Mortgage Performance and Insurance Protections after Natural Disasters*

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Abstract

Diminishing property insurance protections may weaken household financial resilience to natural disasters. We study the effect of California wildfires on mortgage markets and examine insurance protections using novel data on property damages, mortgage performance, and home insurance. Credit risks after natural disasters are greater than previously found and insurance underpayment is significant. Fire damage increases severe delinquency by 3.6 percentage points and prepayment by *16 percentage points*. Insurance settlements are below estimated replacement costs for 39 percent of damaged homes. Underpayment is associated with $190,000 to $284,000 of household losses and 25 percent lower property tax revenue from delayed rebuilding.

Keywords: wildfires, mortgage, prepayment risk, climate risk, physical risk, underinsurance

JEL Codes: G21; G51; Q54

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1 Introduction

The frequency and severity of natural disasters in the United States have increased substantially, costing over $120 billion in damages per year during the past five years (NOAA, 2022). Resulting property damages represent large negative wealth shocks for homeowners. Such shocks can decrease property values, delay mortgage payments, restrict borrowers' access to future credit, and increase lenders' exposure to default risk. Insurance is the primary safeguard to mitigate these risks as it is supposed to fund restoration of damaged property, protect mortgage obligations, and provide liquidity for expenses such as temporary housing.[1] However, insurers in high risk areas have reduced coverage citing the rising costs to insure natural disasters.[2] Diminishing insurance protections may weaken households' financial resilience after natural disasters, which can delay rebuilding of damaged property, lower local tax revenue, and increase credit risk for lenders.

This paper studies the effect of natural disasters on mortgage markets. Then, we quantify the extent of existing insurance safeguards and their impact on households, lenders, and local governments. Specifically, we evaluate mortgage performance after California wildfires by constructing a novel database of property-level damage inspections merged with mortgages and examine insurance protections using administrative home insurance policy and claims data. Analysis of California wildfires provides an informative empirical setting to study the economic effects of natural disasters. Our sample captures a large increase in wildfires since 2017 that reflects a similar rise in physical risks nationwide.[3] Moreover, treatment status is clearly defined because our data precisely measure wildfire damage for each property and the

[1] Cookson et al. (2023) show that crowdfunding and social networks are another source of emergency funding, although these funds tend to accrue to the most well-off.

[2] Several insurers in California, which represent 55 percent of the market share in areas with high fire risk, have stopped writing or capped new policies (Dixon et al., 2018; Kaufman, 2021; Boomhower et al., 2023). Low quality insurers with high insolvency rates and low operational diversification have gained market share in Florida because traditional insurers have renewed fewer existing policies (Sastry et al., 2023).

[3] 13 of California's 20 most destructive fires (by number of structures burned) have occurred since 2017. Billion-dollar disasters of any peril totaled $160 billion in annual damages since 2017, nearly four times the annual damages during the prior 37 years.

distribution of damages is bimodal (properties inside a burn perimeter are either undamaged or completely destroyed).

The contributions of this study are to show that natural disasters present greater risks to mortgage markets than previously quantified and that insurance underpayment exacerbates these risks and reduces household welfare and local tax revenues. We estimate a larger increase in both mortgage delinquency and prepayment rates for damaged properties than existing research, which finds that different perils (e.g., hurricanes, floods, tornadoes) and events (e.g., Hurricanes Harvey and Katrina) lead to small and short-lived increases in delinquency, default, and foreclosure because of insurance, government aid, and hazard mitigation efforts.[4] We attribute our larger estimates to precise measurement of damages, which mitigates attenuation bias, and to the fact that wildfires cause total losses of property. Our reduced-form parameter estimates include existing protections from insurance and government aid, which suggests that risks for mortgage markets will increase if climate scenarios worsen and safeguards weaken. For example in California, greater wildfire risk and a rise in insurer-initiated policy nonrenewals have shifted households toward more expensive insurance with basic fire coverage through Fair Access to Insurance Requirements (FAIR) plans, the state-sponsored insurance of last resort.

We highlight insurance underpayment as a novel mechanism leading to elevated mortgage prepayment, reduced rebuilding, and financial losses for households and local governments. Households receive settlements that are below estimated replacement costs and are not sufficient to rebuild. These insurance market frictions leave fully insured households with large financial deficits in the aftermath of a natural disaster. Households instead use settlements to pay off their mortgage, leading to higher prepayment rates, and many eventually sell their damaged property at a deep discount without rebuilding. Therefore, insurance underpayment effectively shifts the default risk associated with natural disasters to prepayment risk, thereby mitigating banks' and securities investors' exposure by a lesser degree than

[4]See Gallagher and Hartley (2017); Kousky et al. (2020); Ratcliffe et al. (2020); Du and Zhao (2020); Issler et al. (2023); Billings et al. (2022); Panjwani (2022) and An et al. (2022, 2023).

expected. Ultimately, the lack of rebuilding of damaged properties for several years after a wildfire results in tax revenue losses for local governments.

Our analysis yields three key findings. First, we find that wildfires lead to large increases in the delinquency rates for properties that are damaged. In contrast, the delinquency rates for undamaged properties within the fire perimeter remain statistically unchanged after the fire. Different effects of wildfires on damaged and undamaged properties within a fire perimeter highlight the need to precisely measure treatment groups exposed to a wildfire using property-level damages instead of commonly used fire perimeters. In our sample, 55 percent of properties and 58 percent of mortgages within the perimeter remain undamaged. The measurement error introduced by using fire perimeters as a proxy for property damage is exacerbated in California, where stronger building codes specific to wildfires have made newer properties significantly less likely to be destroyed from exposure to a wildfire (Baylis and Boomhower, 2021).[5] Our findings, combined with those of Baylis and Boomhower (2021), suggest an important role for ex-ante disaster mitigation in reducing the physical damages from wildfires and the consequent risks to households, lenders, and local governments.

Second, we estimate that wildfires substantially increase prepayment for damaged properties, which can be an inefficient use of insurance funds; indicate financial losses for households; and pose risks to lenders, servicers, and mortgage-backed securities (MBS) investors. Insurance and government aid reduce lenders' exposure to the default risk caused by natural disasters, but households may use assistance to pay off mortgages and other debts (Gallagher and Hartley, 2017; Gallagher et al., 2023).[6] For lenders, prepayment results in lost interest revenue, which is larger during a low prevailing interest rate period. For MBS investors, prepayments represent the primary credit risk and also change the composition of the securities pools. Kahn et al. (2024) show that wildfire risks affect the whole securitization chain from

[5]Fried (2022) develops a model of climate adaptation and similarly finds that adaptation, such as investments in seawalls and stilts, would reduce the damage from more severe and more frequent storms by one-third.

[6]Damages from natural disasters, except for floods and earthquakes, are covered under the home insurance required by mortgage lenders. Households may, and can be required to, purchase flood insurance through the National Flood Insurance Program administered by the Federal Emergency Management Agency (FEMA).

mortgages to MBS cash flows and while wildfires can generate losses for MBS deals, wildfire exposure can be an important aspect of diversification for investors.

Third, we provide evidence that insurance settlements are not sufficient to rebuild. Our findings rule out the traditional mechanisms of a property sale or refinance as reasons for the observed increase in prepayment. After a wildfire, a household may use insurance settlements toward the rebuilding of the damaged home, the purchase of a new home, or the payment of the mortgage balance. The last alternative results in a mortgage prepayment. A large increase in prepayment, that is not driven by sales or refinances, indicates that many affected households do not use their insurance settlements to rebuild the damaged home or purchase a new home. Indeed, we show that properties destroyed by fires on average receive settlements that are much lower than the insurer-estimated replacement costs that determine coverage limits. When such underpayment occurs, households face strong incentives to apply insurance funds toward the mortgage balance instead of rebuilding. Importantly, we find that underpayment leads to a significant loss of local property tax revenue from damaged properties that persists over several years after a fire because destroyed structures are not restored and property assessments drop.[7]

For our empirical analysis, we construct a novel database linking property-level fire damage to mortgage performance and estimate the effect of 81 wildfires in California on mortgage borrowers' likelihood of delinquency (90 days or more past due) and prepayment (full balance repayment ahead of schedule). We combine wildfire perimeters, property-level damage inspection reports for wildfires that burn at least 1,000 acres and damage at least one structure, and mortgage performance data from 24 large banks between 2013 and 2020. Using a difference-in-differences (DiD) design with multiple treatments, we separately identify the impact of wildfires on both damaged and undamaged properties within fire perimeters relative to our control group of properties located 1 to 2 miles outside of the fire perimeters. We estimate an event study specification, which provides evidence in support of the identifying

[7]Tax implications are exacerbated in California, where Proposition 13 further limits the ability to increase tax revenues from undamaged properties to stabilize public finances.

assumption of parallel trends and shows the impact on mortgage repayment in the 24 months after a wildfire. We find a statistically and economically significant increase in both delinquency and prepayment within the first three months after a fire for damaged properties. Delinquency rates increase by as much as 3.6 percentage points, and prepayment rates increase by as much as 16 percentage points. Before the fire, the average delinquency rate is 1.1 percent, and the average prepayment rate is 1.2 percent. We find no significant changes in delinquency or prepayment for undamaged properties located within a fire perimeter.

