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

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Abstract

This paper studies the effects of wildfires on housing and mortgage markets. We motivate our empirical investigation with a game-theoretic model of homeowners' decisions to rebuild or improve their homes, considering both neighborhood externalities and insurance. We test the model's implications using California data from 2001 to 2015. We find an increase in house prices and square footage in wildfire treatment areas five years post-fire. We also find decreases in mortgage terminations, but little evidence of gentrification. Our analysis of the expected wildfire losses associated with reasonable shocks to temperature cast doubt on the ability of insurance companies to absorb these climate-related losses without a serious reconsideration of property- and casualty-insurance pricing in California.

Key words: Housing, mortgages, climate risk, household finance, moral hazard.

JEL codes: G21, G54

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1 Introduction

Climate change is leading to significant global increases in both the frequency and severity of destructive weather events.[1] The single costliest worldwide disaster in 2018 was the Camp Fire in Paradise, California, which caused overall losses of \$16.5 billion and insured losses of \$12.5 billion.[2] Kramer and Ware (2019) list 15 weather-related disasters in 2019 alone that caused 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 and caused damage estimated at over \$25 billion (Querolo and Sullivan, 2019). In 2020, large disasters in the U.S. caused \$96.4 billion in damage, the fourth-highest inflation-adjusted total since 1980. The costliest 2020 events were Hurricane Laura (\$19 billion) and the Western wildfires (\$16.5 billion),[3] including the 2020 August Complex, the largest wildfire in California history, which burned over 1 million acres.[4,5] The 2021 Dixie fire was the second largest wildfire and the largest single (i.e., not complex) wildfire in California history, with 963,309 acres burned. The persistence of deadly wildfires in recent years underscores the growing risk they pose to both people and the broader economy.

This paper investigates the effect of California wildfire events on housing and mortgage markets. We develop a simple game-theoretic model of homeowners' decisions to rebuild or improve their homes, taking into account both neighborhood externalities and insurance. The model shows that the presence of neighborhood externalities may lead to a "prisoner's dilemma" outcome in the absence of a fire, where homeowners are all better off if everyone invests in their homes, but it is individually optimal for each not to do so, so in equilibrium nobody invests. When a fire occurs, the cost of rebuilding is borne by an insurance company, which may overcome this coordination problem. Finally, we show that in areas close to, but not in, the fire region, the game may have a unique symmetric, mixed-strategy equilibrium, in which all homeowners invest with some strictly positive probability less than one.

Institutional requirements also lead California homeowners to rebuild better homes in the same location after devastating wildfire losses. First, the state of California and most California counties require rebuilding-to-code after partial or total structural losses from wildfires.[6] Second,

[1] There is an extensive literature on how climate change increases the intensity and frequency of extreme weather events such as wildfires, storms, floods, droughts, and hurricanes. See Flannigan et al. (2009); Goss et al. (2020); Moritz et al. (2012); Pechony and Shindell (2010); Wotton et al. (2010) for evidence on wildfires. See Donat et al. (2013); Palmer and Räisänen (2002); Pokhrel et al. (2021); Schlaepfer et al. (2017); Swain et al. (2020); Tabari (2020) for studies on precipitation, storms, floods, and droughts. See Reed et al. (2022); Webster et al. (2005) for evidence on hurricanes and cyclones. See Hulme (2014); Perera et al. (2020); Tebaldi et al. (2006); Zscheischler et al. (2018) for general studies.

[2] Overall in 2018, California wildfires caused \$24 billion of losses and \$18 billion of insured losses (https://www.munichre.com/en/company/media-relations/media-information-and-corporate-news/media-information/2019/2019-01-08-media-information.htm).

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

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

[5] A complex is defined as "two or more individual incidents located in the same general area, which are assigned to a single incident commander or unified command" (see https://www.fs.fed.us/nwacfire/home/terminology.html).

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

many mortgage lenders in California require additional "build-to-code" endorsements.[7] Third, the personal-property allowances found in casualty insurance policies are usually fungible, thus insured homeowners often move personal property reimbursements into covering the expenses of desired improvements such as the size of their house (see Feinman, 2017; Molk, 2018; Schwarcz, 2017). Finally, prior to September of 2018, total-loss payouts based on replacement costs were typically maximized only by rebuilding in place.[8]

These institutional features and the post-fire equilibrium of our model imply that post-wildfire house prices and other quality measures, such as size, should rise in burn-area neighborhoods relative to untreated neighborhoods. Given our house price predictions post-wildfires, we also carry out empirical tests of the post-fire mortgage prepayment and default decisions of affected homeowners relative to those in untreated control areas. Additionally, though not directly part of our model, we analyze empirical tests that are designed to rule out alternate causal channels such as gentrification.

For our empirical tests, we use the fact that scientists at the California Department of Forestry and Fire Protection (CalFire) have established very precise burn-area boundaries for vegetative wildfires in California.[9] These boundaries allows us to identify the exact properties that are inside the wildfire burn area. For each wildfire we construct two control areas: one-mile and one-to-two-mile rings just outside the burn-area boundary. The one-mile control area is in view of the fire but not physically affected; the one-to-two-mile ring borders the one-mile control but experienced neither physical nor visual fire exposure. The treatment and control structure of our data allows us to use a difference-in-differences framework to analyze both short- and long-term effects of wildfires on key housing- and mortgage-related performance outcomes, such as house prices and size, household income, and mortgage default.

Our empirical analysis is at the property address, mortgage, and household level. We assemble our unique database from multiple sources, enabling us to observe the evolution of property characteristics, household attributes, and mortgage contracting and performance, along with the responses of these to wildfires. Our modelling framework directly supports an inquiry into whether house sizes and prices are positively affected by the incidence of a wildfire arising from post-wildfire neighborhood effects and insurance coverage that may serve as a coordination mechanism. Our empirical results indicate that on average, five years after the California wildfires between 2001 and 2015, there were significant increases in house prices and sizes, but little effect on mortgage terminations, in or near the burn areas. Additionally, we find little evidence of gentrification as measured by changes in logarithm of local household income in the wildfire treatment areas.

To assess the broader public policy implication of our results, we carry out an expected loss analysis of the effects of climate shocks on wildfire losses to the California residential single-family

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

[8] The advantages of post-wildfire rebuilding in place after a total loss was significantly reduced with the passage of California Senate Bill 1800 (see https://legiscan.com/CA/bill/AB1800/2017), which prohibited constraints on building in a new location or purchasing an already built home.

[9] See https://frap.fire.ca.gov/mapping/gis-data/.

housing stock. We estimate the probability of wildfire risk for each property, geoprocessing our real estate data with additional data for the meteorological, vegetative, and topographic characteristics of the property sites. These environmental measures allow us to investigate residential real estate at risk in the state as a function of increases in maximum temperature (which is a known causal factor in the increased intensity and incidence of wildfires).[10] Since maximum temperature is also correlated with other climate factors such as relative humidity and wind speeds, we evaluate the longer run maximum-temperature related climate risks to the dollar value of the California housing stock. We find that a 2-degree Fahrenheit shock to maximum daily temperature (corresponding to 0.17 standard deviations), leads to an expected average annual loss of $21 billion to the 2020 assessed values of the California residential housing stock. These estimates may be conservative, given the much larger realized overall losses from the California wildfires of 2018, 2020 and 2021, although these were not average years.

The paper is organized as follows. The model and its empirical implications are presented in Section 2. Section 3 develops the identification strategy and describes the data that we use for our empirical analyses of the effects of wildfire on residential real estate values, the size of rebuilt houses, and mortgage performance. Section 4 presents the empirical results. Section 5 presents the VaR analysis of expected longer-run climate shocks and examines the policy implications for casualty insurance coverage in California. Section 6 concludes.

2 Model

This section provides a simple game-theoretic framework to understand the effects of wildfires on housing markets. The model incorporates two important features influencing households' rebuilding decisions: neighborhood externalities and insurance.

Consider a neighborhood represented by two homeowners $i \in \{1, 2\}$, each owning one property. Housing services are obtained from owning a house and directly improving it, as well as from *neighborhood externalities* — housing services produced by one household affect housing services enjoyed by the other.[11] Let H_i denote the market value of house i in the absence of externalities, and follow Rossi-Hansberg et al. (2010) in assuming that the externalities from the other house are proportional to its (pre-externality) value, with a factor of proportionality λ, so the total market value of house i is

$$\hat{H}_i = H_i + \lambda H_{3-i}.$$

Each homeowner may choose to invest (I) in housing or not to invest (N). The cost of investing, c, is borne by the homeowner in the absence of a fire, and by an insurance company if there is a

[10] Gutierrez et al. (2021) find that across California, but especially in the Sierra Nevada range, the likelihood of fire occurrence increases nonlinearly with daily temperature during the summer, with a one-degree centigrade increase yielding a 19%– 22% increase in risk.

[11] See Davis and Whinston (1961); Durlauf (2004); Ioannides (2002, 2011); Kain and Quigley (1970a,b); Rossi-Hansberg et al. (2010); Schall (1976); Stahl (1976); Strange (1992).

fire.[12] Both homeowners simultaneously decide whether to invest, maximizing the total expected market value of their housing net of construction costs. In the rest of this section, we study the equilibria of this game using baseline parameters $H_1 = H_2 = 66.67$ and $\lambda = 0.5$.

2.1 Equilibrium in the no-fire case

Given these parameters, the payoffs in the no-fire case are as follows:

		Homeowner 2: I	Homeowner 2: N
Homeowner 1	I	$108, 108$	$83, 125$
	N	$125, 83$	$100, 100$

Cell (N, N) If neither homeowner invests (bottom-right), the houses are each worth

$$H_i + \lambda H_{3-i} = 66.67 + (0.5 \times 66.67) = 100.$$

Cell (I, I) Assume that the cost of investment is \$67,[13] and that investing results in a house that is 75% more valuable (ignoring externalities),

$$1.75 \times 66.67 = 116.67.$$

If both homeowners invest (top-left), the payoff to both homeowners net of costs is

$$\hat{H}_i = 116.67 + (0.5 \times 116.67) - 67 \approx 108.$$

Cells (I, N) and (N, I) If only homeowner 1 invests (top-right), we have

$$\hat{H}_1 = 116.67 + (0.5 \times 66.67) - 67 \approx 83,$$
$$\hat{H}_2 = 66.67 + (0.5 \times 116.67) \approx 125.$$

By symmetry, the numbers are reversed when only homeowner 2 invests.

[12] We do not include the cost of insurance in our analysis because it is paid regardless of whether there is a fire or whether the homeowner invests.

[13] The National Association of Home Builders estimates that the renovation of a house that includes kitchen, primary bedroom, living area, primary bathroom, small bathroom, siding, windows, patio or backyard, roof and a standard bedroom has an average cost of 67% of the value of the house.

These payoffs give rise to a classic "Prisoner's Dilemma" game (Luce and Raiffa, 1989; Rapoport, 1960). Both homeowners would prefer to coordinate on investing, but it is a dominant strategy for each not to do so. As a result, in the game's (unique) equilibrium, nobody invests.

2.2 Equilibrium in the fire case

Now suppose a fire burns down both homes, and assume that if the homeowner rebuilds, he or she ends up with the same house as in the "invest" case above. Unlike the no-fire case, if the homeowner rebuilds, the cost is now borne by an insurance company.[14] Now the payoffs are as follows:

		Homeowner 2: I	Homeowner 2: N
Homeowner 1	I	$175, 175$	$117, 58$
	N	$58, 117$	$0, 0$

Cell (N, N) If neither homeowner invests (bottom-right), the (destroyed) houses are worth zero.

Cell (I, I) If both homeowners invest (top-left), the value of both houses is the same as in the no-fire case, but without subtracting the cost of investment,

$$\hat{H}_i = 116.67 + (0.5 \times 116.67) \approx 175.$$

Cells (I, N) and (N, I) If only homeowner 1 invests (top-right), we have

$$\hat{H}_1 = 116.67 + (0.5 \times 0) \approx 117,$$
$$\hat{H}_2 = 0 + (0.5 \times 116.67) \approx 58.$$

By symmetry, the numbers are reversed when only homeowner 2 invests.

