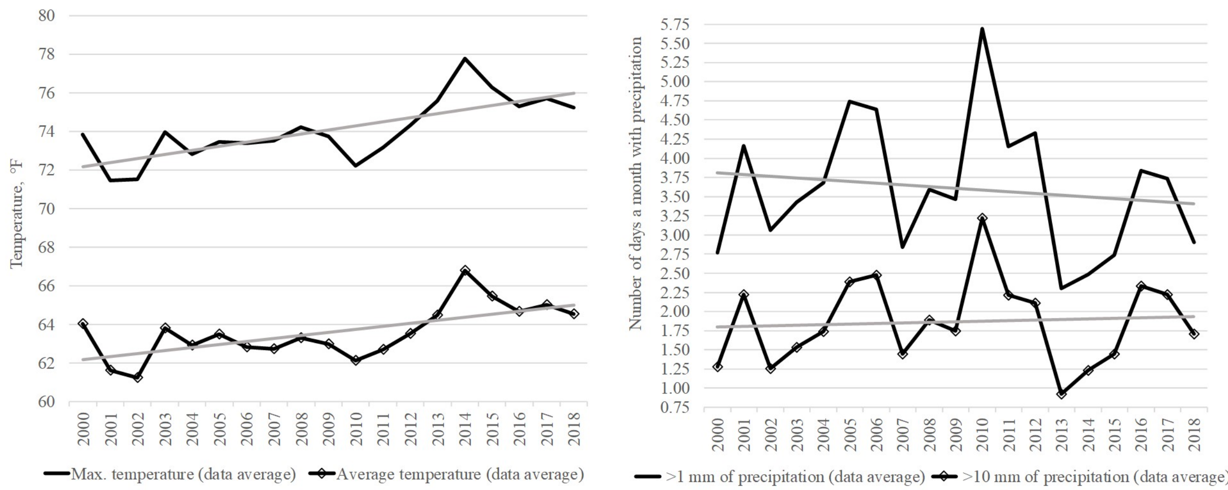


Figure 4: **Weather data over the period of analysis.** This figure shows the dynamics of the monthly mean of four weather-related variables in all the U.S census tracts in California. Panel A displays the mean of the maximum temperature of the month and the mean of the average temperature of the month. 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.

4 Identification Strategy

The simple model in Appendix A predicts that the probability of mortgage default (i.e., delinquency and foreclosure) conditional on a climate-change-driven event (i.e., a wildfire) in the treatment group is lower than the probability of default in the control group (Hypothesis 1). We develop a difference-in-differences (DID) analysis based on the following reduced form model to test this hypothesis:

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

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 zero before the fire f. 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 (i.e., 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 (i.e., control group). Figure 5 displays the map of the mortgages affected in the treatment group, and control groups within a ring of 1 or 2 miles from the fire perimeter.

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

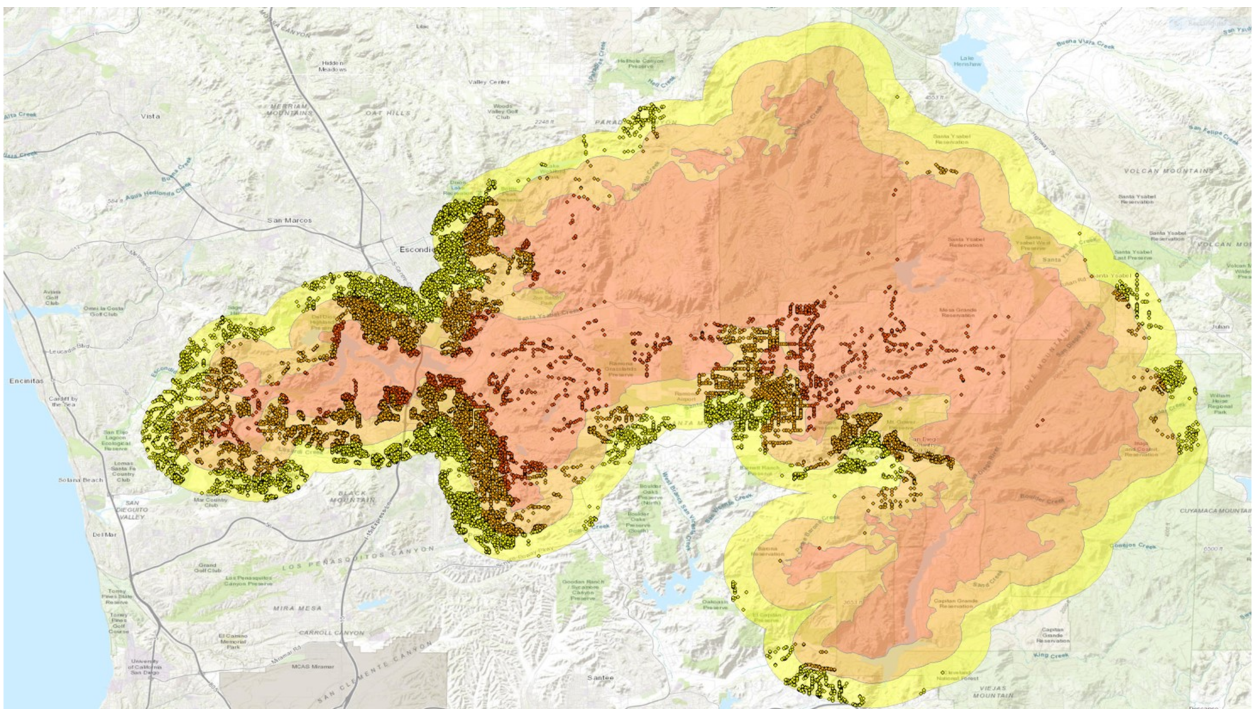


Figure 5: **Witch wildfire and mortgages affected.** This figure shows a map of the location of the properties with mortgages affected by the Witch wildfire. It shows the treatment group area in red, the *Ring 0–1* area in orange, and the *Ring 0–1* area in yellow.