Next, we use administrative policy and claims data for fire-related insurance coverage in California to show that insurance settlements are too low to cover rebuilding costs after fires. Almost 39 percent of post-fire insurance claims are underpaid, meaning the settlement received is lower than the coverage limit, which in most cases is the insurer's ex-ante estimate of the replacement cost for a destroyed property. Households receive settlements that are 26 percent lower than the anticipated rebuilding costs. Underpayment provides strong incentives for households to prepay their mortgage with insurance funds instead of rebuilding.[8] Furthermore, we find a larger increase in prepayment for homes that face greater rebuilding costs due to more severe fires using a triple-difference design. This result supports survey findings that show reconstruction costs exceed existing coverage in California often because of surges in construction prices after fires (Dixon et al., 2018; United Policyholders, 2022). The impact of insurance underpayment on household welfare is large, as back-of-the-envelope calculations imply that households receive about $190,000 to $284,000 less than the counterfactual of full payment as entitled by California law.

Using building permits data, we confirm that households affected by a wildfire do not rebuild. Only 8.9 percent of owners with a damaged property file a new construction permit in California in the two years following a fire. Moreover, damaged properties transact at a higher rate in the four years following a fire, but sale prices decrease by 54 to 74 percent from before the fire, roughly equivalent to the structure share of property values in California. We

[8]We rule out other likely deteriminants of prepayment because any increase in sales and refinances for damaged properties is not quick or large enough to result in an immediate increase in prepayment.

also observe an uptick in new construction loans taken out *after* the damaged property is sold. Based on these findings, we infer that homeowners use their insurance funds to pay off the mortgage, sell the property as a land sale with a destroyed structure, and the new owner borrows a construction loan to rebuild the property. The lack of rebuilding has large public finance implications as property tax revenue from damaged homes decrease by 35.3 to 47.8 percent in the three years following a fire. Underpayment seems to be the primary driver, as the average underpayment rate is associated with a 24.8 percent reduction of property tax revenue among damaged homes relative to no underpayment.

Our results show that wildfires pose a greater risk to mortgage markets than the findings of previous research. After large wildfires, McConnell et al. (2021) find no statistical difference in mortgage repayment, while Issler et al. (2023) find no change in mortgage default and small decreases in prepayment. An et al. (2023) find small increases in delinquency rates for mortgages, credit cards, and personal loans. We estimate that wildfires lead to a much larger increase in mortgage delinquency and prepayment. Our results differ because damage inspection data provide a more precise measurement of property-level damages than these studies' use of wildfire burn perimeters. As many properties inside a burn perimeter do not sustain damage, it is likely that measurement error in identifying treatment groups attenuates the impact of wildfires on mortgage repayment estimated by these studies.[9] Our sample also has a higher concentration of more severe fires occurring after 2017 than the analysis of prepayment in Issler et al. (2023), which further explains the difference in results. Through this paper's focus on mortgage delinquency and prepayment, we identify the immediate frictions that households face when determining whether to rebuild or walk away from a damaged property, and therefore complement the other studies' focus on long-run migration, home prices, and household spending patterns.

This paper is also related to the broader literature on the economic effects of climate risk. Studies of the impact of climate risk on household welfare consider home values, migration,

[9]The magnitude of our estimates of the increase in delinquency for undamaged properties within the fire perimeter is similar to the impact on all properties within a fire perimeter estimated by Issler et al. (2023).

and labor market outcomes. While analyses of the impact of rising sea levels on house prices has yet to reach a consensus, several papers find negative but temporary effects of hurricanes and floods on home prices (Atreya et al., 2013; Ortega and Taşpinar, 2018; Gibson and Mullins, 2020; Fang et al., 2023; Addoum et al., 2021).[10] Similarly, large hurricanes have a small and transitory negative impact on affected individuals' employment, income, and liquidity (Farrell and Greig, 2018; Deryugina et al., 2018; Groen et al., 2020). However, several studies find that large disasters lead to higher out-migration (Deryugina et al., 2018; Boustan et al., 2020; McConnell et al., 2021). From a banking supervision perspective, climate risk may also impact financial systems. Generally, the research on this topic utilizes a stress-testing framework to assess repayment and bank losses under different climate scenarios.[11]

In the remainder of this paper, Section 2 describes our data on wildfire-impacted areas and subsequent loan performance. Section 3 outlines our empirical strategy, and Section 4 presents the estimation results. Section 5 discusses insurance underpayment after wildfires. Section 6 highlights the welfare implications of our findings, and Section 7 concludes.

2 Data

2.1 Data Sources

We rely on five data sets. Wildfire burn perimeters are obtained from Monitoring Trends in Burn Severity (MTBS). Parcel-level wildfire damage reports are provided by CAL FIRE's Damage Inspection (DINS) database. Parcel locations, transactions, and building permits

[10] See Canals-Cerdá and Roman (2021) and Bakkensen et al. (2023) for comprehensive summaries. Several studies find a house price penalty in areas with a high sea-level rise (Bernstein et al., 2019; Baldauf et al., 2020; Keys and Mulder, 2020), while other studies do not (Atreya and Czajkowski, 2019; Murfin and Spiegel, 2020; Hino and Burke, 2021). Heterogeneous climate beliefs may drive differences in the estimated effects of climate risks on home prices and mortgage markets (Bakkensen and Barrage, 2022; Bakkensen et al., 2023).

[11] Researchers and central bankers have conducted stress tests that evaluate transition risks in Colombia (Sever and Perez-Archila, 2021), Europe (Battiston et al., 2017), France (Clerc et al., 2021), Mexico (Roncoroni et al., 2021), the Netherlands (Reinders et al., 2020; Vermeulen et al., 2021), and Norway (Grippa and Mann, 2020). An et al. (2022) focus on physical risks and find that greater hurricane damages under future climate scenarios lead to a significant increase in mortgage delinquency and a smaller increase in default, primarily mitigated by existing disaster assistance.

are obtained from CoreLogic Solutions (CoreLogic). Finally, mortgage origination and performance history are from FR Y-14M regulatory data. All results presented in the figures and tables of this paper are derived from calculations based on these five data sets unless otherwise noted. Details on the contents and usage for each of these data sets are described below.[12]

2.1.1 MTBS Wildfire Perimeters

Monitoring Trends in Burn Severity (MTBS) is an interagency program conducted by the U.S. Geological Survey (USGS) and USDA Forest Service that is dedicated to mapping the spatial extent of wildfires in the United States (Eidenshink et al., 2007). MTBS delineates wildfire burn perimeters by utilizing Landsat satellite imagery to analyze changes in burned areas before and after wildfire events. This data set includes all wildfires that burned over 1,000 acres in the western United States and over 500 acres in the eastern United States from 1984 through 2020. Because we focus only on wildfires for which parcel-level damage reports are also available, our sample of fires is restricted to the subset of California wildfires occurring between 2013 and 2020 that burned at least 1,000 acres and damaged at least one structure. These 81 wildfires are plotted in Figure 1. While fires that burned under 1,000 acres are not included in our sample, the 81 fires included account for 98 percent of the structure damage caused by wildfires in California from 2013 through 2020.