Unlike the no-fire case, it is now a dominant strategy for both homeowners to invest. By increasing the payoff to investing and decreasing the payoff to not investing, the fire has overcome the coordination problem. Overall, the amount of homeowners' housing and their wealth are positively affected by the incidence of a wildfire in the fire case.

[14] Fire casualty insurance is prevalent in California, and is required to take out a mortgage. In 2015, there were 8,338,235 residential homeowners policies (see http://www.insurance.ca.gov/0400-news/0100-press-releases/2021/upload/nr117ResidentialInsurancePolicyAnalysisbyCounty12202021.pdf), compared with a 1–4 family housing stock of 8,840,169 units (see https://www.infoplease.com/us/census/california/housing-statistics).

2.3 Inner control region

Now suppose there are two other homeowners $i \in \{1, 2\}$ in the inner control region, that is, the unburned area closest to the fire area. Houses in inner control region experience externalities from the homes in the fire, that is, if homeowners in the fire area invest, then homeowners in the inner control region enjoy additional payoffs equal to λ_{fire} times the average value of the renewed homes in the nearby fire area (\$116.67 each, from above), where $\lambda_{\text{fire}} = 0.15$. Therefore, the total market value of house i in the inner control region is

$$\hat{H}_i = \begin{cases} H_i + \lambda H_{3-i} + \lambda_{\text{fire}} \times 116.67 & \text{if at least one homeowner invests,} \\ H_i + \lambda H_{3-i} & \text{if neither homeowner invests.} \end{cases}$$

The payoffs for the inner control region are now as follows:

		Homeowner 2: I	Homeowner 2: N
Homeowner 1	I	$134, 134$	$109, 151$
	N	$151, 109$	$100, 100$

Cell (N, N) If neither homeowner invests (bottom-right), the houses are worth \$100 each, as in the no-fire case.

Cell (I, I) If both homeowners invest (top-left), the value of both houses is the same as in the no-fire case, \$108, plus the additional externalities from the rebuilt houses in the fire area,

$$\hat{H}_i = 108 + 0.15 \times 116.67 \approx 134.$$

Cells (I, N) and (N, I) If only homeowner 1 invests (top-right), we have

$$\hat{H}_1 = 83 + 0.15 \times 116.67 \approx 109,$$
$$\hat{H}_2 = 125 + 0.15 \times 116.67 \approx 151.$$

By symmetry, the numbers are reversed when only homeowner 2 invests.

This game has a unique symmetric equilibrium in which both homeowners play a mixed strategy of I with probability 0.35 and N with probability 0.65.[15] Overall, the amount of homeowners'

[15] The game also has two non-symmetric, pure-strategy equilibria: (N, I) and (I, N).

housing and their wealth are positively affected by the incidence of a wildfire, not only in the fire case (see Subsection 2.1), but also in the inner control region.

2.4 Testable implications

House size and price Our model predicts that there will be coordinated replacement and/or remodeling of homes within burn areas, implying higher prices for newly rebuilt homes in treated areas. Additionally, the model's inner-control equilibrium indicates that coordination externalities associated with post-wildfire rebuilding in the treated region will also spill over to affect homes prices in boundary areas. Thus, we should see higher post-wildfire prices for houses in inner-control areas than in outer-control areas that do not physically abut the wildfire region. Furthermore, the model indicates that other characteristics of houses, such as their square footage, would also be expected to increase especially because the within-the-home personal property component of post-fire casualty coverage is often fungible and can be invested in the re-construction. Again, we would expect these spillover effects on house size to be greater for houses in the inner-control than the outer-control regions.

Gentrification Although our model does not make unambiguous predictions about gentrification after a wildfire, numerous prior studies have found that disaster recovery often leads to rapid gentrification in affected areas.[16] We therefore also carry out robustness tests to determine whether wildfire burn-areas experience post-fire in-migration of higher-income residents relative to control areas. Such a finding would represent an alternative causal channel, outside our model, from wildfire to house prices.

Mortgage performance At first glance, it seems that destruction of a home by a fire would lead to a higher likelihood of mortgage default. But while this is certainly a possible outcome, especially when there is under-insurance or fire-related trauma, the model's prediction that full insurance leads to rebuilding of a higher-quality home after a fire in turn makes mortgage default unlikely, perhaps even less so than before the fire. The overall sign and magnitude of the effect thus remains an empirical question.

3 Identification and data

This section provides a detailed description of the identification strategy and our empirical approach. It also describes the housing and mortgage data that we use to test the implications of the model.

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

3.1 Identification strategy and empirical approach

To construct the quasi-experimental design that is the basis of our empirical approach, we first geoprocess the universe of single-family residential houses in California over time and then identify those that were located within a CalFire-defined burn area involving at least ten properties on the same date as the burn-area wildfire. These wildfire-treated properties are assigned a dummy variable *Fire* that takes the value 1 if the house fell within the boundary of the burn-area at the time of the wildfire and 0 otherwise. The first control group, identified by the dummy variable *Control1*, consists of those houses located within a 1-mile ring around the perimeter of the burn-area on the same date as the treatment wildfire. The second control group, identified by the dummy variable *Control2*, consists of those houses that were located within a 1-mile ring outside the perimeter of the *Control2* area, again on the same date as the treatment wildfire. Houses found with *Control1* and *Control2* allow us to test for the post-wildfire effects on houses within the treatment area relative to those within the control areas following the logic of our model.[17]

Figure 1 shows an example of our assignment process applied to the October 21, 2007 Witch Fire in San Diego County. The darker orange area includes the properties within the CalFire-designated burn area and the lighter orange and yellow area are the two control rings at distances of 1 and 2 miles, respectively. The Witch Creek fire destroyed 1,446 single family residential homes. The properties within the 1-mile periphery did not burn but were often visually exposed to the remains of the fire, whereas the 2-mile area had neither visual nor physical exposure to the fire. Since 2003 San Diego County Planning and Development Services, like most California counties and municipalities, has required all fire-related repaired and rebuilt homes to be built to meet current building codes. In addition, San Diego County, like the rest of California, has earthquake requirements for newly constructed homes such that modern buildings have had to meet higher standards of seismic design in order to obtain a building permit since 1954.[18]

We implement a difference-in-differences (DID) approach based on these treatment and control groups. The DID model is based on the following empirical specification. For house i in fire area j in year t, we have

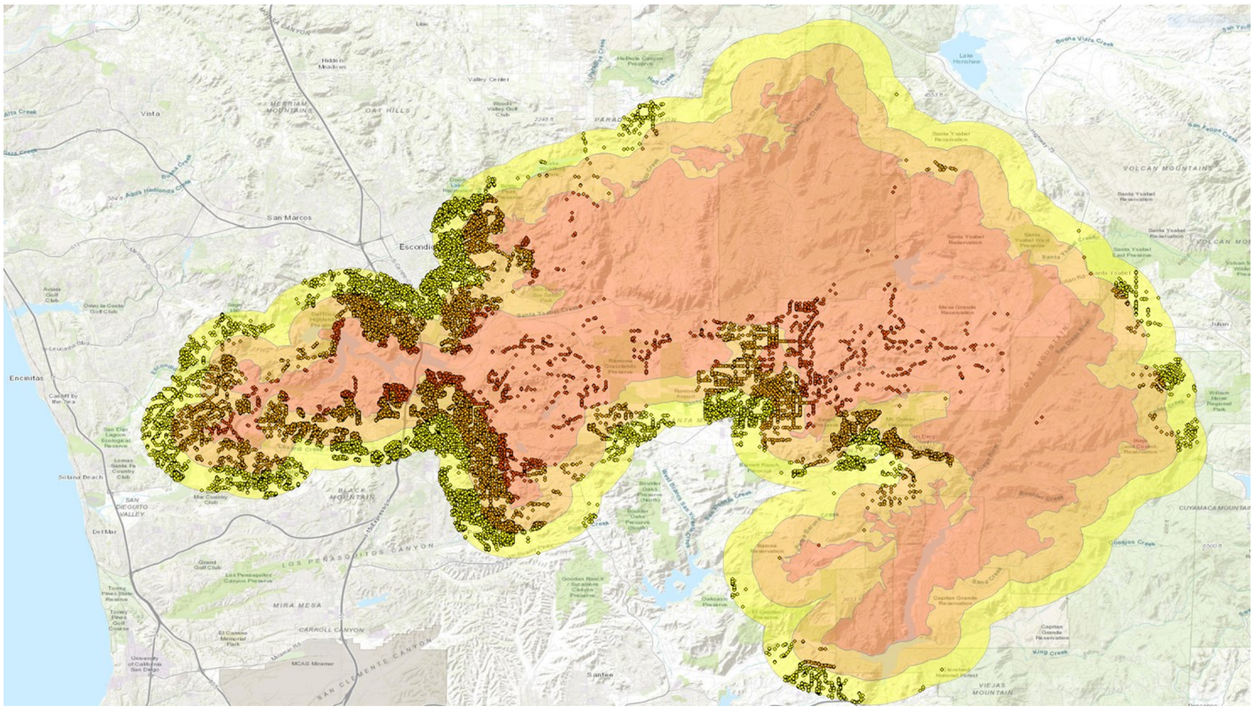
$$\begin{aligned} Y_{ijt} = {} & \alpha_i + \alpha_{jt} + \beta_0 + \beta_1 Fire_i \\ & + \sum_{k \in \{-5,\ldots,-2,0,1,\ldots,5\}}^{5} \gamma_k I(t = \text{fire year}_j + k) \times Fire_i + \epsilon_{it}, \end{aligned} \tag{1}$$

where the dependent variable, Y_{ijt}, is the outcome variable of interest, α_i is a house-specific fixed effect and α_{jt} is a year $\times$ fire fixed effect. We are interested in the magnitude and significance of the coefficients γ_k, that is, the coefficients of the interaction terms between the post-fire j time

[17] Although we are not using building-by-building damage data, we know from CalFire that between 2014 and 2019 about 93% of structures within the fire treatment boundaries were destroyed (see `https://frg.berkeley.edu/damage-inspection-and-research-implications-on-the-california-structure-ignition-problem/`).

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

Figure 1: **San Diego Witch Fire property locations, burn area and the inner and outer control areas.** This figures maps the location of the properties that were affected by the 2007 Witch wildfire. It shows the treatment burn-area in red, the inner control, *Control1*, defined as a 1-mile peripheral ring shown in orange, and the outer control, *Control2*, defined as a 2-mile peripheral ring shown in yellow.



indicator variables, $I(t = \text{fire year}_j + k)$, and $Fire_i$.[19]

3.2 Housing and mortgage data

Table 1 presents summary statistics for our housing and mortgage data. Our primary empirical test focuses on the central prediction of the post-fire equilibrium of our model that there will be coordinated replacement and/or remodeling of homes within burn areas, so that the post-wildfire prices of newly rebuilt homes in treated areas would be expected to be higher than the post-wildfire prices in control areas. The data used to estimate Equation (1) are repeat-sales transaction data from ATTOM Data Solutions. These data include all houses, with or without mortgages, within the *Fire* (Treatment), *Control1*, or *Control2* locations for which the wildfire event involved at least 10 homes.

[19] An extensive recent literature discusses potential problems with, and solutions for, estimating "staggered" difference-in-differences, where groups are treated at different times, each group acting as a treated group in some periods and as a control group in others (see, for example, Athey and Imbens, 2022; Baker et al., 2022; Borusyak et al., 2023; Callaway and Sant'Anna, 2021; Cengiz et al., 2019; de Chaisemartin and D'Haultfœuille, 2020, 2023; Dube et al., 2023; Gardner, 2021; Gibbons et al., 2019; Goodman-Bacon, 2021; Imai and Kim, 2021; Jakiela, 2021; Liu et al., 2022; Roth et al., 2023; Sant'Anna and Zhao, 2020; Strezhnev, 2018; Sun and Abraham, 2021). In our case, each treated group has a separate control group that is *never* treated, so these issues do not cause a problem.