The model also predicts that the probability of default conditional on a climate-change-driven event for a house in both the treatment and control groups decreases with: (i) the probability of rebuilding; (ii) the house price conditional on rebuilding; and (iii) the house price conditional on non-rebuilding (Hypothesis 2). We build upon the DID analysis in equation (1) to test this hypothesis:

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

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.[13] We provide empirical results using two definitions for this variable. First, we define $bigfire_f$ as the number of mortgages affected by fire f. Second, we define it 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, that is, fires that affect a number of mortgages at least one standard deviation above the mean of the number of mortgages affected by all fires.[14] Both definitions of $bigfire_f$ allow us to provide a straightforward interpretation of the magnitude of our results.

5 Empirical Results

In this section we show the empirical result of our analysis. We study the causal relationship between mortgage performance (i.e., delinquency and foreclosure) and climate-change-driven events (i.e., 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 postsale, or REO. First, we implement the difference-in-differences (DID) approach that we described in the previous section. Second, we use panel data and develop an instrument based on weather data and a panel data methodology in order to provide further empirical results and address potential endogeneity concerns.

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

[14] 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.

5.1 Difference-in-differences approach

We use a time frame of 6 months before and after a fire event.[15] We geolocalise all the mortgages in our database as well as the shapes of the wildfires that we obtain from the California Fire Department. 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* that takes the value of 1 if the active mortgage falls inside the wildfire zone and 0 otherwise. We consider a ring of 1 mile around the perimeter of the wildfire zone, *Ring 0–1*. The set of mortgages that fall in the *Ring 0–1* conform the control group. We define the dummy variable $afterfire$ that takes the value of 1 after the fire if the mortgage has been involved in a fire either as part of the treatment or control group event 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], $bigfire$ is a variable equal to the number of mortgages affected by the wildfire. Therefore, here we define big fires as fires that affect a large number of mortgages. In column [4], we define $bigfire$ as a dummy variable that takes the value of 1 if the mortgage is affected by a fire that is 1 standard deviation above the average wildfire in terms of mortgages affected.[16] The coefficients in these two columns show that although delinquency increases on average after a wildfire, it decreases inside the wildfire zone (treatment group) for big fires.

We also study the neighborhood effects of climate-change-driven events. Columns [5] and [6] 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 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

[15] We use the period of 6 months before and after the event to present our baseline results. Our results are robust to using periods of analysis from 3 to 12 months.

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

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]–[4], 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 [5]–[6], 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	Fire	Ring 0-1	Ring 0-1
Control group:	Ring 0-1	Ring 0-1	Ring 0-1	Ring 0-1	Ring 1-2	Ring 1-2
bigfire:	—	—	Mortgages affected	Dummy	—	—
	[1]	[2]	[3]	[4]	[5]	[6]
treatment*bigfire*afterfire			-5.62e-06***	-0.00614**		
			(1.97e-06)	(0.00252)		
treatment*afterfire	0.00134	0.00143	0.00680***	0.00525**	-0.00120***	-0.00108***
	(0.00105)	(0.00115)	(0.00263)	(0.00226)	(0.00037)	(0.00040)
treatment*bigfire			-8.48e-07	-0.00126		
			(7.02e-07)	(0.00094)		
bigfire*afterfire			-3.21e-07	-0.00094		
			(4.24e-07)	(0.00061)		
afterfire	0.00459***	0.00479***	0.00494***	0.00502***	0.00579***	0.00587***
	(0.00026)	(0.00029)	(0.00036)	(0.00034)	(0.00026)	(0.00028)
treatment	6.83e-05	-0.00031	0.00071	0.00067	0.00012	0.00031**
	(0.00038)	(0.000423)	(0.00097)	(0.00088)	(0.00013)	(0.00015)
bigfire			-5.17e-07***	-0.00084***		
			(1.52e-07)	(0.00022)		
Mortgage controls	No	Yes	Yes	Yes	No	Yes
Observations	208,422	177,532	177,532	177,532	412,604	350,590
R-squared	0.002	0.011	0.011	0.011	0.002	0.012

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]–[4], 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 [5]–[7], 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:	Fire	Fire	Fire	Fire	Ring 0-1	Ring 0-1
Control group:	Ring 0-1	Ring 0-1	Ring 0-1	Ring 0-1	Ring 1-2	Ring 1-2
bigfire:	—	—	Mortgages affected	Dummy	—	—
	[1]	[2]	[3]	[4]	[5]	[6]
treatment*bigfire*afterfire			-5.49e-06***	-0.00605***		
			(1.58e-06)	(0.00198)		
treatment*afterfire	0.00105	0.00116	0.00610***	0.00463**	-0.00076***	-0.00052*
	(0.00081)	(0.00088)	(0.00217)	(0.00184)	(0.00027)	(0.00030)
treatment*bigfire			-5.23e-07	-0.00079		
			(4.62e-07)	(0.00064)		
bigfire*afterfire			3.20e-07	-6.10e-05		
			(3.24e-07)	(0.00047)		
afterfire	0.00270***	0.00279***	0.00264***	0.00280***	0.00345***	0.00331***
	(0.00019)	(0.00021)	(0.000258)	(0.00025)	(0.00020)	(0.00021)
treatment	7.04e-05	-0.00021	0.00040	0.00036	6.34e-05	0.00013
	(0.00027)	(0.00027)	(0.00068)	(0.00062)	(9.00e-05)	(0.00010)
bigfire			-2.74e-07**	-0.00041***		
			(1.06e-07)	(0.00015)		
Mortgage controls	No	Yes	Yes	Yes	No	Yes
Observations	208,422	177,532	177,532	177,532	412,604	350,590
R-squared	0.001	0.007	0.007	0.007	0.001	0.008