2.1.2 CAL FIRE Damage Inspection Data

CAL FIRE's DINS database identifies the universe of parcels that were damaged or destroyed by wildfires from 2013 through 2020 (California Department of Forestry and Fire Protection, 2020).[13] For each parcel, damage is assessed by in-person visual inspections by teams of

[12] All analysis was done using the high-performance computing cluster hosted by the Center for the Advancement of Data and Research in Economics (CADRE) at the Federal Reserve Bank of Kansas City (Lougee et al., 2018).

[13] Data was obtained by the authors through a public records request.

damage inspection specialists. The final data set identifies the extent of the damage (no damage, affected, minor, major, destroyed), the assessor parcel number, the parcel location (latitude/longitude), the parcel address, and limited structure characteristics.[14] Unaffected parcels are not included for most of the fires. Among the parcels that sustained wildfire damage, 92 percent are classified as destroyed (see Figure A.3). Therefore, we do not consider the intensive margin of destruction and instead classify parcels as damaged or undamaged.

2.1.3 CoreLogic Residential Public Records

We use CoreLogic public records to identify parcel-level latitude/longitude locations, addresses, and assessor parcel numbers (CoreLogic, 2020). In addition to parcel location and building characteristics, we also obtain information on property transactions, including transaction type (e.g., mortgage, refinance, construction loan) and sale price. For each fire-month, we calculate the distance (in meters) from each parcel to the closest MTBS wildfire perimeter. We retain parcels that fall either within a wildfire perimeter or 1 to 2 miles ($\sim$ 1.6 to 3.2 kilometers) outside a wildfire perimeter in a given month. For parcels falling within a wildfire perimeter, we classify them as damaged or undamaged by merging with DINS data. Recall that DINS contains the universe of damaged parcels but generally does not include undamaged parcels. Therefore, we classify any parcel with a DINS designation of "no damage" and any parcel falling within the fire perimeter but not included in DINS as undamaged.

Figure 1 displays an example of the parcels included in our analysis and the corresponding damage status for the Camp Fire, which burned over 14,000 single-family residences in Northern California in 2018. As shown, not all properties in the burn perimeter sustain damage, even for the largest fire in our sample. Across all fires, 58 percent of our mortgage sample and 55 percent of our properties sample within burn perimeters do not sustain damage, underscoring the importance of incorporating DINS data in addition to wildfire perimeters in order to identify damaged parcels.

[14] See Figure A.1 for an example damage report and Figure A.2 for details on each damage category.

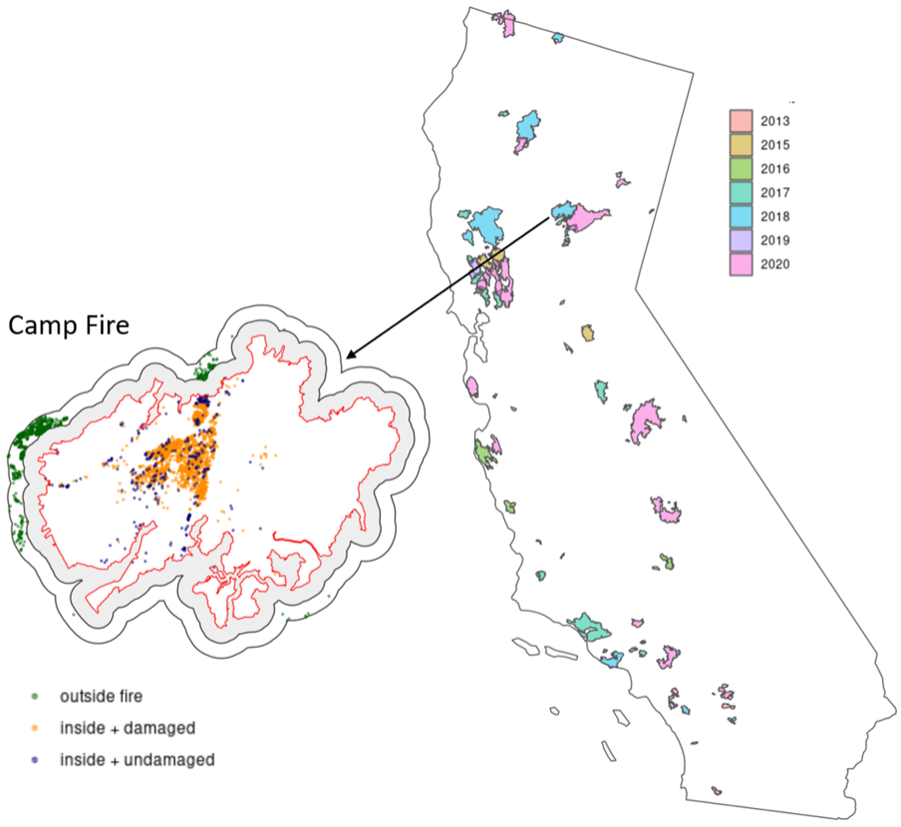


Figure 1: Donut Design of Regression Framework

Note: Figure illustrates wildfire boundaries for all wildfires between 2013 and 2020. Inset shows the wildfire boundary of the Camp Fire as well as the status of properties matched to that fire. Within the boundary, red dots denote homes that were damaged by the wildfire and green dots denote structures that were not affected by the wildfire. The gray ring is the omitted region of properties less than a mile from the wildfire boundary. The outer ring with blue dots indicates structures that are within 1 to 2 miles of the wildfire boundary.

2.1.4 CoreLogic Building Permits

We use CoreLogic building permits data to identify post-disaster construction activity. The data are collected from individual municipalities' permitting offices (instead of county tax assessor offices for public records data). Since our focus is on post-disaster building activity, we focus on permits related to new construction. By merging this data with the CoreLogic public records data, we are able to identify which parcels were rebuilt (or in the process of being rebuilt) and which parcels did not have any new construction following a wildfire.

2.1.5 Federal Reserve FR Y-14M Mortgage Performance

We obtain monthly mortgage performance history and origination characteristics for first-lien loans from FR Y-14M (Federal Reserve, 2020). Large banks submit these data to the Federal Reserve as part of the stress testing program, with our sample including 24 institutions. These data are collected monthly starting in June 2012 and contain monthly loan performance, borrower characteristics, and property characteristics. The monthly performance history allows us to identify loans that are delinquent or have been prepaid. The borrower characteristics include credit score, debt-to-income ratio, loan-to-value (LTV) ratio, loan term, loan purpose, loan amount, and interest rate. The property characteristics include the address, which allows us to identify the property's fire damage treatment status.

2.2 Data Construction

We combine the data from Section 2.1 to generate a loan-fire-month data set and a property-fire-month data set. For the loan-level data set, we match every fire event with all loans on single-family residential properties inside or within 1 to 2 miles of the wildfire boundary. For each loan-fire, we then pull in the loan performance data starting 24 months before the fire through 24 months after the fire. Therefore, for each fire, we have a balanced four-year

window of mortgage performance data.[15] For the property-level data set, we additionally include homes for which we do not observe a mortgage in order to track property transactions before and after the fire. We match all single-family residences inside or within 1 to 2 miles of the wildfire boundary to a damage status. As shown in Table 1, our analysis sample includes 84,413 loan-fire observations, which account for 24.8 percent of the 340,543 property-fire observations.[16]

Table 1: Sample Construction

Sample	Inside + Damaged	Inside + Undamaged	Outside Fire	Total
Single Family Houses	23563	28829	288151	340543
Mortgages	5230	7361	71822	84413

While this construction is generally clean, there are a few notable complications that must be addressed. First, the same loan may be affected by multiple fires. If these fires are more than 24 months apart, then we treat them almost as separate observations (still including only one loan fixed effect). Our key assumption is that any effects of the wildfire should fade out after two years. Second, loan-fire histories may overlap (e.g., the same loan may be affected by a fire only one year after it was affected by another fire). In these cases, we opt to keep the loans in our analysis, but we drop the pre-fire periods that overlap with the post-fire period of another fire. This does create an unbalanced panel for loans that are affected, but because of the disastrous nature of wildfires, our view is that including post-fire observations as pre-fire controls for another fire would incorrectly identify those loans as "unaffected" by a wildfire at that point in time.

Table 2 contains borrower-level summary statistics by treatment group in the month before a wildfire. The first column presents mean borrower characteristics, loan terms, and property characteristics for all properties in our sample outside the fire zone, which represents

[15] Prepayment is considered a terminal state, and we assume that the loan maintains that status for the full duration of our observation window.