Given our focus on wildfire pricing effects, we filter the data to include all houses for which we have at least one pre-wildfire and one post-wildfire transaction price over the period January 1996 through April 2018 (about 28% of all transactions observed over the period).[20] For each house, we construct an annual panel of interpolated transaction prices by applying the monthly growth rates of Zillow price indices by zip code to interpolate the pre-wildfire transaction prices up to the wildfire date and similarly interpolating one or more post-fire transaction prices back to the wildfire date again using the Zillow indices.

The upper section of Panel 1 of Table 1 presents summary statistics for the house price data, which is an unbalanced annual panel of interpolated prices for all houses with repeat transactions that were located in the Treatment, *Control1*, and *Control2* locations from 2000 through 2018. As shown in Table 1, the mean transaction price in the panel for both the treatment and control locations was $525,831 with a standard deviation of $496,150. The lower section of Panel 1, Table 1 reports the percentage of annual transactions that were located in a Fire Treatment, the *Control1*, and *Control2* locations. As shown, 4.32% of the overall panel of transactions prices were in the fire treatment locations. The *Control1* transactions comprise 46.27% of the interpolated transactions and the *Control2* transactions comprise 49.42% of the interpolated transactions.

The second implication of our model is that other characteristics of houses, such as their square footage, would be expected to increase. The data for this application of Equation (1) is again all houses with pre- and post-wildfire repeat sales found in the Treatment, *Control1*, or *Control2* locations. The data for this analysis are a customized ATTOM panel data set that provides updated annual snapshots of the assessed square footage of each property, thus allowing measurement of remodeling and rebuilding effects.[21] As shown in the table, the average square footage over the period was 2,045 square feet with a standard deviation of 4,604.

Our third alternative analysis of the housing panel data, again applying Equation (1), focuses on the potential causal effects of gentrification on house prices. We construct a house-level annual panel of the income of the household head from Data Axle. Data Axle models the annual income of the household heads using the MRI/Simmons annual Survey of the American Consumer. The estimated income model is updated based on changes in Census Bureau data, changes from latest MRI survey, actual changes in the surveyed household income, and changes in the Data Axle consumer data. The data used in the Data Axle income model include about 35 individual, household, and consumer life style characteristics and about 26 geoprocessed Census data fields.[22] We then merge these

[20] The repeat-sales observations represent 27.4% of the transactions in the treatment locations, 28.9% of the *Control1* transactions, and 28.0% of the *Control2* transactions. Thus, use of the repeat sales data does not appear to introduce additional sample-selection issues other than those that are standard with the use of all repeat-sales methodologies (e.g., the S&P CoreLogic Case-Shiller National Home Price Index and the Federal Housing Finance Agency's monthly House Price Index).

[21] The pre- and post-fire reporting of square footage data was less complete than the transaction data, leading to a 35% contraction in the sample size to about 1.9 million observations. However, the composition of the sample across treatment and control locations is nearly identical to the interpolated price panel: fire 0.0427, *Control1* 0.4573, *Control2* 0.5000.

[22] The algorithm does not include any ethnic, racial, religious indicators, or credit data, assuring that biases and Fair Credit Reporting Act guidelines are not issues.

data with the annual housing panel from ATTOM.[23] As shown in the table, the average annual household income over the period was \$142,231 with a standard deviation of \$92,231.

As discussed above, our model only indirectly addresses the effects of wildfires on mortgage performance. The data focus of the mortgage performance analysis includes all houses with mortgages in the Treatment, *Control1*, and *Control2* locations from January 2000 to April 2018. The houses-with-mortgages-data set is constructed with a statistical merge of all houses with mortgages in the ATTOM Data Solutions full transactions data set, again for houses located in the Treatment, *Control1*, and *Control2* areas, and loan-level mortgage origination and performance data from the Black Knight McDash.[24] Our merged data include information on mortgage characteristics, the interest rate, and the amortization schedule as well as underwriting characteristics such as the FICO score and the loan-to-value ratio. We construct a quarterly panel for each mortgage from its origination date to its final payment or the end of the sample, April 2018. The performance data include event dates for default, which we measure as sixty or more days delinquent, for prepayment, or all terminations, which is measured as either prepayment or default.

The upper section of Panel 2, Table 1, presents the summary statistics for the mortgage origination and performance variables. As shown, the mean loan amount at origination was \$318,611 with a standard deviation of \$244,059. The average loan-to-value ratio at origination was 68.3%, the mean interest rate on the mortgages is 5.4% and the average credit score is 719.0. The total termination rate for all of the loans observed in the treatment, *Control1*, *Control2* from 2000 through 2018 was 2.96%. The frequency of prepayment terminations was about 2.41% and the frequency of default terminations was 0.55%. As shown in the lower section of Panel 2, Table 1, about 2.7% of the houses with mortgages are located in treatment locations, whereas the rest of the sample falls into either *Control1* (41.8%) or *Control2* (55.5%).

4 Wildfire effects on housing and mortgages

This section presents our empirical results, looking at the effect of wildfires on house prices, house size, gentrification and mortgage performance, respectively.

4.1 House price

Figure 2 plots the estimated parameters γ_k from Equation (1) from 5 years before a fire to 5 years after, with dependent variable $Y_{ijt} = \log\left(\text{price}_{ijt}\right)$.[25] The left-hand part of the figure ($k < 0$, in red) allows us to examine the "parallel trends" assumption prior to the treatment date; with parallel trends, we should see $\gamma_k = 0$ for all $k < 0$. The right-hand part of each graph ($k \geq 0$, in blue)

[23] The Data Axle data merge leads to a 53% shrinkage in the size of the available panel relative to the interpolated price panel. Again, the composition of the sample across the treatment and control locations is nearly identical to the interpolated price panel: fire 0.0417, *Control1* 0.4568, *Control2* 0.5014.

[24] The details of our statistical merge methodology are reported in Bartlett et al. (2022). The merge rate between the two data sets for California is about 92%.

[25] Since the regression contains both a constant term and a fire dummy, we cannot separately identify all of the γ_k due to collinearity. We therefore omit γ_{-1} from the regression (effectively setting γ_{-1} to zero).

Table 1: **Summary statistics: House and mortgage characteristics.** This table presents the summary statistics for the period 2000 to 2018. The summary statistics are organized by data source. The upper panel of the table reports summary statistics for houses (both with and without mortgages) for which we have a pre- and post-fire transaction prices. The house price and square footage variables were obtained from ATTOM Data Solutions transactions data and are measured annually. The household income data for these houses come from Data Axle and are also measured on an annual basis. The treatment indicator is for houses located within a CalFire defined burn-area involving at least 10 houses. The *Control1* indicator is defined for houses geolocated within a one mile wide perimeter to the fire treatment area. The *Control2* indicator is defined for houses located within the one mile wide perimeter to the *Control1* perimeter. The lower panel of the table reports summary statistics for houses with mortgages (hence houses with fire casualty insurance) measured in pre- and post-fire periods. The mortgage analysis data were obtained through a statistical merge of properties in the ATTOM Data Solution transactions data and loan-level mortgage performance data from McDash Black Knight Financial Services. Treatment and control variables are calculated by identifying all the properties geolocated in the fire (treatment) area or in *Control1* or *Control2* for all of CalFire identified wildfires where at least ten houses burned from 2000 to 2018. The mortgage panel is measured on a quarterly basis.

Panel 1. Housing variables:					
	Mean	Std. Dev.	p10	p90	Obs.
House price ($)	525,831	496,150	189,492	875,087	2,427,125
Size (sq. ft.)	2,045	4,604	1,120	3,192	1,893,737
Income ($)	142,506	92,023	51,000	250,000	1,366,061
Treatment and Control Indicators:					
	Mean	Std. Dev.	p10	p90	Obs.
Fire (Treatment)	0.0432	0.2034	0.0000	1.0000	2,427,125
Control1	0.4627	0.4987	0.0000	1.0000	2,477,125
Control2	0.4942	0.5000	0.0000	1.0000	2,477,125

Panel 2. Mortgage variables:					
	Mean	Std. Dev.	p10	p90	Obs.
All terminations	0.0296	0.1695	0.0000	0.0000	9,477,280
Terminations for prepayment	0.0241	0.1532	0.0000	0.0000	9,477,280
Terminations for default	0.0055	0.0742	0.0000	0.0000	9,477,280
Original loan amount ($)	318,611	244,059	113,000	567,000	9,477,280
Original property value ($)	514,511	468,046	189,409	850,019	9,413,623
Original interest rate	0.054	0.014	0.035	0.068	9,477,035
Original credit score	719.0	64.2	637.0	791.0	8,009,075
Original term (months)	337.0	73.9	180.0	360.0	9,475,584
Original LTV	0.666	0.231	0.374	0.899	9,477,280
Treatment and Control Indicators:					
	Mean	Std. Dev.	p10	p90	Obs.
Fire (Treatment)	0.0271	0.1623	0.0000	1.0000	9,477,280
Control1	0.4176	0.4932	0.0000	1.0000	9,477,280
Control2	0.5553	0.4969	0.0000	1.0000	9,477,280

shows the estimated treatment effect for each year. Panels (a) and (b) of Figure 2 show the results when using *Control1* and *Control2* as the control groups, respectively.

These figures show two main results. First, the difference in the pre-trend between the treatment and control groups are not statistically different than zero, that is, the pre-intervention "parallel-trends assumption" holds when we analyze the effect of wildfires on house prices starting 5 years before the occurrence of the wildfire. Second, there is a positive and significant increase in house prices in the treatment group (*Fire* areas) in the 5-year period after the wildfire event. This effect is sizeable. It ranges from an average about 2% higher house price in the treatment group during the first year after the fire to 6% after 4 years. The effect is present not only when using the one mile wide ring as the control group (panel a), but also when using the ring located from 1 to 2 miles outside the fire border (panel b).

Additionally, panel (c) of Figure 2 presents the results for the model's prediction that an inner-control area, *Control1*, should exhibit higher post-wildfire price increases than a more distant outer-control area, *Control2*, which does not physically abut the wildfire region. As shown, *Control1* does exhibit positive house price growth relative to more distant *Control2*, at least for the first three years post the wildfire. Consistent with our model, it does appear that positive price effects of the coordination externalities within the wildfire treatment area do spill over into the abutting *Control1* locations.

4.2 House size

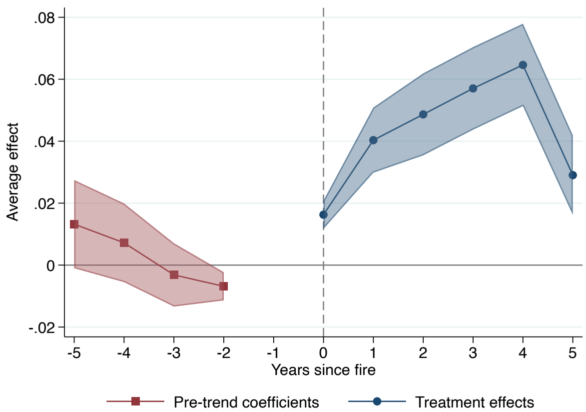
Similar to Figure 2, Figure 3 plots the estimated parameters γ_k from Equation (1) from 5 years before a fire to 5 years after, with dependent variable $Y_{ijt} = \log(\text{size}_{ijt})$. Panels (a) and (b) show the results when using *Control1* and *Control2* as the control groups, respectively.

These figures again show two main results. First, the pre-fire results support the parallel-trends assumption. Second, there is a positive and significant increase in house sizes in the treatment group (*Fire* areas) compared with the control areas in the 5-year period after the wildfire event. The magnitude of this effect ranges from 0.27% to 1.46% (average: 0.69%), being significant one year after the wildfire and increasing up to year 3, when most rebuilding has already taken place. The effect is present both using both the one-mile wide ring (Panel a) and the 1-to-2-mile ring (Panel b) as the control group. Finally, Panel c compares the two control groups. Although the spillover effects are significantly positive for the post-wildfire year, the effects are very much smaller for *Control1* relative to *Control2*, becoming statistically indistinguishable from zero by year 2.