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). Notice that the mean of the variables of delinquency and foreclosure in are no statistically different in 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 the use of 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 variables; the 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 for each property. 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 that also have positive relationships with big fire events.

To better interpret the results reported in Table 10, we plot maps for the deterministic assignments for properties in Northern and Southern California in Figure 6. 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 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 7 and Figure 8, 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 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. 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

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 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). 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*** 3,306***
				(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	0.000	0.008	0.008	0.009

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 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).

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.

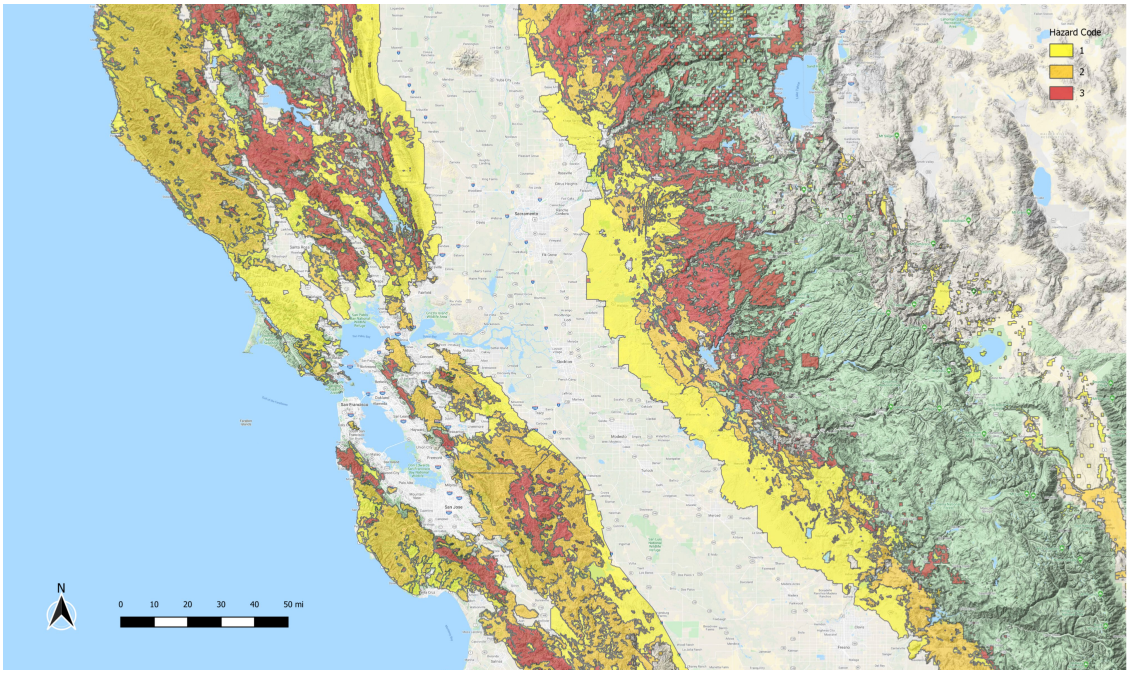
Seasonal time series variations in EBFL are also reported in Table 13, *Panel C.* As expected, EBFL is lower in the winter months and then rises to more than a billion dollars per month in the mid summer to late fall months (July through October) that together are

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.