[16] An estimated two-thirds of California homes have a mortgage, which implies that our mortgage sample accounts for 35 percent of all mortgages in the fire perimeter and surrounding 1- to 2-mile ring (Johnson, 2022).

our control group. Columns 2 and 3 reports the mean differences, relative to the control group, for damaged properties and undamaged properties inside the fire zone, respectively. Columns 3 and 4 present analagous within-fire mean differences relative the control group. Loan terms and measures of borrower risk (e.g. credit score, debt-to-income ratio, and loan-to-value ratio) are similar for mortgages that are damaged by fires to mortgages that are outside the burn perimeter.

We do note that loan amounts are larger inside the fire zone, which seems to be represented by larger differences in property characteristics across different treatment groups. Properties inside the fire perimeter are larger and located on bigger lots. Furthermore, undamaged homes inside the fire zone are more newly built. These property differences may impact the likelihood of burning – we further discuss how these differences affect the interpretation of our results in section 4.

2.3 Descriptive Analysis

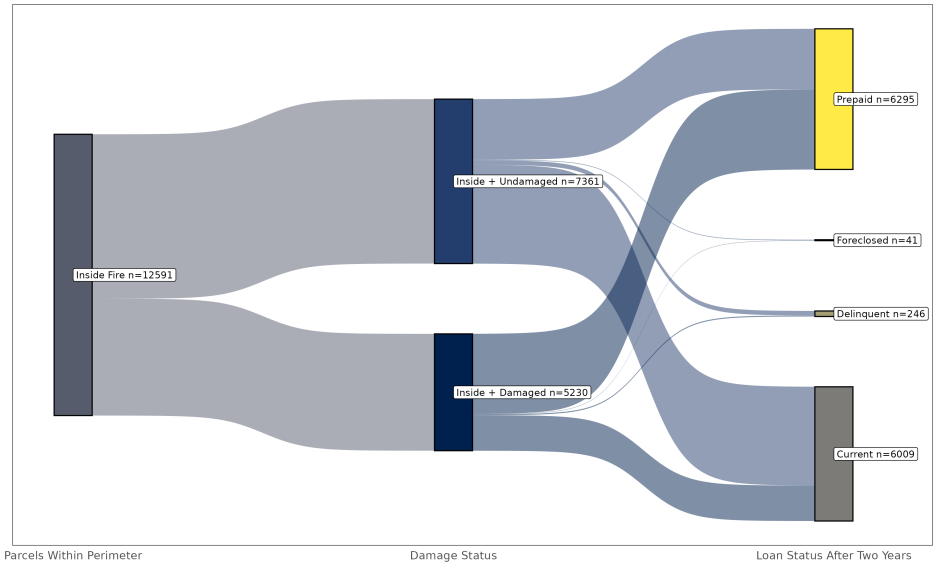
Before proceeding with our empirical strategy, we visually summarize the impact of wildfires on prepayment and delinquency for loans falling within a wildfire perimeter in Figure 2. As shown in the top panel, our sample contains 12,591 parcels inside a wildfire perimeter at the onset of a fire, only 5,230 of which sustain damage. This once again highlights the importance of incorporating parcel-level damage reports into our analysis; it is not reasonable to assume that all parcels falling within a wildfire perimeter are damaged. Finally, the top panel shows the loan status 24 months post-fire.[17] The bottom panel shows that prepayments increase immediately in the month of the fire and further spike one to two months after the fire. Borrowers also become past due on their mortgage within one to two months after the fire, but the overall share of loans past due subsides six months after the fire. Two years after the fire, most of these delinquencies become current or prepay, with very few loans entering foreclosure.

[17] Figure A.4 provides snapshots of loan performance three and six months after a fire.

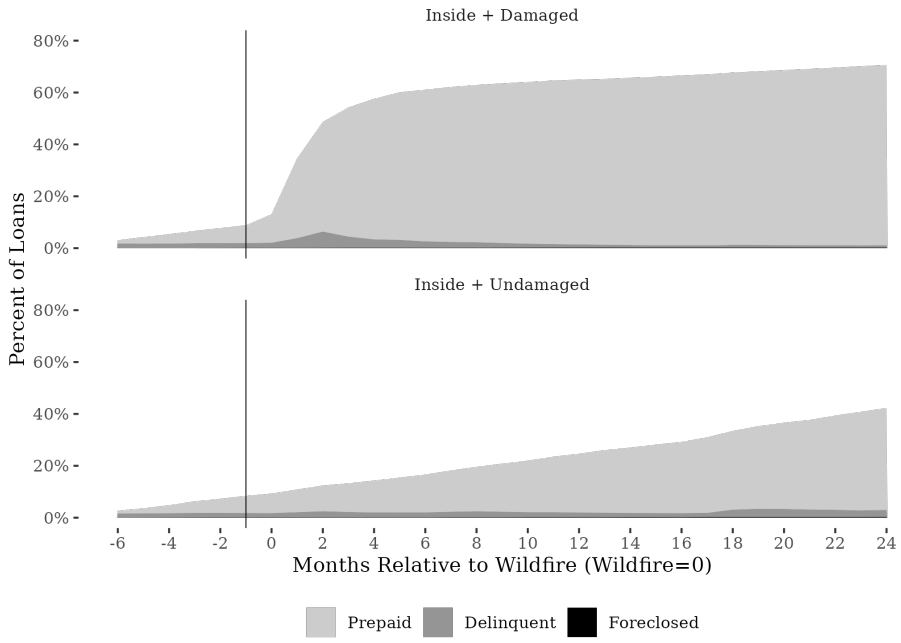
Table 2: Comparison of Summary Statistics across Treatment Groups

	Outside Fire	Damaged	Undamaged	Damaged	Undamaged
	Mean	Mean Difference		Mean Difference within Fire	
Interest Rate	4.055***	0.137	-0.124**	-0.053	-0.170***
	(0.028)	(0.097)	(0.046)	(0.049)	(0.032)
log(Loan Amount)	12.667***	-0.178	0.336***	0.215*	0.347***
	(0.040)	(0.216)	(0.097)	(0.102)	(0.073)
Remaining Balance (%)	80.414***	1.403*	2.743***	0.699	1.233**
	(0.299)	(0.559)	(0.753)	(0.456)	(0.474)
Remaining Term	258.562***	1.917	10.385**	3.3024*	7.344**
	(1.203)	(2.172)	(3.238)	(1.495)	(2.379)
Credit Score	746.904***	0.858	6.743***	1.473	7.666***
	(1.610)	(3.014)	(1.769)	(2.674)	(1.563)
LTV	63.219***	2.005	-2.709*	-3.000*	-3.490***
	(0.586)	(2.879)	(1.074)	(1.266)	(0.817)
Debt-to-Income	25.728***	-2.267***	-1.033**	-0.901**	-1.185**
	(0.277)	(0.495)	(0.395)	(0.314)	(0.379)
Delinquency Rate	0.014***	-0.002	-0.003	0.005*	0.001
	(0.001)	(0.003)	(0.002)	(0.002)	(0.001)
Prepayment Rate	0.017***	-0.005*	-0.005*	-0.000	0.001
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Year Built	1973.895***	4.268	9.618***	3.321	11.511***
	(1.321)	(3.557)	(1.587)	(4.042)	(1.702)
Building Size (Sq. Ft.)	2126.627***	21.991	722.107***	467.410**	771.830***
	(65.070)	(217.752)	(163.568)	(142.456)	(153.139)
Lot Size (Sq. Ft.)	25141.327***	77279.558**	74086.126***	86264.122***	77011.933***
	(2228.999)	(24960.132)	(20266.620)	(20019.476)	(20421.854)
Burn Probability	0.002***	0.002*	0.004***	0.003***	0.005***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)

Note: Table contains loan-level summary statistics by treatment group in the month before the wildfire (event time $t = -1$). Credit score, debt-to-income (DTI), loan-to-value (LTV), and loan amount are as of origination. Interest rate varies by month for adjustable rate mortgages. Delinquent is equal to one if the loan is at least three months behind in event time $t = -1$ and zero otherwise. Prepayment is equal to one if the loan is prepaid in event time $t = -1$ and zero otherwise. Columns 2 and 3 show the mean differences for damaged and undamaged properties inside a fire zone, relative to properties outside the fire zone. Columns 4 and 5 show the within-fire mean differences for damaged and undamaged properties, relative to properties outside the fire zone.