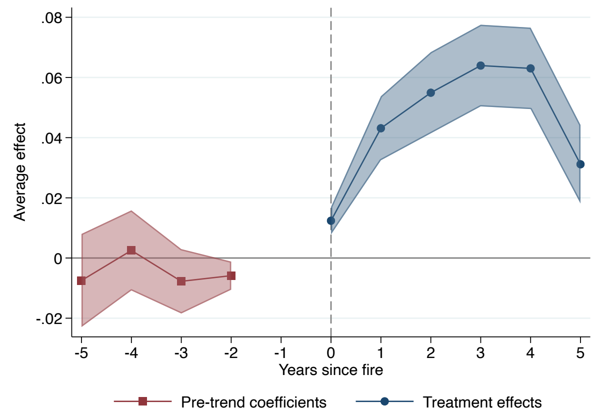
4.3 Gentrification

Whether natural disasters in an area lead to gentrification has previously been found to depend on many factors,[26] including the neighborhood's characteristics before the disaster, the type and

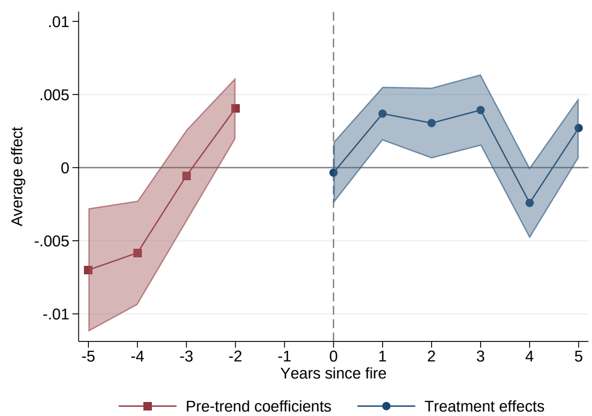
[26] Smith (1998) defines gentrification as "the process by which central urban neighborhoods that have undergone disinvestments and economic decline experience a reversal, reinvestment, and the in-migration of a relatively well-off, middle- and upper middle-class population." According to the Department of Housing and Urban Development



(a) Treatment versus *Control1*

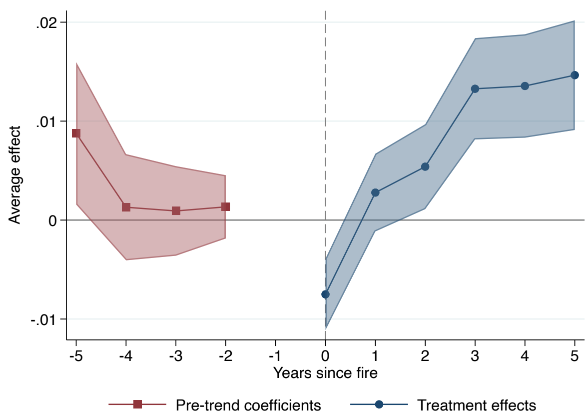


(b) Treatment versus *Control2*

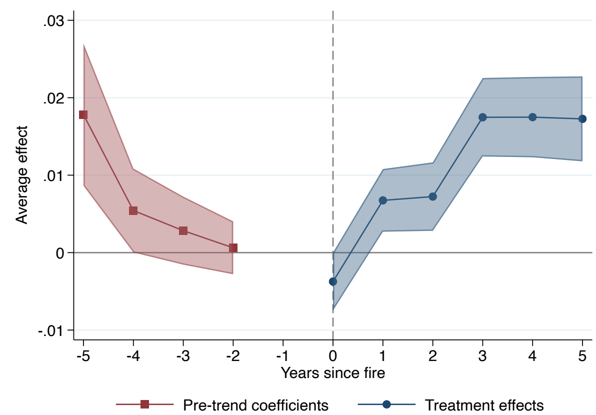


(c) *Control1* versus *Control2*

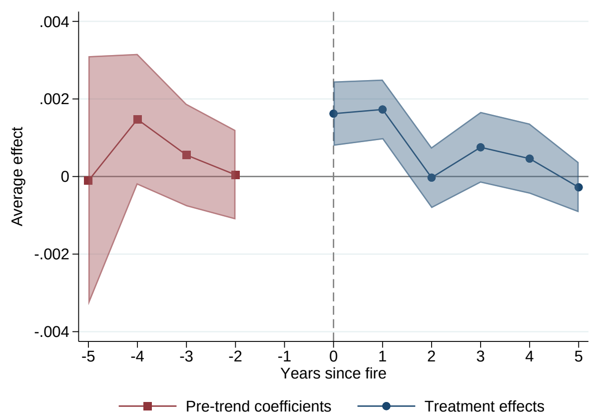
Figure 2: **Effect of wildfires on house prices.** This figure shows the estimated effects of wildfires on the logarithm of house prices in California. The average effect is represented by the coefficients of interest, γ_k, with the difference-in-differences specification in equation (1). Their 95% confidence intervals are shown in bands around the estimates. In panel (a), houses in the *Fire* and *Control1* correspond to the treatment and control groups, respectively. In panel (b), houses in the *Fire* and *Control2* correspond to the treatment and control groups, respectively.



(a) Treatment to *Control1*



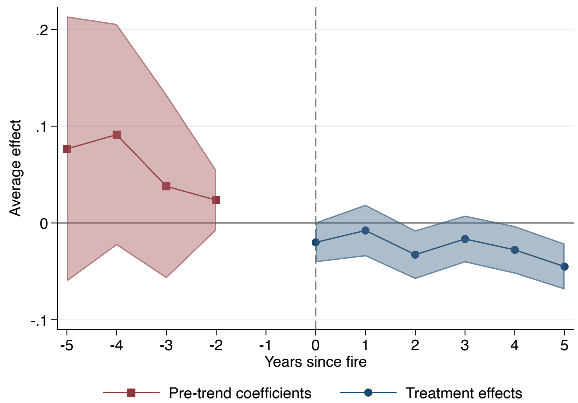
(b) Treatment to *Control2*



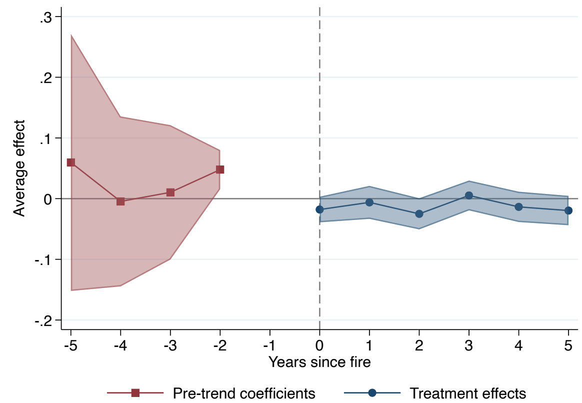
(c) *Control1* to *Control2*

Figure 3: **Effect of wildfires on house size.** This figure shows the estimated effects of wildfires on the logarithm of house size in California. The average effect is represented by the coefficients of interest, γ_k, with the difference-in-differences specification in equation (1). Their 95% confidence intervals are shown in bands around the estimates. In panel (a), houses in the *Fire* and *Control1* correspond to the treatment and control groups, respectively. In panel (b), houses in the *Fire* and *Control2* correspond to the treatment and control groups, respectively.

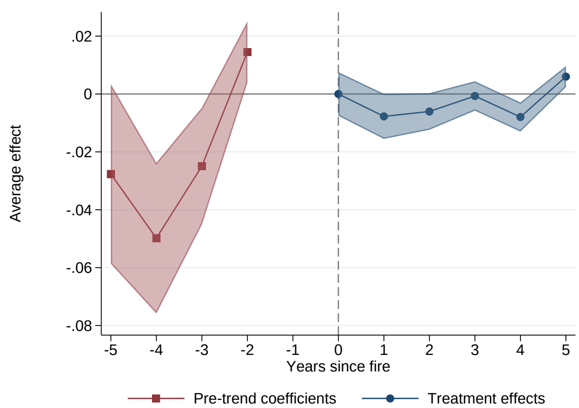
extent of the losses, and the response of government and other agencies after the disaster.[27] To investigate Figure 4 plots the estimated parameters γ_k from Equation (1) from 5 years before a fire to 5 years after, with dependent variable $Y_{ijt} = \log(\text{income}_{ijt})$. Panels (a) and (b) show the results when using *Control1* and *Control2* as the control groups, respectively. As in the prior figures, the pre-fire results support the parallel-trends assumption. The income difference between treatment and control groups after a fire is not statistically different from zero, and is actually slightly negative, suggesting little gentrification in the treatment area. Finally Panel c shows little



(a) Treatment versus *Control1*



(b) Treatment versus *Control2*



(c) *Control1* versus *Control2*

Figure 4: **Effect of wildfires on gentrification.** This figure shows the estimated effects of wildfires on the logarithm of household income. The average effect is represented by the coefficients of interest, γ_k, with the difference-in-differences specification in equation (1). Their 95% confidence intervals are shown in bands around the estimates. In panel (a), houses in the *Fire* and *Control1* correspond to the treatment and control groups, respectively. In panel (b), houses in the *Fire* and *Control2* correspond to the treatment and control groups, respectively.

(1979), gentrification occurs when "a neighborhood occupied by lower-income households undergoes revitalization or reinvestment through the arrival of upper-income households."

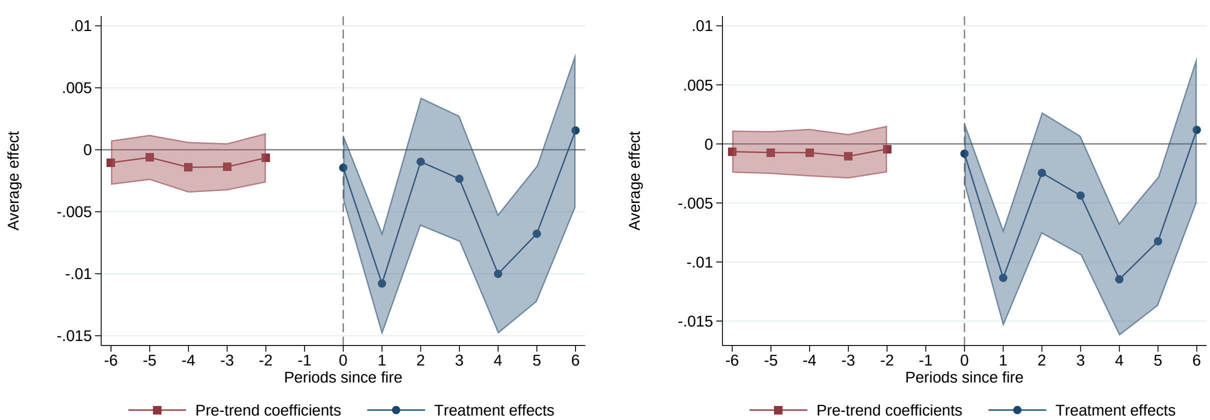
[27] See, for example, Berke et al. (1993); Bolin and Stanford (1998); Kamel and Loukaitou-Sideris (2004); Lee (2017); Olshansky et al. (2012, 2008); Peacock et al. (1997); Powers (2006); Quarantelli (1999).

difference between the inner and outer control groups, either before or after a fire.

4.4 Mortgage performance

Similar to Figure 2, though with a different time scale to reflecting the shorter horizon that is relevant here, Figures 5–7 plot the estimated parameters γ_k from Equation (1) from 6 quarters before a fire to 6 quarters after, with the dependent variable being a dummy variable for all terminations (Figure 5), prepayment (Figure 6) or default (Figure 7). In each case, Panels (a) and (b) show the results when using *Control1* and *Control2* as the control groups, respectively.