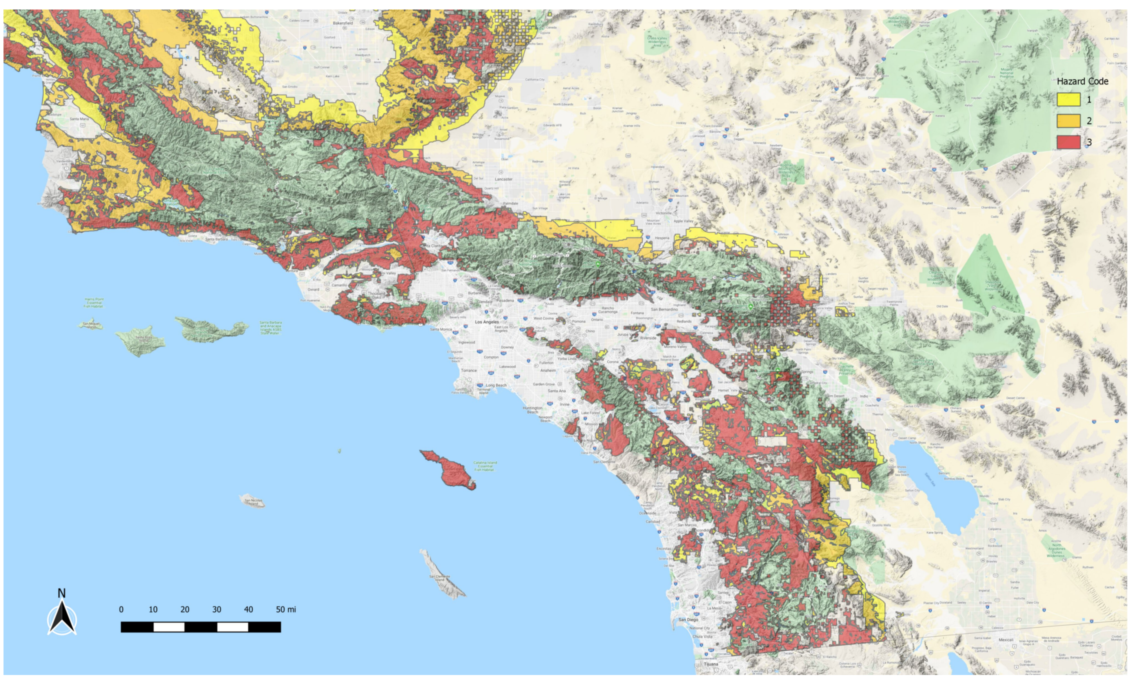
	OLS	OLS	IV
Big fire:	Num. of mortgages per wildfire	Dummy	Dummy
	[1]	[2]	[3]
Big fire	-1.42e-07**	-0.0116**	-0.05794**
	(6.33e-08)	(0.00512)	(0.02664)
LTV	2.72e-09	2.78e-09	-8.37e-08
	(2.92e-08)	(2.93e-08)	(3.60e-06)
coupon-interest rate diff.	-2.211*	-2.210*	-0.375
	(1.146)	(1.145)	(1.050)
Month max. 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	OLS	IV
Big fire:	Num. of mortgages per wildfire	Dummy	Dummy
	[1]	[2]	[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	—

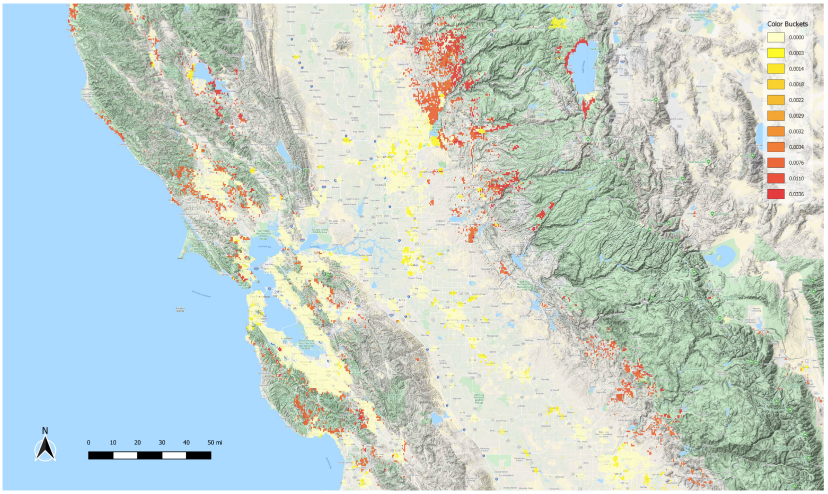


(a) Northern California

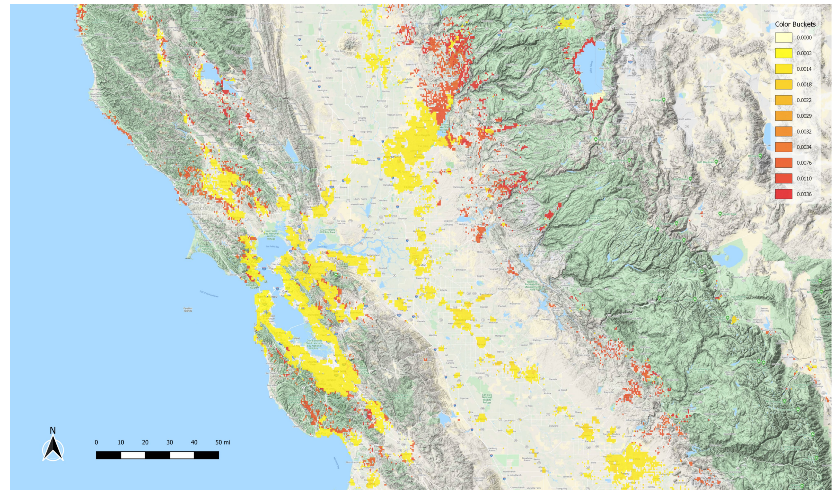


(b) Southern California

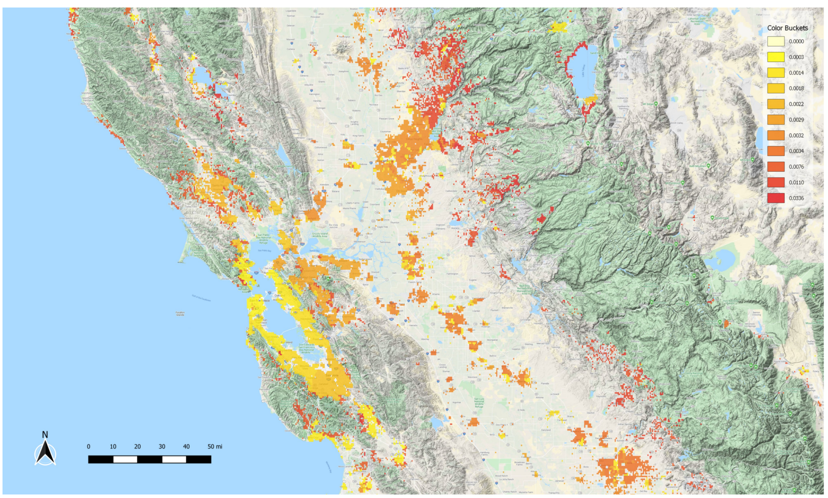
Figure 6: Northern and Southern California deterministic fire codes