(a) Loan Status Two Years After Fire



(b) Monthly Loan Status

Figure 2: Loan Status Flows After Wildfires

Note: Figure illustrates the decomposition of loans within wildfire boundaries based on whether or not the home was damaged by the wildfire. The top panel shows mortgage status two years post-fire (current, delinquent, foreclosed, or prepaid), and the bottom panel tracks monthly loan status.

3 Analysis

Our goal is to examine the impact of wildfire damage to one's house on delinquency and prepayment risk.[18] In order to estimate the causal effect of wildfires on mortgage repayment, we use a difference-in-differences (DiD) framework with varying treatment intensities. We use quasi-experimental variation from California wildfires, which we measure with our unique data on burn perimeters and property-level damage inspections, to disentangle the impact of fires on damaged homes from the effect on undamaged homes that are within the fire perimeters. For both treatment intensities, our control group consists of properties that are 1 to 2 miles outside of the wildfire boundary. We exclude homes in the 1-mile ring outside of the wildfire and utilize a donut design to mitigate bias from spillover effects on homes directly outside of the fire perimeter.[19]

We use the following framework,

$$Y_{ift} = \beta_1 Damaged_{ift} + \beta_2 InsideFireZone_{ift} + \lambda_{ft} + \lambda_i + \epsilon_{ift},$$

where Y_{ift} is an indicator for our outcome of interest (delinquency or prepayment). $Damaged_{ift}$ is an indicator for whether home i was damaged by fire f in month t. $InsideFireZone_{ift}$ is an indicator for whether home i was not damaged but inside the perimeter of wildfire f in month t. λ_{ft} consists of fire-year-month fixed effects, to control for different time paths for different fires (i.e., separately capture the behavior of nondamaged loans for each fire event). Finally, λ_i is a loan-level fixed effect.

β_1 and β_2 are our coefficients of interest. β_1 estimates the effect of having one's home damaged by a wildfire on prepayment or delinquency relative to homes 1 to 2 miles outside of

[18] Throughout this paper, we use "loan" and "home" interchangeably because it is too cumbersome to write "whether loan i was secured by a property that was damaged by a wildfire." We prefer to refer to homes being affected or damaged by wildfires, while loans become delinquent or are prepaid.

[19] Issler et al. (2023) discuss that homes in the 1-mile ring outside of the perimeter were often visually exposed to the fire and estimate large externalities of the wildfires on these homes.

the wildfire perimeter. β_2 estimates the effect of having one's home inside a wildfire perimeter (but *not* damaged) on prepayment or delinquency relative to homes 1 to 2 miles outside of the wildfire perimeter. Inside the burn perimeter, even undamaged houses may be affected by the wildfire (e.g., having to evacuate, dealing with damaged infrastructure, job interruptions). On the other hand, homes 1 to 2 miles away from the wildfire boundary should not be affected (or at least have a substantially reduced risk of being affected) by the wildfire.

This identification strategy relies on the parallel trends assumption. To provide some evidence that parallel trends hold in the pretreatment periods, we estimate an event study specification:

$$Y_{ift} = \sum_{t=-24;t\neq-1}^{t=24} \beta_{1t} Damaged_{ift} + \sum_{t=-24;t\neq-1}^{t=24} \beta_{2t} InsideFireZone_{ift} + \lambda_{ft} + \lambda_i + \epsilon_{ift}. \quad (1)$$

Several recent studies have documented the challenges of using such two-way fixed-effect regressions to identify the average treatment-on-the-treated effect, ATT (Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021; Borusyak et al., 2021; Sun and Abraham, 2021). These papers show that applications often use earlier-treated groups as controls for later-treated groups, which can lead to estimation bias, and may not contain never-treated groups, which can lead to underidentification.

To address these concerns, we follow a "stacked regression" design in which λ_{ft} interacts our time fixed effect with each fire event (Cengiz et al., 2019; Baker et al., 2022; Bradt and Aldy, 2022). Therefore, these threats to identification do not apply to our within-fire comparison because, for each fire, treatment occurs simultaneously at a single date for the treatment group, and the control group remains as the never-treated group. Our results do not change if we include a vector X_{ift} on the right hand side of Equation 1 to control for time-varying borrower and loan characteristics, such as current interest rate, credit score, and the share of balance remaining. The similarity in results across specifications alleviates concerns that the impact of treatment on these controls may bias estimates of β_1 and β_2

(Caetano and Callaway, 2023; Roth et al., 2023). Finally, we report standard errors clustered at the zip code level for all of our results.

4 Results

The top panel of Figure 3 shows that there is little evidence of pre-trends in delinquency for loans within the wildfire perimeter (whether damaged or not). We see a dramatic increase in delinquency starting three months after the fire and peaking at 3.6 percentage points within four to six months after the fire.[20] The increase then gradually declines in the six to 24 months after the fire, likely either due to loans curing (from being made whole from insurance payments) or because loans continue into default and are no longer reported as delinquent. For similar homes within the wildfire boundary that are not damaged by the wildfire, there is no significant change in delinquency after the fire. At best, there may be a muted 0.4 percentage point increase in delinquency four months after the fire, but this quickly fades back to be indistinguishable from zero. While there may be some minor effects of wildfire on undamaged houses, those possible effects pale in comparison with the dramatic increase in delinquency seen for damaged houses.

As a benchmark, the 3.6 percentage point increase in delinquency is *three times* the average delinquency rate of 1.1 percent. Such a large increase in delinquency may impact banks' liquidity but nonetheless provides a transitory view of mortgage performance. Therefore, we focus the remainder of the paper on the impact of wildfires on mortgage prepayment, which is the most common terminal state for our sample of loans inside fire perimeters. Within two years after a fire, almost all of the loans inside a fire perimeter are either current or are prepaid (Figure 2). In our sample, only 41 properties are foreclosed and 246 remain delinquent after two years.

[20] Since we define delinquency as 90 days past due, three months is the fastest a loan can become delinquent if the fire is the triggering event.

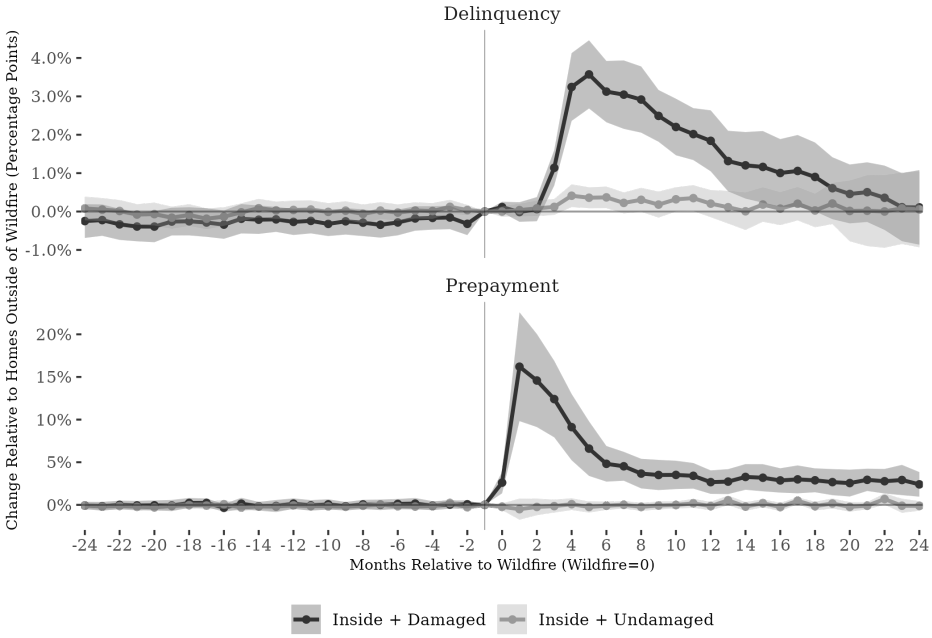


Figure 3: Event Study of Wildfire on Delinquency and Prepayment

Note: Figure illustrates the coefficients for damaged (β_{1t}) and undamaged (β_{2t}) parcels estimated from the event study specification in Equation 1. The top panel presents results for delinquency and the bottom panel presents results for prepayment. Regression controls for fire-month and loan fixed effects. Shaded regions indicate 95% confidence intervals clustered by zip code.