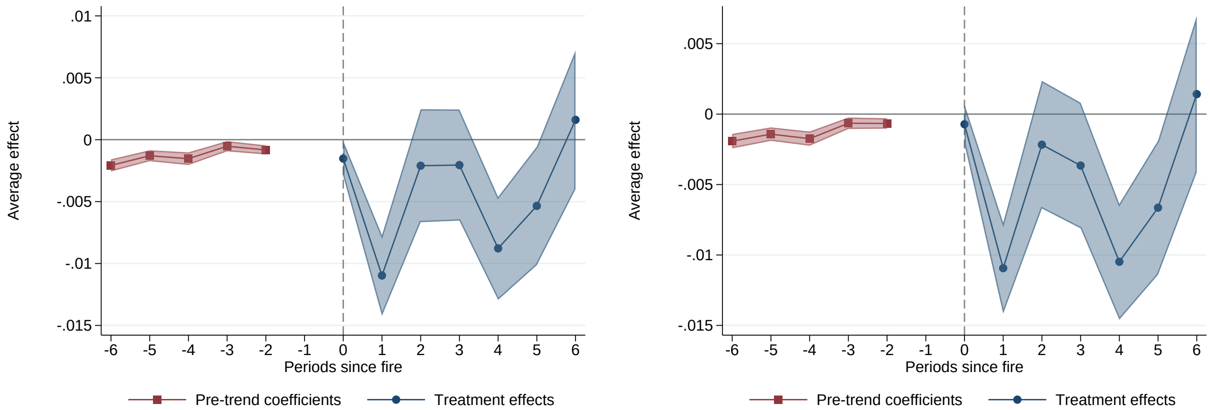
In all of these regressions, there are no apparent pre-trends. Figure 5 shows a *drop* in overall mortgage terminations for houses in the treatment group relative to those in both control groups following a fire. Figure 6 shows very similar results looking just at prepayments, while 7 shows very similar results looking just at prepayments, while Figure 7a and Figure 7b show the results of the effects of wildfires on mortgage defaults for the houses with mortgages in the Treatment location relative those in the *Control1* locations and for the Treatment location relative relative to those in the more distant *Control2* location. These figures confirm that most of the effects of wildfires on mortgage terminations do not come from defaults, since none of the post-wildfire γ_k's are statistically significantly different from zero. These results suggest that the rebuilding codes and the upward post-wildfire effects on rebuilt houses, essentially extinguish the default option for most borrowers. The pre-trend plots again indicate no significant pre-trends in default.



(a) Treatment versus *Control1* (b) Treatment versus *Control2*

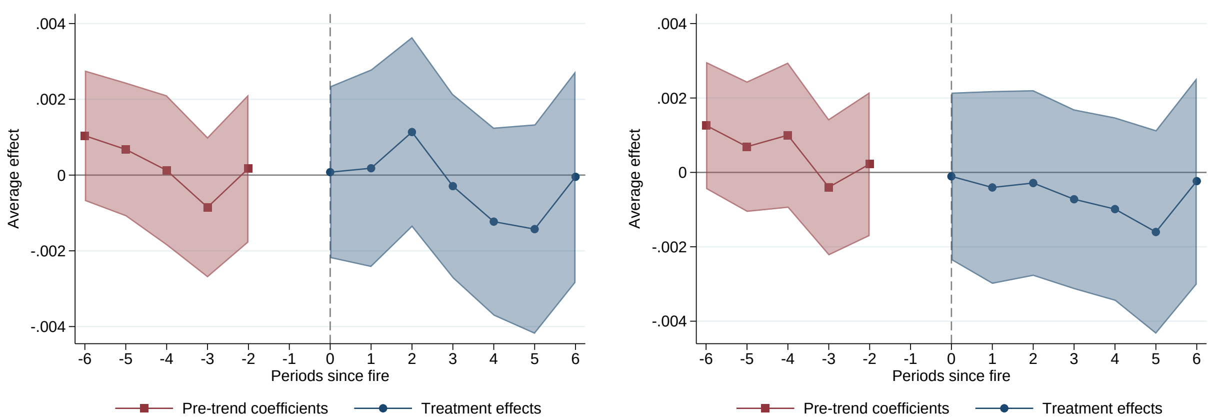
Figure 5: **Effect of wildfires on mortgage terminations.** This figure shows the estimated effects of wildfires on mortgage terminations in California, using quarterly data. The average effect is represented by the coefficients of interest, γ_k, with the difference-in-differences specification in equation (1). Their 95% confidence intervals are shown in bands around the estimates. In panel (a), houses in the *Fire* and *Control1* correspond to the treatment and control groups, respectively. In panel (b), houses in the *Fire* and *Control2* correspond to the treatment and control groups, respectively.

Finally, Figure 8 compares the two control groups, *Control1* and *Control2*, with Panel (a)



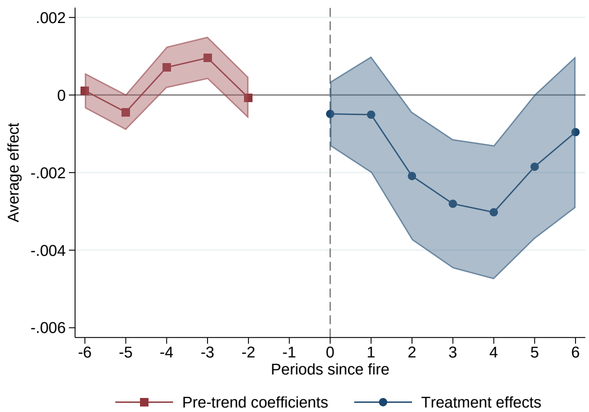
(a) Treatment versus *Control1* (b) Treatment versus *Control2*

Figure 6: **Effect of wildfires on mortgage prepayment.** This figure shows the estimated effects of wildfires on mortgage prepayments in California, using quarterly data. The average effect is represented by the coefficients of interest, γ_k, with the difference-in-differences specification in equation (1). Their 95% confidence intervals are shown in bands around the estimates. In panel (a), houses in the *Fire* and *Control1* correspond to the treatment and control groups, respectively. In panel (b), houses in the *Fire* and *Control2* correspond to the treatment and control groups, respectively.

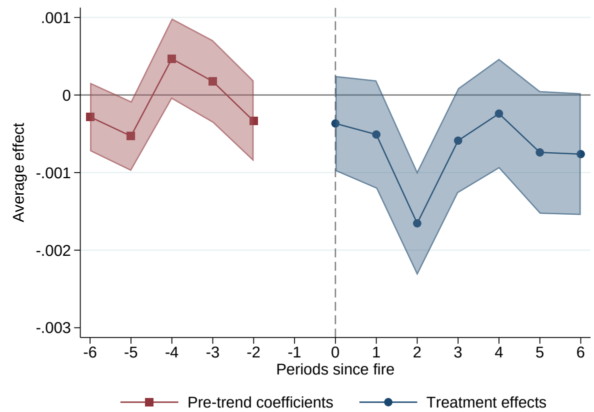


(a) Treatment versus *Control1* (b) Treatment versus *Control2*

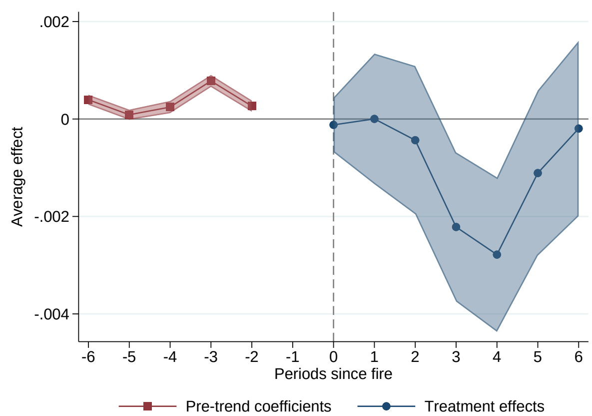
Figure 7: **Effect of wildfires on mortgage default.** This figure shows the estimated effects of wildfires on mortgage default in California, using quarterly data. The average effect is represented by the coefficients of interest, γ_k, with the difference-in-differences specification in equation (1). Their 95% confidence intervals are shown in bands around the estimates. In panel (a), houses in the *Fire* and *Control1* correspond to the treatment and control groups, respectively. In panel (b), houses in the *Fire* and *Control2* correspond to the treatment and control groups, respectively.



(a) All terminations



(b) Default



(c) Prepayment

Figure 8: **Effect of wildfires on mortgage terminations, Control1 versus Control2.** This figure shows the estimated effects of wildfires on mortgage default in California, using quarterly data. The average effect is represented by the coefficients of interest, γ_k, with the difference-in-differences specification in equation (1). Their 95% confidence intervals are shown in bands around the estimates. In each case, houses in the *Control1* and *Control2* correspond to the treatment and control groups, respectively.

showing all terminations, Panel (b) showing prepayment, and Panel (c) showing default. Similar to the results above, there are no obvious pretrends. All three graphs look similar, and indicate a slight reduction in all forms of termination post-fire for the *Control1* area compared with *Control2*.

5 Quantifying wildfire risks to the housing stock

In this section, we quantify the expected effects of wildfires on the value of residential properties in California. We estimate the *expected loss* (EL) for houses that can potentially be affected by wildfires in a manner similar to that used for defaultable loans:

$$\textit{Expected loss}\text{ (EL)} = \textit{probability of wildfire}\text{ (PW)} \times \textit{dollar loss given wildfire}\text{ (LGW}_{\$}\text{)}.$$

We also consider the effect of a shock to maximum temperature on the overall wildfire risk exposure of the California housing stock.

5.1 Estimation of expected wildfire losses

A preliminary stage in estimating the expected loss (EL) of wildfires on the value of residential properties in California is to allocate the California land mass to urban nodes (measured at latitude and longitude with nearest neighbor nodes at 1.5 kilometers) and rural nodes (measured at latitude and longitude with nearest neighbor nodes at 4.5 kilometers).[28,29] We estimate EL in two steps. First we estimate the average daily PW for each node based on historical climate, topological, and vegetative data at the nodes from 2001 through 2015. Second, we measure the value of the housing stock as the aggregate assessed value for houses in areas defined by the nodes and we estimate the $\text{LGW}_{\$}$, which is constant in the area represented by each node.

The first step towards estimating EL is calculating the probability $p = PW(l, t)$ that a house will experience a wildfire in its node location l at time t. We estimate a reduced-form model with three sets of predictors: $X_{\text{weather}}(l, t)$, $X_{\text{physical}}(l, t)$, and $X_{\text{season}}(l, t)$, which denote, respectively, a vector of weather variables at the node, a vector of physical characteristics, and a vector of seasonal variables (e.g., month of the year). We simplify notation by excluding the arguments l and t from now on. We assume a linear relationship between the predictor variables and the log-odds of the wildfire event,

$$log\frac{p}{1-p} = \beta_0 + \beta_{\text{weather}}X_{\text{weather}} + \beta_{\text{physical}}X_{\text{physical}} + \beta_{\text{season}}X_{\text{season}} + \epsilon, \tag{2}$$

[28]Our goal is to provide the estimate of the aggregate expected loss for a specific year (i.e., 2020). To achieve this, we need a long series of past data on historical climate to estimate PW (e.g., period 2001–2015). We perform our analysis at a granular nodal level because the California Department of Agriculture and CalFire did not start collecting property-level post-wildfire damage data until 2013 (see https://frg.berkeley.edu/damage-inspection-and-research-implications-on-the-california-structure-ignition-problem/).