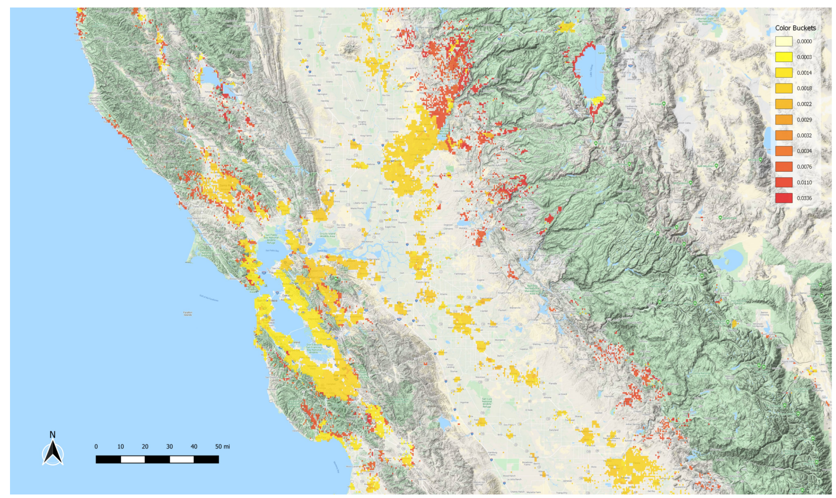
(a) January



(b) April

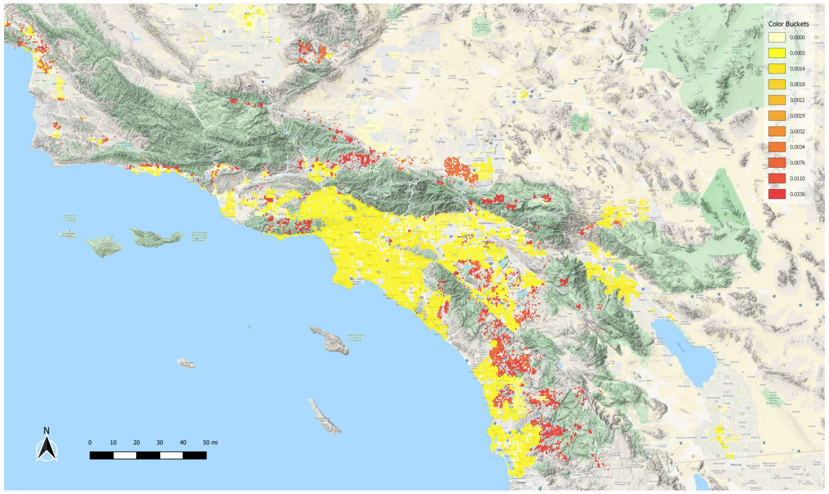


(c) July

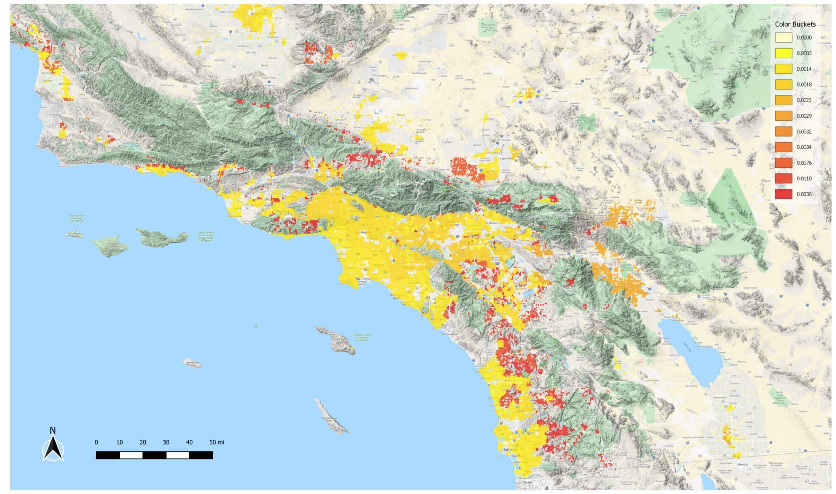


(d) October

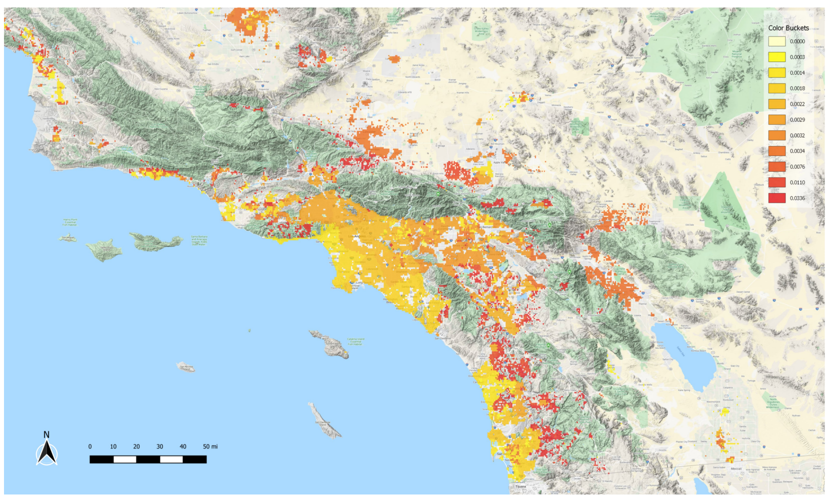
Figure 7: Northern California probabilistic fire estimates, 2017