The bottom panel of Figure 3 shows that there is little evidence of pre-trends in prepayment for loans within the wildfire perimeter (whether damaged or not). Immediately after the fire, we see a dramatic increase in prepayment of about 16 percentage points; it then gradually declines (but is still elevated) for 24 months after the fire. For similar homes within the wildfire boundary that are not damaged by the wildfire, there is no significant change in prepayment after the fire. As a benchmark, the 16 percentage point increase in prepayment is *thirteen times* the average prepayment rate of 1.2 percent. Accumulating these impacts over time, we find that 68 percent of damaged properties prepay within two years after a fire. Properties that are undamaged or outside the fire perimeter prepay at a substantially lower rate of 37 percent and 33 percent, respectively.

4.1 Robustness

The lack of evidence for pre-trends in our results suggests the parallel trends assumption likely holds. As a result, our estimates of β_1 and β_2 identify the average treatment-on-the-treated effect, ATT, for two treatment groups relative to homes outside of fire perimeters: damaged properties and undamaged properties inside a fire perimeter. However, this does not imply that we recover the average treatment effect, ATE, which would require that both burn perimeters and fire damage occur randomly. While the timing of the fire is plausibly random, one concern may be that the assignment of a property to a damaged treatment status may not be random as household investments in property adaptations impact the likelihood of burning (Baylis and Boomhower, 2021). A randomized comparison in the setting of a natural disaster likely does not exist.

While the ATE is additionally useful to understand the impacts of a treatment if it were to be expanded to areas that do not experience fires, valid identification of the ATT measures the impacts on fire-affected homes. For our research question, the ATT is a more informative parameter than the ATE for two reasons. First, the ATT from our specification with multiple treatments allows us to disentangle the impact of fire damage in addition to

the impact of being located inside a fire perimeter. The large difference in treatment effects across different treatment groups is a key empirical finding of this paper. Second, the ATT is particularly informative in settings where researchers are interested in the counterfactual of reducing a detrimental treatment (e.g. reducing smoking among smokers or limiting fire damage among exposed homes). In our setting, the ATT measures the financial benefits of policies or mitigation efforts that would prevent fire damage in areas where fires are prevalent. Therefore, this parameter is sufficient for our research goal of understanding the impact of wildfires on the mortgage market.

We also conduct robustness checks using two different samples to ensure our results are not being driven by outlier fires and misspecification of the control group. First, we exclude the Camp Fire in 2018 to ensure that our estimated results are not driven by the largest event. The Camp Fire damaged 2,623 homes in our mortgage sample, representing 50 percent of all mortgages in our sample. Figure A.5 confirms that the pattern of findings is qualitatively similar and the magnitude of the increase in delinquency rates is identical. Even though the magnitude of the increase in prepayment is smaller when we exclude the largest fire in our sample, prepayment rates for homes damaged by all other fires increase by 9 percentage points relative to homes outside of the fire perimeters.

Second, Figure A.6 shows that our results are robust to changing our control group to be homes located within 5 to 6 miles (8 to 9.6 kilometers) outside of the fire perimeter. Choosing a control group farther from the fire perimeter reduces the likelihood of spillover effects from the fire on homes outside the perimeter.

4.2 Determinants of Prepayment

In the aftermath of a wildfire, prepayments can potentially be driven by home sales, refinancing, or homeowners insurance payouts.[21] We can infer which of these three channels are driving

[21] Some prepayment may be driven by disaster aid provided by FEMA or the Small Business Administration Disaster Loan program. We calculate that between 2012 and 2019, only 350 SBA Disaster Loans were given out in California. These loans are designed to cover any *uninsured* losses that homeowners may still face.

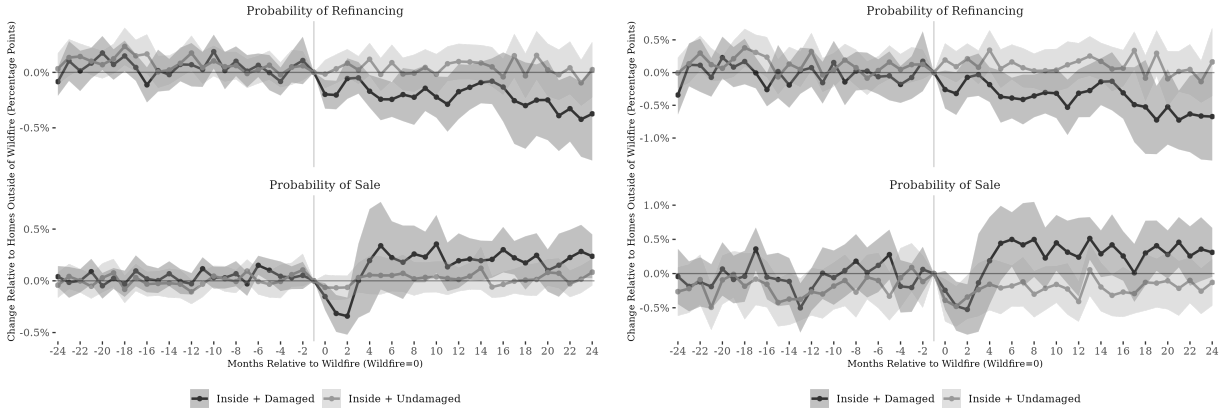
our prepayment results by observing whether the properties associated with prepaid loans in our sample are sold after a fire and the timing of the transactions. Only 35 percent of damaged properties that prepay are sold within two years of a fire. In comparison, 47 percent of undamaged properties and 50 percent of properties outside a fire perimeter that prepay are sold within two years after a fire. The timing of sales and refinances after a fire further confirms that the large immediate increase in prepayments is driven by insurance payouts.

We estimate Equation 1 using indicators for whether a property was refinanced or sold in the months leading up to and after a wildfire. Figure 4 shows results from this estimation using two samples: The top panel uses the sample of all properties in the vicinity of a wildfire from CoreLogic public records, and the bottom panel uses the same sample of mortgages from FR Y-14M as our estimation of the impact on mortgage repayment. Results from both samples confirm that sales activity for damaged parcels does not begin to increase until at least four months after a fire. In fact, the sample of properties highlights an immediate decline in sales for damaged properties.

Refinance activity among damaged properties does not differ from that of unaffected properties until at least 10 months after a fire, when we see refinancing among damaged properties decline.[22] An increase in sales occurring more than four months after a fire clearly does not lead to the large spike in prepayment we observe in the first three months after a fire, as shown in Figure 3. Furthermore, the estimated impact of wildfire damage on sales is significantly lower than the 16 percentage point increase in prepayment.

Similarly, for FEMA Individuals and Households Program (IHP), we calculate that between 2012-2019, 5,349 grants were approved for homeowners in California with the median grant being $1,838. The IHP program is to help disaster recovery and can provide money for temporary housing, housing repairs (but only to make a home safe, not to restore it to pre-disaster condition), essential needs (e.g., food, water, clothing), and funeral expenses. Furthermore, IHP funds are capped at $32,000 to $36,000 depending on the year. Given the low number of people receiving disaster aid, the low aid amounts, and the fact that SBA loans and aid are primarily meant to fund uninsured expenses, we believe that these sources of funding are unlikely to be a key driver of prepayment.

[22]The long-term decline in refinance may be explained by the higher sales rate for these properties. It is less likely that these newly purchased homes would be immediately refinanced. A decline in refinancing further rejects the hypothesis that prepayments are driven by refinancing.



(a) Properties affected by wildfire (b) FR Y-14M mortgages affected by wildfire

Figure 4: Home Sales and Refinancings Around Wildfire Events

Note: Figure illustrates the coefficients for damaged (β_{1t}) and undamaged (β_{2t}) parcels estimated from the event study specification in Equation 1, with indicators for refinance and sales, respectively, as the outcome variable. The top panel presents results for the sample of all properties in the vicinity of a fire, and the bottom panel presents results for the sample of mortgages we use to estimate mortgage repayment outcomes. Regression controls for fire-month and loan fixed effects. Shaded regions indicate 95% confidence intervals clustered by zip code.