[29]We determine rural nodes in areas on U.S. National Forest Service land. Appendix A provides further details about the definition and characteristics of these nodes.

where $\beta \equiv (\beta_0, \beta_{\text{weather}}, \beta_{\text{physical}}, \beta_{\text{season}})$ is the vector of model parameters. The data used to estimate Equation (2) include 48,391 nodes and 643 fires over the fire seasons from June 2001 to October 2015. The weather measures include the daily averages of hourly wind speed, maximum temperature, relative humidity, and wind direction. Our physical measures include the slope and elevation for each node as well as measures of each node's exposure to housing density within or near the Wildland Urban Interface (WUI) or the Wildland Urban Intermix.[30]

Table 2 reports the estimation results for the daily log odds of node-level wildfire in California over the 2001 to 2015 period. As shown, the logistic regression indicates a strong positive relationship between the daily probability of a wildfire and the nodal daily average wind speed, the daily average maximum temperature, the slope, and the elevation, high vegetative coverage, and the months of September and October. Average relative humidity, as expected, has a statistically significant and negative association with nodal wildfires. As anticipated, the Santa Anas and Diablos, which are hot high-speed westward flowing winds to low-pressure zones off the California coast, also have positive and statistically significant effects on the probability of wildfire. Since human ignitions account for essentially all wind-dominated fires in California (see Abatzoglou et al., 2018), higher intermix or interface of housing units with vegetation is positively and statistically significantly associated with the log-odds of wildfire.

Afterward, we apply the logistic regression model reported in Table 2 to compute the expected daily probability of wildfire for the actual (or shocked) average daily weather and WUI characteristics of each node for each year.[31] Our evaluation sample includes 18,780 nodes with adjoining housing and a total of 9,114,700 housing units (single, duplex, triplex, and quadruplex properties) and with a total 2020 assessed value of \$4.2 trillion.[32] As a control for the differential characteristics of the housing stock in the node, we replace the measure of the node's slope and elevation with the weighted average slope and elevation of all properties that are located close to the node. To compute the expected annual property losses (base case and shock case), we assess each node's yearly survival probability measured as the product of one minus the assessed nodal probability) for the annual fire season (i.e. the product over 152 days).

The second step to estimate EL is to compute the $\text{LGW}_{\$}$. The expected annual property loss is given by the sum over all nodes of the product of the aggregate assessed value of all properties associated with each node times the calculated annual nodal survival probability. The base case for the expected effects of wildfire on the California housing stock is calculated as the 2020 assessed value of the residential properties. For this calculation, we are assuming a 100% loss in the event of a fire. We are also assuming that the losses to the housing stock are pre-insurance payouts, thus

[30] The Federal Register defines the Wildland Urban Interface as places where "humans and their development meet or intermix with wildland fuel." Interface communities are communities "where structures directly abut wildland fuels" and intermix communities are communities "where structures are scattered throughout a wildland area." 'Urban Wildland Interface Communities Within the Vicinity of Federal Lands That Are at High Risk From Wildfire," Federal Register 1/4/2001 https://www.federalregister.gov/documents/2001/01/04/01-52/urban-wildland-interface-communities-within-the-vicinity-of-federal-lands-that-are-at-high-risk-from

[31] Appendix B provides a detailed description of the process to calculate the expected daily probabilities of wildfire.

[32] For each house, we determine the nearest neighbor node. For urban the nearest maximum distance is 1.5 kilometers and for rural the maximum is 4.5 kilometers.

Table 2: **Logistic regression of the probability of wildfires.** This table presents the logistic regression analysis of the probability that small geographic locations, measured as 48,391 nodes in California, will experience a wildfire over the period 2001 through 2015. The daily node measurements for weather characteristics include maximum temperature, wind speed, relative humidity, the slope of the node, and its elevation. The physical characteristics also include measures for the percentage of vegetative coverage, and low, medium, and high nodal exposure to the Wildland Urban Interface (WUI) measured as either, *intermix*, where housing is intermingled with the WUI or, *interface*, where housing borders the WUI. We also include two measures for the direction of the wind as indicator variables for northeasterly (NE) and southeasterly (SE) winds and two measures for California's historical peak fire season, September and October. ***, **, and * denote statistical significance at the 0.1%, 1%, and 5% levels, respectively.

	Coefficient	Std. Error	z	P> |z|	[0.025	0.975]
Intercept	-11.8423***	0.048	-248.918	0.000	-11.936	-11.749
Weather Characteristics:						
Wind Speed	0.5212***	0.005	110.602	0.000	0.512	0.530
Maximum Temperature	0.3840***	0.020	19.657	0.000	0.346	0.422
Relative Humidity	-1.2912***	0.023	-56.735	0.000	-1.336	-1.247
NE Wind (Diablo)	1.1187***	0.027	40.823	0.000	1.065	1.172
SE Wind (Santa Ana)	0.2143***	0.033	6.402	0.000	0.149	0.280
Physical Characteristics:						
Slope	0.3929***	0.010	38.755	0.000	0.373	0.413
Elevation	0.1925***	0.016	11.967	0.000	0.161	0.224
Vegetation	0.3406***	0.046	7.438	0.000	0.251	0.430
WUI: low intermix	0.7153***	0.057	12.634	0.000	0.604	0.826
WUI: med. intermix	0.8160***	0.085	9.637	0.000	0.650	0.982
WUI: high intermix	1.9037**	0.711	2.676	0.007	0.509	3.298
WUI: low interface	1.0559***	0.124	8.497	0.000	0.812	1.299
WUI: med interface	1.6368***	0.072	22.776	0.000	1.496	1.778
WUI: high interface	1.8699***	0.097	19.230	0.000	1.679	2.060
Peak fire months:						
September	0.2374***	0.032	7.472	0.000	0.175	0.300
October	0.9184***	0.034	26.879	0.000	0.851	0.985
No. of observations	110M					
Pseudo R^2	0.178					
Log-Likelihood	–84946					
Log-Likelihood p-value	0.000					

Table 3: **Expected loss to California residential real estate from wildfires.** This table shows the expected loss (EL) to California residential real estate from wildfires under a base case measured as the actual averages of daily maximum temperature, relative humidity, wind speed, vegetative coverage, and proximity or intermix with the Wildland Urban Interface (WUI) and for a climate change shock in which the maximum temperature increases by 2.00 degrees Fahrenheit (corresponding to a 0.16644 standard deviation shock to the maximum temperature for a day). The table reports the base case in annual expected losses in millions of dollars (column 1) and as a percentage change of the fixed 2020 assessed value of $2.046 trillion for residential single-family, duplex, triplex, quadruplex, condos, homeowners associations, and timeshare properties located outside of Central Business Districts (column 2). We fix the assessed values of the housing for all years at their 2020 values to highlight the effects of the climate changes only rather than the combined effects of each year's assessed value and climate change effects. Our climate change shock reflects a 2.00-degree Fahrenheit change to daily maximum temperature controlling for the correlations of maximum temperature with relative humidity and wind speed, again assuming the status quo in insurance coverage for wildfires observed over the period 2001 to 2015. The expected annual wildfire losses are reported in $ millions of 2020 assessed value losses in column 3 and the percentage change of the fixed 2020 assessed value is reported in column 4. Column 5 reports the difference in the expected base case wildfire losses and the climate-shocked expected wildfire losses in $ millions of 2020 assessed value.

Year	[1] Base case. Expected loss before shock ($ M)	[2] Base case. Expected loss before shock (%)	[3] Climate shock. Expected loss after shock ($ M)	[4] Climate shock. Expected loss after shock (%)	[5] (Shock - Base case). Expected loss Difference ($ M)
2001	11.763	0.58	14.203	0.69	2.440
2002	12.038	0.59	14.511	0.71	2.474
2003	21.324	1.04	25.812	1.26	4.488
2004	11.770	0.58	14.206	0.69	2.436
2005	12.187	0.60	14.727	0.72	2.539
2006	16.305	0.80	19.736	0.96	3.431
2007	40.627	1.99	48.714	2.38	8.087
2008	26.901	1.32	32.606	1.59	5.705
2009	18.664	0.91	22.629	1.11	3.965
2010	11.152	0.55	13.475	0.66	2.323
2011	10.794	0.53	13.035	0.64	2.241
2012	17.324	0.85	20.998	1.03	3.674
2013	22.828	1.12	27.654	1.35	4.826
2014	16.441	0.80	19.928	0.97	3.487
2015	10.701	0.52	12.951	0.63	2.250
Mean	17.388	0.85	21.012	1.03	3.624

they represent the potential exposure of the insurance industry to wildfire casualty claims.[33]

Table 3 presents the results of the base case and the climate-shocked evaluation of the California housing stock exposure to wildfire, measured at the nodal assessed house values times the estimated nodal propensity for wildfire in that year. We find that the mean expected annual wildfire loss to the residential housing stock in California is \$17.388 billion (column 1; bottom), which is 0.85% of the \$2.045 trillion stock (column 2; bottom). Our estimate for the peak year of 2007 is a \$40.627 billion expected loss, which is about 2% of the aggregate \$2.045 trillion 2020 assessed value for the non-CBD nodes. The actual measurements for the 2007 fire season included extreme maximum temperatures and Santa Ana winds that were associated with the San Diego Witch and Guejito fires, among others.[34] The other large expected loss years, again due to actual climate measurements in the respective years, are found for 2003 (a \$21.324 billion expected loss), 2008 (a \$26.901 billion expected loss), and 2013 (a \$22.828 billion expected loss).[35]

5.2 The effect of a shock to maximum temperature on housing stock

This subsection presents the quantification analysis of the effect of a 2-degree increase in the maximum temperature on the housing stock in California. Maximum temperature is a causal factor in the increased intensity and incidence of wildfires and is also highly correlated with other climate factors such as relative humidity and wind speeds. Figure 9 exhibits the dynamics of the maximum temperature for the West Climate Region in the U.S. and shows a long-run upward slope trend line for the period 1895–2022. To measure the expected effects of such climate change shock, we re-calculate the expected probability of wildfire at each node given a 2-degree Fahrenheit shock (0.17 standard deviations) to each node's maximum daily temperature. We anchor the assessed values at their 2020 reported values to distinguish the effect of the maximum temperature shock from differences in the levels of assessed value and size over time.[36]

Columns 4 and 5 of Table 3 report the results of the climate change-related shock defined as a 2-degree Fahrenheit shock to each node's observed maximum daily temperature. The mean expected loss from this climate shock is \$21.012 billion (column 3; bottom) or a 1.03% expected percentage change in the base case \$17.388 billion assessed value (column 4; bottom). The overall expected

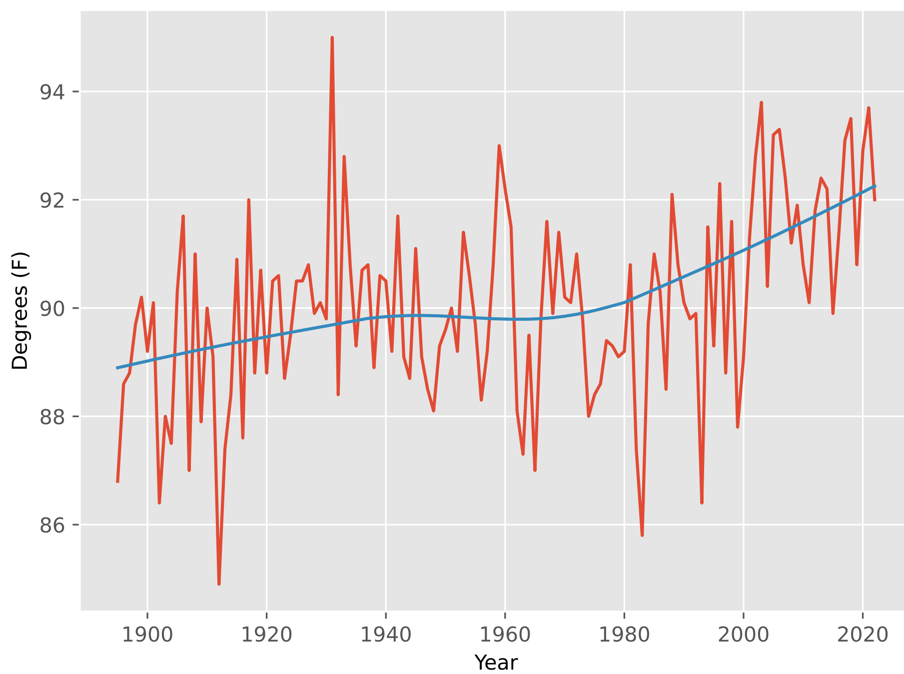
[33] To reduce the impact of the large urban Central Business Districts (CBD) with multi-story housing density located in nodes with essentially zero probability of wildfire, we further filter out all nodes with an average annual wildfire probability of less than 0.15%. This further filter reduces our nodal and housing sample to 4,752,238 non-CBD properties with a 2020 assessed value of \$2.045 trillion located in 14,393 nodes.