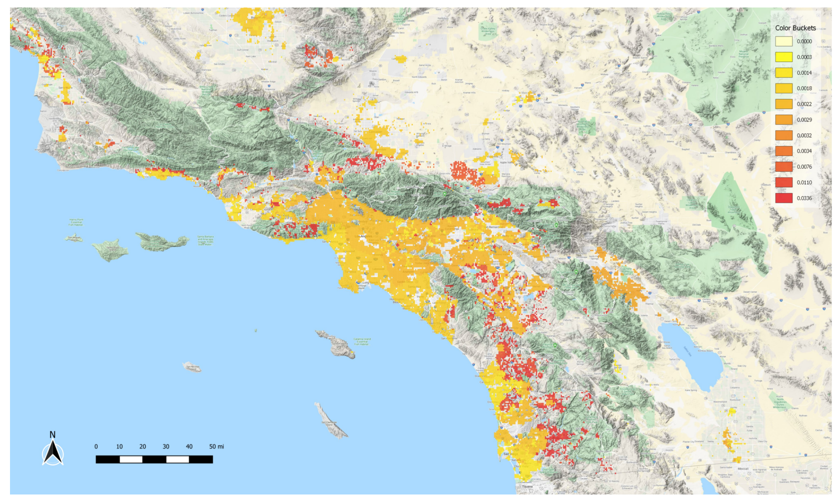
(a) January



(b) April



(c) July



(d) October

Figure 8: Southern California probabilistic fire estimates, 2017

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) × (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		

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.

Overall, these results suggest that that probabilistic models of big fire risks are tractable and informative. Additionally, the static deterministic Hazard Zone maps do not accurately order risk, and nor would they be expected to accurately price 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 which treat California wildfires as primary perils. Given 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). 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.[17] A recent Rand study found that "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

[17] 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.

for 2017" (Dixon et al., 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 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.[18]

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.
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.

Our results suggest that wildfire risk in the California mortgage market is as much as

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

$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 A Simple Theoretical Model

In this section, we build a simple theoretical model that exhibits the externalities and moral hazard discussed above. It generalizes the model of households' mortgage decisions with default and prepayment options in Deng, Quigley, and Van Order (2000) by including climate change risk. In a frictionless world with house insurance, households will be indifferent to the occurrence of climate-change-driven events because they would get the exact house value at the time of the event. However, there are at least two frictions that make the household potentially better off in the case of an event. First, most insurance policies are obliged to build up to code. Therefore, most households that experience climate-change-driven event may end up owning a house of higher quality than the one that they had before the event. This creates a moral hazard problem related to the existence of house insurance. The second friction is related to externalities in the neighborhood's investments and the optimal resolution coordination problem derived from it. 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 increases the probability that they continue meeting their mortgage payments, even if the house has been damaged.

A.1 Model setup

We assume an economy with households that borrow using mortgages on their houses as collateral in a perfectly competitive market without transaction costs. At each point of 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 of 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 climate-change-driven events. The value of the house, H_t, is one of the state variables of the model. For simplicity, we assume a 3-period model. At time $t = 1$, there is a a probability, p_F, that an exogenous climate-change-driven event (i.e, a wildfire) occurs. In such a case, there is a probability p_T that the house falls in a treatment area (i.e., the house gets highly affected by the fire) and a probability $1 - p_T$ that the house falls in a non-treatment group (i.e., the house is near the fire area, but it is not affected by the fire). If the house is in the treatment area, then its price becomes H^t_{1f}. If it is in the non-treatment group, then its price becomes H^{nt}_{1f}. Moreover, there is a probability p_R that the house is rebuilt up to code and ends with a value of H^t_{2fu} at time $t = 2$. If the house falls in the non-treatment group, then its value will also be affected by the fact that the treatment area is rebuilt or not. It there is rebuilding, then the price of the non-treatment house goes up to H_{2fu}^{nt}, but if there is no rebuilding, then the price becomes H_{2fd}^{nt} at time $t = 3$. If there is no fire, then the house price increases with conditional probability p_H or decreases with probability $1 - p_H$ at each period. Figure 9 shows a sketch of the process for the value of the house.