However, it is possible that increased sales contribute to the persistently higher prepayment rates for damaged properties after six months, as we see the rate of sales for damaged properties consistently exceeding the rate for properties that are undamaged or outside the fire zone. We track the sale of affected properties by estimating an annual event study over a eight year window around a fire. The top panel of Figure 5 shows that the sales rate for damaged homes increases by 4 to 5.7 percent in the four years after a fire, relative to properties outside the fire zone.[23] The bottom panel shows that the sale price for damaged homes is significantly lower in the years following a fire. Sales prices in the four years after the fire for damaged homes are 54 to 74 percent lower than the year before the fire.[24] This drop in price is similar to the average structure value as a share of property value of 57 percent for our sample of zip codes in the year before the fire (Davis et al., 2021). These results indicate that

[23]These annual event study coefficients are consistent in magnitude with the monthly coefficients in Figure 4. The monthly coefficients show that the uptick in sales in the first year is driven by an increase in sales starting 5 months after a fire.

[24]We convert estimates of $\hat{\beta}_{1t}$, which measure log changes in price of -0.77 to -1.34, to percent changes.

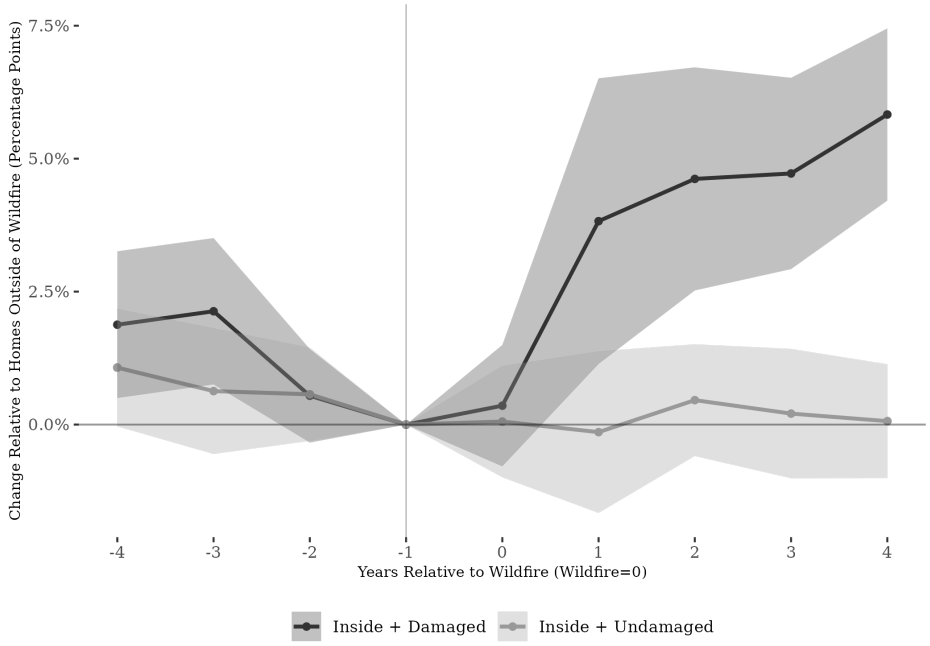
the damaged property transactions reflect land sales where homeowners sell their property without rebuilding.

4.3 Rebuilding

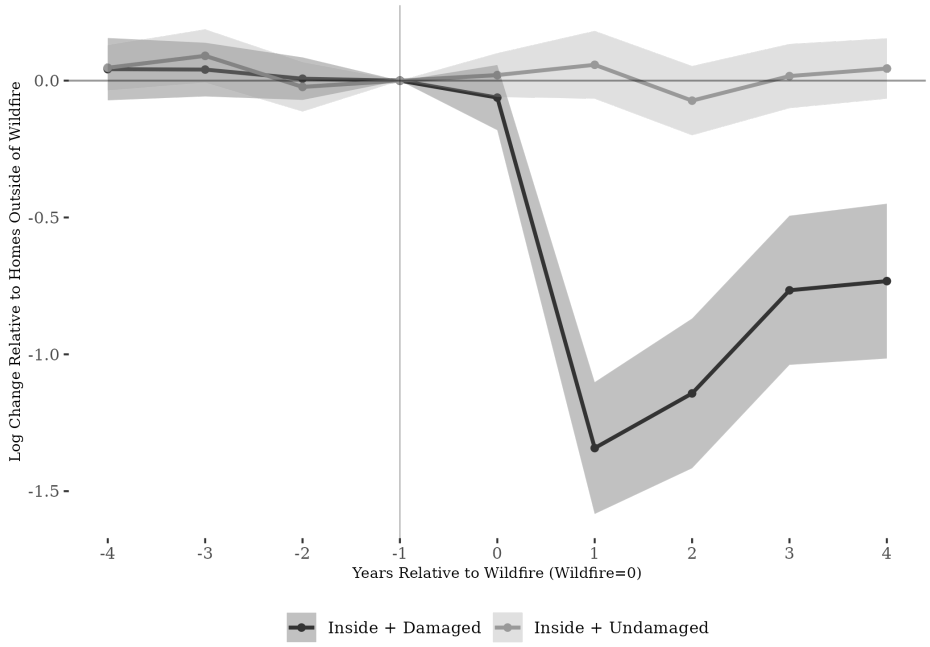
We examine rebuilding activity for damaged properties using the likelihood of filing a building permit for new construction and of borrowing a construction loan. As shown in the top panel of Figure 6, rebuilding activity, measured by building permits, is low for at least two years after a property is damaged. Even two years after a wildfire, only 8.9 percent of damaged properties have filed a new construction permit.

In the bottom panel of Figure 6, we estimate an annual event study with the likelihood of taking out a construction loan as the outcome and report the coefficients for damaged homes. The figure shows estimates from both the entire sample and the sample of homes that have not sold prior to the timing of the construction loan. There is a small overall uptick of construction loans for damaged properties, by up to 1.2 percent, in the four years after a fire. However, the prevalence of construction loans remains unchanged, increasing by less than 0.5 percent, among homeowners who have held on to their property after incurring fire damage. This difference suggests that the new buyer of a damaged home borrows a construction loan to rebuild or restore the property.

While the damaged home's initial owner can rebuild without a construction loan due to the availability of insurance funds, the collection of results showing a lack of building permits, significantly lower transaction price, and higher takeup rate of construction loans by the purchaser suggests that the original homeowner sells the damaged property before restoring it. Taken together, our findings support the following chain of events after a fire for damaged properties. Starting immediately after a fire, several damaged properties prepay their mortgage, possibly using their insurance claim. Few households file a permit to rebuild. Over time, more damaged properties are sold at significantly lower prices, which suggest a