[34] The Witch and Guejito Fires combined to burn 197,000 acres, killed two people, injured 40 firefighters, and destroyed 1,141 homes and 239 vehicles. Legal claims after the fires totaled \$5.6 billion (see https://en.wikipedia.org/wiki/Witch_Fire#:~:text=The%20Witch%20and%20Guejito%20Fires,settled%202%2C500%20lawsuits%20for%20damages).

[35] The 2003 California fire season included the 10th largest California wildfire, the Cedar Fire in San Diego. This fire burned 2,800 homes and caused 15 fatalities. (see https://en.wikipedia.org/wiki/2003_California_wildfires). The 2008 fire season included the Montecito Tea fire (https://en.wikipedia.org/wiki/Tea_Fire) that burned 210 homes and the Los Angeles, Slymar Fire that burned 630 structures, "Southern California November Wildfire of 2008: One of the 25 Largest Fire Losses in U.S. History,"(see https://www.portlandoregon.gov/fire/article/326554). The 2013 fire season included the Rim Fire, which became California's 3rd largest wildfire and burned 112 structures (see https://en.wikipedia.org/wiki/2013_California_wildfires).

[36] Our use of the 2020 tax-assessed value is likely to be an underestimate, due to the effects of Proposition 13.

Figure 9: **Maximum annual temperature**. The red line shows the annual maximum temperature for the West Climate Region between 1895 and 2022 from the National Oceanographic and Atmospheric Administration (see https://www.ncei.noaa.gov/access/monitoring/climate-at-a-glance/regional/time-series), with LOWESS trend line (Cleveland, 1979) in blue.



effect of this climate change shock over the fifteen-year sample period increases expected daily losses by \$3.624 billion (column 5; bottom). The largest years of expected losses due to climate change are 2003, 2007, 2008, and 2013. Importantly, all of these fire seasons have now been surpassed by both the size, lethality, and destructiveness of the California wildfires of 2018, 2020, and 2021.

Figure 10 presents the expected annual wildfire losses in millions of dollars for locations in Northern and Southern California. The scale for both maps is from red to yellow, an annual expected loss of from \$11 to \$8 million; light green to blue-green, an annual loss from \$8 to \$4 million; and light to dark blue, an annual loss of \$4 to less than \$1 million. As discussed above, in locations where the annual expected probability of wildfire was less than 0.15%, the CBD areas are shown in white. Subfigure (a) of Figure 10 plots a heat map for the San Francisco Bay Area of Northern California and Subfigure (b) plots a heat map for the Los Angeles Basin in Southern California. As shown, these plots both indicate urban locations with very high expected annual losses between \$8 to \$11 million. The red to yellow colored areas have high expected probabilities of wildfire risk as well as high-valued residential real estate exposure. Most of these locations are found on steeply sloped sites in the urban WUI interface areas surrounding that are especially prone to downslope wind-driven fires such as those surrounding Los Angeles, San Diego, and Oakland. The blue-green areas are also quite at risk for annual wildfire losses to residential property. Our topographic maps also indicate very rural areas shown in a soft green, which are also very likely to be prone to wildfire risks due to their topographic, climate, and exposure to WUI interface and intermix, however, they do not have the residential real estate exposure that is the focus of our VaR analysis.

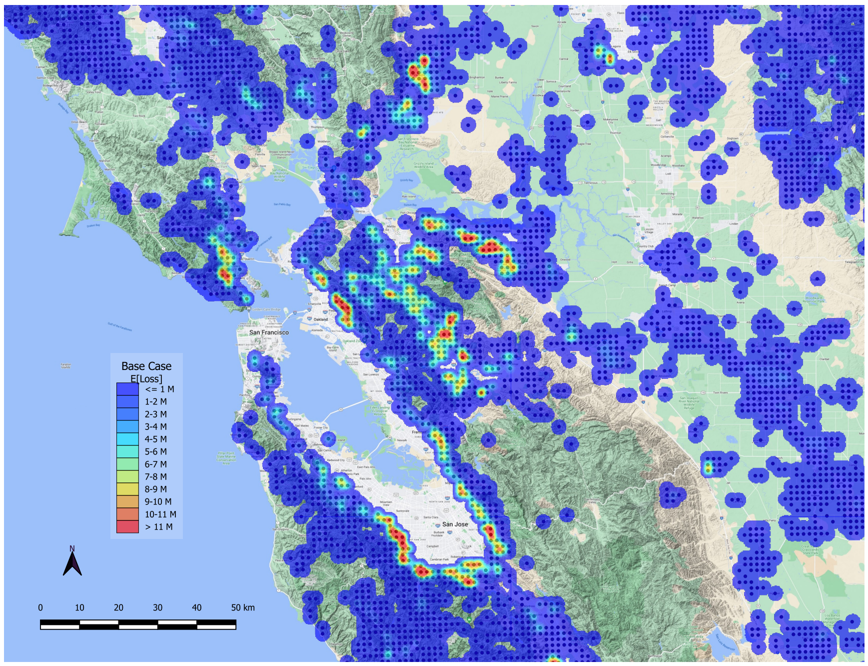
The magnitude of these expected and realized losses is a very significant factor in the increasing reluctance of private insurance carriers to renew or write new casualty insurance policies in California. As of June 2023, State Farm, the nation's biggest home insurer by premium volume, decided not to write new homeowner policies, "...due to historic increases in construction costs outpacing inflation, rapidly growing catastrophe exposure, and a challenging reinsurance market," as did Allstate.[37] Last year another big insurer, American International Group, notified thousands of high-net-worth clients in California that their home policies would not be renewed.[38]

Regulatory frictions are another frequently cited concern for the long-term viability of homeowner fire casualty insurance in California. In 1988, California voters passed Proposition 103, which required insurance companies to receive "prior approval" from the California Department of Insurance (CDI) before implementing property and casualty insurance rates. As shown by Oh et al. (2022), casualty insurance rates in states like California with high regulatory frictions have not adequately adjusted in response to the growth in losses. In addition, California state insurance regulations require wildfire insurers to set rates for future annual catastrophic coverage as the

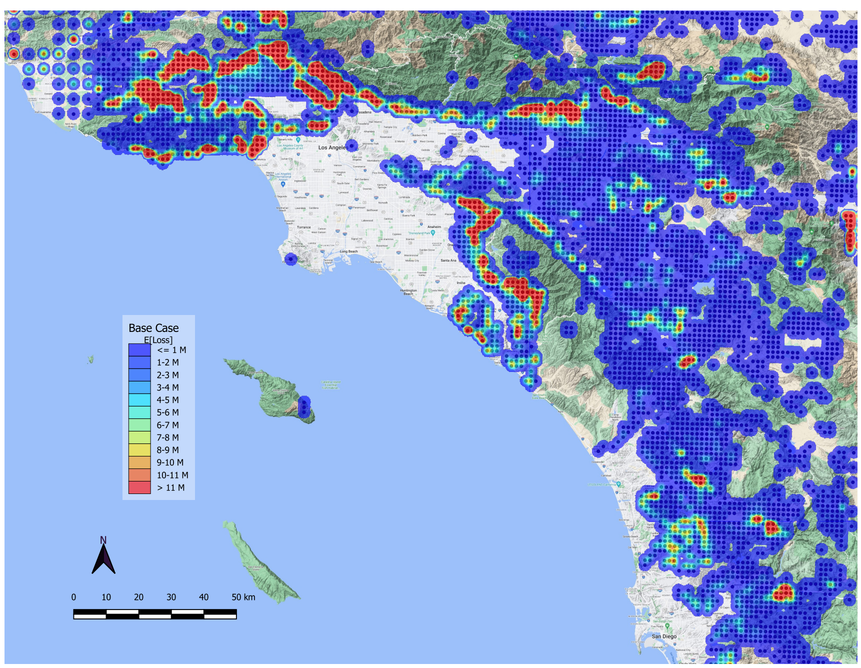
[37] See Wall Street Journal articles https://www.wsj.com/articles/state-farm-halts-home-insurance-sales-in-california-5748c771 and https://www.wsj.com/articles/allstate-stops-selling-new-home-insurance-policies-in-california-citing-wildfire-risks-2827174.

[38] See https://www.spglobal.com/marketintelligence/en/news-insights/latest-news-headlines/aig-to-exit-california-homeowners-insurance-market-at-january-end-68512476.

Figure 10: **The San Francisco Bay Area and the Los Angeles Basin expected annual 2020 assessed value losses (in millions of dollars) due to wildfires.** The upper panel of this figure presents a plot of the average expected losses from 2001 through 2015 measured in 2020 assessed values from a climate shock of 2.00 degrees Fahrenheit to observed maximum daily temperature (corresponding to a 0.16644 standard deviation shock to the maximum temperature for a day) for the San Francisco Bay Area. The lower panel presents the average expected losses over the same period from the same climate shock for the Los Angeles Basin area including San Diego. The scale of the color coding ranges from red, which indicates a loss of greater than $11 million, to dark blue, which indicates a loss of less than $1 million.



(a) Northern California: Bay Area



(b) Southern California: Los Angeles Basin fraction of damages accrued from the 20-year historical mean rather than statistical, or actuarial, models such as the model estimated for our value at risk evaluation. Additionally, the CDI does not allow for the costs, or changes in the cost, of reinsurance risk to be included in insurer rate requests. As a result, California's annual rates now rank next to the lowest in the U.S. (see Oh et al., 2022) perhaps threatening the future ability of California homeowners to successfully rebuild and continue to make their mortgage payments after large and destructive wildfires.[39]

On September 21, 2023, California Governor Gavin Newsom issued an Executive Order to authorize the State Insurance Commissioner, Ricardo Lara, to exercise his authority to stabilize California's property insurance markets.[40] At the same time, the CDI introduced the California Sustainable Insurance Strategy, which will allow insurance carriers in the future to apply forward-looking catastrophe models to more accurately accurately assess and price climate-related risks in exchange for expanded property insurance coverage in risky areas.[41] The insurance commissioner's office is currently in the process of developing regulations for how exactly the new models can be used for rate setting in the future.[42]

6 Conclusions and policy implications

This paper studies the effects of wildfires on housing and mortgage markets. We motivate our empirical investigation with a simple game-theoretic model of homeowners' decisions to rebuild or improve their homes, taking into account both neighborhood externalities and insurance. The model shows that the presence of neighborhood externalities may lead to a "prisoner's dilemma" outcome in the absence of a fire. In contrast, for post-wildfire homeowners with fire casualty insurance, the cost of rebuilding is borne by an insurance company, which, for certain parameters, can overcome the coordination problem. Our model directly supports our inquiry into whether house sizes and prices are positively affected by the incidence of a wildfire due to the coordinating effects of neighborhood rebuilding activity and insurance coverage. Our empirical results indicate that on average five years after the wildfires that occurred in California between 2001 and 2015 there were significant increases in house prices and sizes and little effect on mortgage terminations. Additionally, we find little evidence of gentrification, as measured by changes in the logarithm of household income in the wildfire treatment areas.

Recent supportive evidence that our modeling framework and empirical results, based on the 2001 through 2015 era of California wildfires, have more general implications for the rebuilding dynamics found in more recent burn areas such as the Paradise California 2018 Camp Fire that destroyed 9,700 single family residential homes and killed 85 people. According to the City of

[39] From 2012 to 2021, the direct incurred loss ratio was 59.7% in the U.S. and 73.9% in California. Direct underwriting profit was 3.6% in the U.S. and −13.1% in California. Since 2022, AIG and Chubb have left the high-value home insurance market. State Farm, Farmers, Allstate, USAA, Travelers, and Nationwide have all either limited or paused writing new policies. (https://www.insurance.ca.gov/01-consumers/180-climate-change/SustainableInsuranceStrategy.cfm).