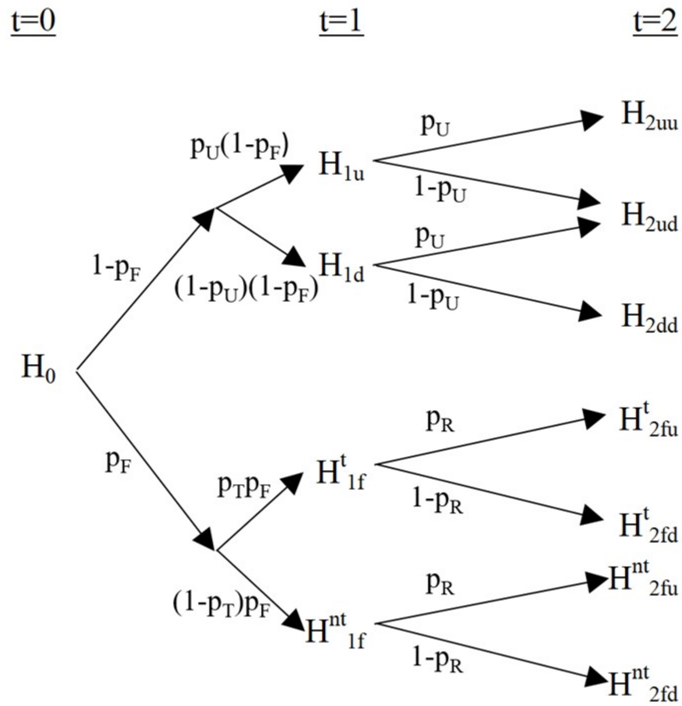


Figure 9: **House prices tree.**
This figure shows a sketch of the process for house prices in a 3-period model. In time 0, the house price is H_0. A climate-change-driven event (i.e., a wildfire) can only occur at time $t = 1$ with probability p_F. There is a probability p_T that the house falls into the treatment group (i.e., it is directly affected by the wildfire). If there is no climate change event, then the house price follows a binomial tree in which the price increases with conditional probability p_H or decreases with probability $1 - p_H$. In case of a climate-change-driven event, there is a probability of rebuilding, p_R, (e.g., the house and other houses in the neighborhood are rebuilt to code) and the house price becomes H_{2fu}^{t} or H_{2fu}^{nt} if the house is in the treatment or control group, respectively. If there is no rebuilding, then the house price decreases to H_{2fd}^{t} or H_{2fd}^{nt}, respectively.

Interest rates. The interest rate is one state variable of the model. Let r_t denote the interest rate in the mortgage markets. 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 competitive fixed rate, r_t, a fix maturity,

T, and an initial loan-to-value, LTV_1. The value of the household's mortgage at time t, M_t, is determined in equilibrium and depends on the fix periodic payment or coupon rate, c, the interest rate, r_t, the house value, H_t, the outstanding balance of the mortgage, B_t, and the remaining number of periods of the mortgage, $T - t$, as well as the probability of climate-change-driven events, p, and the net bailout, F.

A.2 Equilibrium and model predictions

The value of the mortgage at each point on time and 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. We solve the model using a backward induction approach and we obtain the following testable hypotheses:

Hypothesis 1: *If $H^t_{2fu} > H^{nt}_{2fu}$ and $H^t_{2fd} > H^{nt}_{2fd}$, then the probability of default conditional on a climate-change-driven event in the treatment group is higher than the probability of default in the control group.*

Hypothesis 2: *The probability of default conditional of a climate-change-driven event for a house in the treatment (control) group decreases with the probability of rebuilding, p_R, the house price conditional on rebuilding, H^t_{2fu} (H^{nt}_{2fu}), and the house price conditional on non-rebuilding, H^t_{2fd} (H^{nt}_{2fd}).*

References

Addoum, Jawad M., David T. Ng, and Ariel Ortiz-Bobea, 2020, Temperature shocks and establishment sales, *Review of Financial Studies* 33, 1331–1366.

Alok, Shashwat, Nitin Kumar, and Russ Wermers, 2020, Do fund managers misestimate climatic disaster risk?, *Review of Financial Studies* 33, 1146–1183.

Baldauf, Markus, Lorenzo Garlappi, and Constantine Yannelis, 2020, Does climate change affect real estate prices? Only if you believe in it, *Review of Financial Studies* 33, 1256–1295.

Bansal, Ravi, Dana Kiku, and Marcelo Ochoa, 2016, Price of long-run temperature shifts in capital markets, Working Paper 22529, NBER.

Barnett, Michael, William Brock, and Lars Peter Hansen, 2020, Pricing uncertainty induced by climate change, *Review of Financial Studies* 33, 1024–1066.

Baylis, Patrick, and Judson Boomhower, 2019, Moral hazard, wildfires, and the economic incidence of natural disasters, Working Paper 26550, NBER.

Bernstein, Asaf, Matthew T. Gustafson, and Ryan Lewis, 2019, Disaster on the horizon: The price effect of sea level rise, *Journal of Financial Economics* 134, 253–272.

Choi, Darwin, Zhenyu Gao, and Wenxi Jiang, 2020, Attention to global warming, *Review of Financial Studies* 33, 1112–1145.

Cignarale, Tony, Joel Laucher, Kenneth Allen, and Lisbeth 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, Jorge Inzulza, Camillo Boano, and Camila 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, Mike, 1995, The case for letting Malibu burn, *Environmental History Review* 19, 1–36.

Deng, Yongheng, John M. Quigley, and Robert Van Order, 2000, Mortgage terminations, heterogeneity and the exercise of mortgage options, *Econometrica* 68, 275–307.

Dixon, Lloyd, Flavia Tsang, and Gary Fitts, 2019, The impact of changing wildfire risk on California's residential insurance market, Technical Report CCCA4-CNRA-2018-008, California Natural Resources Agency.

Engle, Robert F., Stefano Giglio, Bryan T. Kelly, Heebum Lee, and Johannes Stroebel, 2020, Hedging climate change news, *Review of Financial Studies* 33, 1184–1216.

Flannigan, Mike D., Meg A. Krawchuk, William J. de Groot, B. Mike Wotton, and Lynn M. Gowman, 2009, Implications of changing climate for global wildland fire, *International Journal of Wildland Fire* 18, 483–507.

Florida, Richard, 2019, How natural disasters can spur gentrification, https://www.citylab.com/environment/2019/02/gentrification-causes-new-orleans-natural-disasters-hurricane-katrina/582499/.