[40] https://www.gov.ca.gov/wp-content/uploads/2023/02/Feb-13-2023-Executive-Order.pdf.

[41] https://www.insurance.ca.gov/01-consumers/180-climate-change/SustainableInsuranceStrategy.cfm.

[42] https://www.politico.com/news/2023/09/21/newsom-orders-action-on-wildfire-insurance-00117488.

Paradise, as of August 9, 2023, there have been 2,926 single family building permit applications received, 2,702 single family building permits issued, and 2,042 certificates of occupancy issued. The significant rebuilding activity has occurred even after a wildfire that was the most destructive in California history and destroyed much of the pre-fire infrastructure of the town of 26,000.[43] Similar to the results of our study, we find five years post-fire that of the 1,416 rebuilt single family residential Paradise homes (78% of these homes were destroyed by more than 50%),[44] the average square footage of the rebuilt homes is 86.94 square feet larger than the 2017 pre-fire square footage of the burned homes and the rebuilt houses are more valuable with an average change in the assessed value from the 2017 assessed value of $62,982. Of the rebuilt single family residential homes that remained owned by the same owner pre- and post-fire, the rebuilt homes are on average 141.5 square feet larger and are more valuable by a $50,902 change in the pre- and post-fire assessed value. These dynamics are especially remarkable given that the Camp Fire occurred after the passage of California Senate Bill 1800, which significantly reduced the requirements to rebuild in place after wildfires.[45]

The Paradise fire also provides further out-of-sample supportive evidence for our model calibration. There are two nearest nodes to Paradise, one north of the town and the other south. Compared with the overall average estimated annual probability of fire of 1.35%, the estimated probability for the Paradise North node is 6.5% and for the Paradise South node is 3.4%. Thus we accurately indicate the relatively high likelihood of wildfire risk to Paradise, even though our sample included no actual wildfires for those nodes.

The more sobering policy implications of this study are associated with our model-based estimation of the expected residential real estate losses from wildfires given reasonable shocks to maximum temperature and its associated effects on wind speeds and relative humidity. All of the results reported in the paper precede the 2023 departures of major casualty insurance carriers from the state, especially for new issuance of residential fire casualty insurance policies. The effects of current insurance regulation policies — which prohibit the use of probabilistic models to price wildfire risks to single-family residential properties — and perhaps other frictions, such as not allowing reinsurance rates to be included in the rate structure, appear to be leading to serious risks to California homeowners and their ability to access the U.S. mortgage market (which requires homeowner insurance).

These issues have led to very large increases in the reliance of California homeowners on the California Fair Plan, which was never intended to provide long-term insurance products for the current expected levels of wildfire risk. They also underlie the regulatory aims of the 2023 California Sustainable Insurance Strategy, which are stated as:

1. **Increasing Insurance Availability and Access:** The strategy seeks a commitment from insurance companies to write a minimum of 85% of their statewide mar-

[43]See https://makeitparadise.org/weekly-updates/town-of-paradise-weekly-update-8-9-2023/
[44]https://calfire-forestry.maps.arcgis.com/apps/webappviewer/index.html?id=5306cc8cf38c4252830a38d467d33728.
[45]https://legiscan.com/CA/bill/AB1800/2017.

ket share in historically underserved areas identified by the Insurance Commissioner. This ensures that insurance remains available to all, especially in high-risk regions.

2. **Decreasing FAIR Plan Policyholders:** Priority is given to homes and businesses that mitigate wildfire risk by following the Insurance Commissioner's *Safer from Wildfires* regulation facilitating a return to the open market and increasing options for consumers.
3. **Allowing Catastrophe Models and Mitigation:** The strategy incorporates new catastrophe risk models that consider mitigation and hardening requirements, leading to more accurate risk pricing and offering discounts for consumers. This means more accurate rates for all Californians so they don't pay more than they should.
4. **Modernizing the FAIR plan:** by expanding commercial coverage limits to $20 million per structure the strategy addresses coverage gaps, benefiting homeowner associations, affordable housing, and infill developments.[46]

The specific rules that will be implemented in the future to address the competing demands of this new regulatory strategy are at this time a work in progress.

[46]The strategy also allows for an "exploration of California-only net costs of reinsurance" (https://www.insurance.ca.gov/01-consumers/180-climate-change/upload/Sustainable-Insurance-Strategy-Fact-Sheet.pdf).

A Measurement of wildfire propensity data

As discussed in Section 5, our reduced-form model has three sets of time and location-specific predictors: weather characteristics, physical characteristics, and indicators for peak fire months. The California meteorological data were measured for the years 2000 to 2015 as daily averages of hourly data for urban nodes (measured at latitude and longitude where the nearest nodal neighbors are 1.5 kilometers apart) and for rural nodes (measured at latitude and longitude where the nearest nodal neighbors are 4.5 kilometers apart). We include all of the 48,391 nodes that represent the entire state of CA.

Our nodal measures for weather include daily averages of the hourly maximum temperature, wind velocity, and the relative humidity at maximum temperature (see Vahmani et al., 2019).[47] We also include two indicators for northeasterly originated winds that blow westward, called Diablos, and southeasterly originated winds that blow westward, called Santa Anas. Santa Ana winds have been the driving force behind many of Southern California's most devastating fires (see Billmire et al., 2014; Jin et al., 2013; Kochanski et al., 2013), as have the Diablo winds of Northern California with their similarly low relative humidity, high temperatures, and very high wind speeds (see Bowers, 2018; Keeley and Syphard, 2019; Liu et al., 2021).

The physical variables include measures at each node for the slope and elevation.[48] The Wildland Urban Interface (WUI) measures are composite indicators for the degree of urban building intensity (low is 2 to 8 structures, medium is 9 to 120 structures, and high is more than 120 structures) interacted with the proximity to the Wildland Urban Interface measured as either *intermix*, where structures are intermingled with the WUI, or *interface* where structures border the WUI.[49] We also include an indicator variable for vegetation at the node. The fire season is May through October.

The summary statistics for our nodal weather and physical characteristics are reported in Table 4. As shown in the table, the average daily temperature over the period is 28.007 degrees Celsius with a standard deviation of 6.67 degrees Celsius. The average data relative humidity at maximum temperature is 0.321 and the standard deviation is 0.167. The average wind speeds are 2.993 meters per second with a standard deviation of 2.119 meters per second. Diablo The average nodal slope was 11.555 degrees with a standard deviation of 11.941 and the average elevation was 583.817 meters with a standard deviation of 639.543 meters. On average 66% of the nodes had important vegetative coverage. The WUI: low intermix was found in 6.57% of the nodes, the WUI:

[47] The weather data are simulated using a regional climate model, the Weather Research Forecasting (WRF) model coupled with an Urban Canopy Module(UCM) (`https://ral.ucar.edu/solutions/products/urban-canopy-model`) to downscale historical North American Regional Reanalysis (NARR) data (`https://psl.noaa.gov/data/gridded/data.narr.html`) to create nodal measurements at latitude and longitude. The measures were then validated using National Oceanic and Aeronautical Administration (NOAA) measurement station data.

[48] Slope and elevation were measured by the authors using topographical raster data from the U.S. Geological Services (`https://apps.nationalmap.gov/downloader/`) and geoprocessing this information using QGIS software to compute slope.

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

Table 4: **Summary Statistics for the Logistic Regression.** This table presents the summary statistics for the logistic regression for the daily probability of wildfire at nodes in California between 2001 and 2015 over the fire season months of May through October. The weather characteristics are measured as daily averages for each of the 48,391 nodes. The physical characteristics are measured as averages across nodes. The Wildland Urban Interface (WUI) measures are composite indicators for the degree of urban building intensity (low is 2 to 8 structures, medium is 9 to 120 structures, and high is more than 120 structures) interacted with the proximity to the Wildland Urban Interface measured as either *intermix*, where structures are intermingled with the WUI, or *interface* where structures border the WUI. We also include an indicator variable for vegetation at the node.

Logistic Regression Variables	**Mean**	**Std. Deviation.**
Weather characteristics (Time series of daily measurement)		
Temperature (degrees Celsius)	28.007	6.676
Relative humidity at time of max temperature	0.321	0.167
Wind speed (Meters per second)	2.993	2.119
Indicator for Diablo Wind	24.86	
Indicator for Santa Ana Wind	30.86	
Physical Characteristics (Cross section across geographic nodes)		
Slope (Degrees)	11.555	11.941
Elevation (Meters)	583.817	639.543
Indicator for Vegetation (Percentage)	60.21	
Indicator for WUI: low intermix (Percentage)	6.57	
Indicator for WUI: med. intermix (Percentage)	1.91	
Indicator for WUI: high intermix (Percentage)	0.01	
Indicator for WUI: low interface (Percentage)	0.99	
Indicator for WUI: med interface (Percentage)	2.48	
Indicator for WUI: high interface (Percentage)	1.30	
No. of observations	110M	
No. of nodes	48,391	
No. of days per year	152	
No. of years	15	

medium intermix was found on 1.91% of the nodes, and the WUI: high intermix was found on only 0.01% of the nodes. The WUI: low interface was found in 0.99% of the nodes, the WUI: med interface was found on 2.48% of the nodes, and the WUI: high interface was found on 1.3% of the nodes. All of the integer variables for the logistic regression were rescaled to standard normal variates to reduce the dispersion in the measurement units of the variables.

B Expected wildfire-related losses to housing value

To account for the assessed value of the housing stock, we geoprocess every property in our ATTOM Data Solutions administrative data into its respective node location and then measure the at-risk property value as the ATTOM reported property tax assessed value in 2020.[50] The merge of the housing data with the nodal locations leaves us with 18,780 housing-endowed nodes, 9,114,700 housing units, and an assessed value of $4.2 trillion.

As discussed in Section 5, we apply the logistic regression model to compute the expected daily probability of wildfire for the actual (or shocked) average daily weather and WUI characteristics of each node for each year. As a control for the differential characteristics of the housing stock in the node, we replace the measure of the node's slope and elevation with the weighted average slope and elevation of all properties that are located close to the node. To compute the expected annual property losses (base case and shock case), we assess each node's yearly survival probability (measured as the product of one minus the assessed nodal probability) for the annual fire season (152 days). The expected annual property loss is given by the sum over all nodes of the product of ATTOM's assessed 2020 property value for the node and calculated annual nodal survival probability. The base case for the expected effects of wildfire on the California housing stock is calculated as the 2020 assessed value of the residential properties within each node times the expected daily probability of wildfire for each node.

For this calculation, we are making the strong assumption that the log-odds of wildfire and the losses given wildfire are the same as each other. We are also assuming that the losses to the housing stock are pre-insurance payouts, thus they represent the potential exposure of the insurance industry to wildfire casualty claims. To reduce the impact of the large urban Central Business Districts (CBD) with multi-story housing density located in nodes with essentially zero probability of wildfire, we further filter out all nodes with an average annual wildfire probability of less than 0.15%. This further filter reduces our VaR calculation sample to 4,752,238 non-CBD properties with a 2020 assessed value of $2.045 trillion located in 14,393 nodes.

To measure the expected effects of a climate change shock, we re-calculate the expected probability of wildfire at each node given a 2 degree Fahrenheit shock to each node's maximum daily temperature (0.17 standard deviations). For this calculation, we control for the average correlations between maximum temperature, wind speed, and relative humidity over the period 2001 through

[50] We anchor the assessed values at their 2020 reported values so as to distinguish the effect of the maximum temperature shock from differences in the annual levels of property assessed valued and size of the housing stock over time. Our use of the 2020 tax assessed value is likely to be an underestimate due to the effects of property 13.

2015. We measure the expected effects of the shock to maximum temperature on the wildfire risk as the estimated shocked wildfire probability within each node times the 2020 assessed value of properties in the node. Here again, we assume that the log-odds of the probability of wildfire and the losses given wildfire are the same.

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