Forster, Margaret, and Sophie Shive, 2020, Corporate governance and pollution externalities of public and private firms, *Review of Financial Studies* 33, 1296–1330.

Freeman, Lance, 2005, Displacement or succession? Residential mobility in gentrifying neighborhoods, *Urban Affairs Review* 40, 463–491.

Gude, Patricia H., Kingsford Jones, Ray Rasker, and Mark C. Greenwood, 2013, Evidence for the effect of homes on wildfire suppression costs, *International Journal of Wildland Fire* 22, 537–548.

Gude, Patricia H., Ray Rasker, and Jeff van den Noort, 2008, Potential for future development on fire-prone lands, *Journal of Forestry* 106, 198–205.

Guerin, Emily, 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, Roger B., Susan Stewart, and Volker Radeloff, 2009, Demographic trends, the wildland-urban interface, and wildfire management, *Society and Natural Resources* 22, 777–782.

Hong, Harrison, G. Andrew Karolyi, and José A. Scheinkman, 2020, Climate finance, *Review of Financial Studies* 33, 1011–1023.

Hong, Harrison, Frank Weikai Li, and Jiangmin Xu, 2019, Climate risks and market efficiency, *Journal of Econometrics* 208, 265–281.

Jeffrey, Tom, Shelly Yerkes, Denise Moore, Frances Calgianao, and Rhea Turakhia, 2019, 2019 wildfire risk report, Technical report, CoreLogic.

Kramer, Katherine, and Joe Ware, 2019, Counting the cost 2019: A year of climate breakdown, Technical report, Christian Aid.

Krueger, Philipp, Zacharias Sautner, and Laura T. Starks, 2020, The importance of climate risks for institutional investors, *Review of Financial Studies* 33, 1067–1111.

Lee, Dalbyul, 2017, Neighborhood change induced by natural hazards, *Journal of Planning Literature* 32, 240–252.

Loomis, John, 2004, Do nearby forest fires cause a reduction in residential property values?, *Journal of Forest Economics* 10, 149–157.

Lueck, Dean, and Jonathan Yoder, 2016, Clearing the smoke from wildfire policy: An economic perspective, Policy Series 56, PERC.

Manku, Hardeep, 2020, Jolted by California wildfires, re/insurers recalibrate their risk appetite, Analyst report, S&P Global.

Mann, Michael L., Peter Berck, Max A. Moritz, Enric Batllori, James G. Baldwin, Conor K. Gately, and D. Richard 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, Sebastián, Susan Stewart, David Helmers, Miranda Mockrin, Roger Hammer, and Volker 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, Max A., Marc-André Parisien, Enric Batllori, Meg A. Krawchuk, Jeff Van Dorn, David J. Ganz, and Katharine Hayhoe, 2012, Climate change and disruptions to global fire activity, *Ecosphere* 3, 1–22.

Murfin, Juston, and Matthew 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, Robert B., Laurie A. Johnson, Jedidiah Horne, and Brendan Nee, 2008, Longer view: Planning for the rebuilding of New Orleans, *Journal of the American Planning Association* 74, 273–287.

Ouazad, Amine, and Matthew E. Kahn, 2019, Mortgage finance in the face of rising climate risk, Working Paper 26322, NBER.

Querolo, Nic, and Brian 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, Volker, Roger Hammer, Susan Stewart, Jeremy Fried, Sherry Holcomb, and Jason McKeefry, 2005, The wildland-urban interface in the United States, *Ecological Applications* 15, 799–805.

Radeloff, Volker C., David P. Helmers, H. Anu Kramer, Miranda H. Mockrin, Patricia M. Alexandre, Avi Bar-Massada, Van Butsic, Todd J. Hawbaker, Sebastián Martinuzzi, Alexandra D. Syphard, and Susan 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, Paul, 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, Gregory L, 2017, *Flame and Fortune in the American West: Urban Development, Environmental Change, and the Great Oakland Hills Fire*, first edition (University of California Press).

Smith, Rachel 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, Kyle M., Tyron J. Venn, and David E. Calkin, 2010, The effects of wildfire and environmental amenities on property values in northwest Montana, USA, *Ecological Economics* 69, 2233–2243.

van Holm, Eric Joseph, and Christopher K. Wyczalkowski, 2019, Gentrification in the wake of a hurricane: New Orleans after Katrina, *Urban Studies* 56, 2763–2778.

Weber, Joe, and Bronwen Lichtenstein, 2015, Building back: Stratified recovery after an EF-4 tornado in Tuscaloosa, Alabama, *City and Community* 14, 186–205.

Wibbenmeyer, Matthew, 2017, Burning down the house: Wildfire and the benefits of natural disaster mitigation, Working paper, UC Santa Barbara.

Williams, A. Park, John T. Abatzoglou, Alexander Gershunov, Janin Guzman-Morales, Daniel A. Bishop, Jennifer K. Balch, and Dennis P. Lettenmaier, 2019, Observed impacts of anthropogenic climate change on wildfire in California, *Earth's Future* 7, 892–910.

Wotton, B. Mike, Charles A. Nock, and Mike D. Flannigan, 2010, Forest fire occurrence and climate change in Canada, *International Journal of Wildland Fire* 19, 253–271.

Zhou, Naaman, 2019, Australian bushfires: Death toll rises as fires sweep across South Australia and NSW, https://www.theguardian.com/australia-news/2019/dec/21/australian-bushfires-death-toll-rises-as-temperatures-soar-in-severe-heatwave, The Guardian.