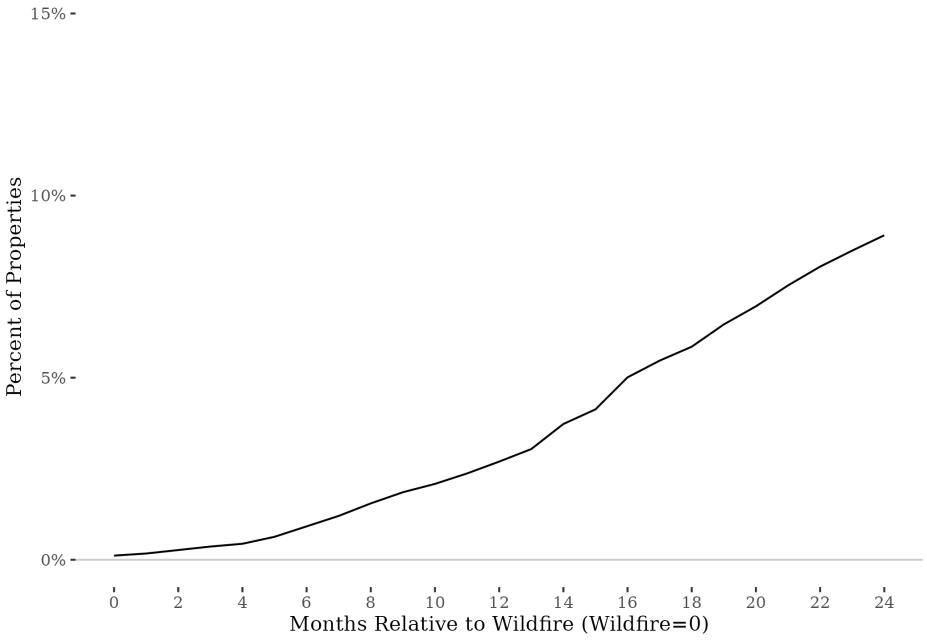
(a) Annual Probability of Sale



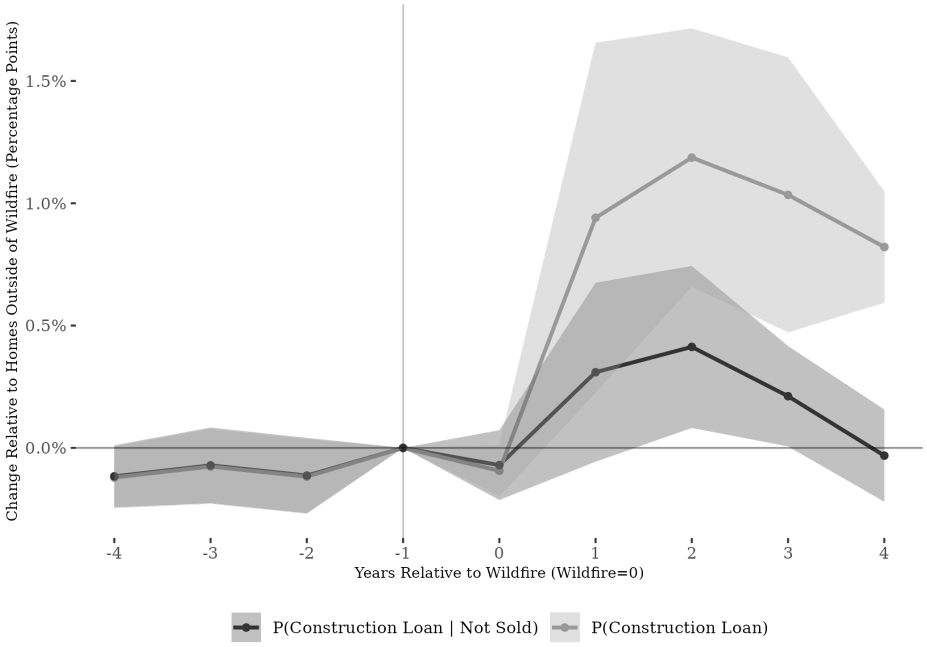
(b) Log Sales Price

Figure 5: Annual Sales Rates and Prices Around Wildfire Events

Note: Figure illustrates the coefficients for damaged (β_{1t}) and undamaged (β_{2t}) parcels estimated from an annual version of the event study specification in Equation 1. The outcomes for the top and bottom panels are an indicator for a sale and the log sale price, respectively. Regression controls for fire-year and loan fixed effects. Shaded regions indicate 95% confidence intervals clustered by zip code.



(a) Building Permits for Damaged Properties



(b) Construction Loans for Damaged Properties

Figure 6: Annual Sales Rates and Prices Around Wildfire Events

Note: The top panel illustrates the monthly trend in building permits among damaged properties after a fire. The bottom panel plots the coefficients from an annualized event study of damaged properties with the likelihood of borrowing a construction loan as the outcome. We estimate the regression for the entire sample of damaged homes and for damaged homes that have not sold. Regression controls for fire-year and loan fixed effects. Shaded regions indicate 95% confidence intervals clustered by zip code.

land sale with an unrestored structure. Some new owners then take out a construction loan to rebuild the damaged property.

5 Insurance

As the change in sales and refinances after fires is insufficient to explain the pronounced increase in prepayments, we turn our attention to households' use of insurance funds to pay off mortgages. A household's decision to pay off a mortgage after a fire implies that the borrower opted to walk away from the damaged property rather than rebuilding it. While households may face a large financial loss from selling a home in a damaged condition, it may still be optimal to sell if proceeds from the sale and insurance claims sufficiently cover the payment of any remaining mortgage balance and the down payment on a new property. Alternatively, rebuilding becomes less attractive if insurance funds do not sufficiently cover rebuild costs or households face delays due to surges in construction demand from large local concentrations of damaged properties. In this section, we examine these mechanisms by describing the role of insurance after wildfires and estimating whether insurance payments are sufficient to rebuild.

5.1 Background

Damages from wildfires are generally covered under homeowners insurance policies.[25] Typical policies include coverage for the replacement cost value (RCV) of the dwelling and additional structures of the residence, personal property, living expenses during the loss of use of the residence, personal liability, and medical payments to others. Each of these coverages is limited to a share of the dwelling coverage, known as Coverage A, unless the homeowner opts to purchase additional coverage.[26] Over 88 percent of California homeowners insurance

[25] Homeowners insurance policies account for 95 percent of all fire-coverage policies on owner-occupied single-family homes in California based on California insurance data detailed in Section 5.2.

[26] For example, in California, living expenses during the loss of use of the residence are normally limited to 20 percent of the Coverage A limit (California Department of Insurance, 2021). If the loss is related to a state

policies hold extended RCV coverage, under which the settlement can exceed the Coverage A limit, commonly by an additional 20, 25, 50, or even 100 percent, to account for any increased cost of construction and compliance with local building codes after a fire. As a condition of holding extended RCV coverage, insurers require that the Coverage A limit equals the RCV (Klein, 2023).

In the aftermath of a fire, the homeowner and insurance adjuster negotiate a settlement. The insurer sends the settlement to the lender to hold in escrow. The lender then releases funds to the borrower, who may use the settlement to rebuild the home, buy or build a home at a different site, or pay the mortgage. If the borrower finds that the insurance funds are not sufficient to rebuild, the borrower must provide contractor quotes to the insurer and request additional funds. However, this process is not simple in practice and faces several frictions.

Under California Insurance Code §2051.5, established into law in 2004 under Assembly Bill 2199, residents are entitled to the lesser of the full extended coverage limit and the quoted costs of rebuilding the home at the original site regardless of the household's decision to rebuild, buy, or newly build a home at a different site.[27] Yet, insurance adjusters dispute this right, and as a result, several households do not receive their entitlements (Bach and Wade, 2018). A survey of homeowners after six large California wildfires since 2013 suggests that many homeowners do not receive settlements that are sufficient to rebuild: 42 percent to 66 percent of the respondents are underinsured and would not be fully covered to replace or rebuild their home (United Policyholders, 2022). These figures highlight two mechanisms that leave households without enough funds to rebuild, even if they carry insurance.

First, households may be *underpaid* after a fire, relative to their coverage. In such cases, the negotiated settlement can be below the policy coverage limit, leading to an ex-post deficit. Commonly, insurers initially pay households the Actual Cash Value (ACV), which

of emergency, insurance will cover at least 24 months of additional living expenses (CA Ins Code §2051.5 (b) (2)).

[27] If the homeowner decides to purchase a new house, the claim entitlement is also capped by the price of the house.

deducts material depreciation from the estimated replacement costs. Insurers then release the additional funds, up to the lesser of the replacement cost and coverage limit, only if the household rebuilds and provides multiple contractor quotes. This practice runs contrary to California law, which gives residents 24 months to recover their full benefits even if they purchase a home elsewhere, often due to lack of information regarding the law from out of state insurance adjusters and large national insurers. Under the assumption that the Coverage A limit accurately estimates the replacement cost of the structure, claim payments received below the limit would be insufficient to rebuild. However, the settlement may cover the remaining mortgage balance. Therefore, the household decision to prepay may be a symptom of large welfare losses due to lower-than-anticipated claim settlements. Using policy and claims data, we estimate substantial underpayment rates and associated deficits in Section 5.3.

Second, households may be *underinsured*. That is, they carry too little insurance and their Coverage A limits and extended coverages are not enough to cover a full property rebuild. Underinsurance can occur for several reasons. Insurers may be unwilling to write policies in areas with high fire risk, and households may not desire to pay high premiums for the relatively low-probability event of a total loss. While theoretically possible, we think this explanation to be unlikely because 88 percent of policies have some form of extended RCV coverage, therefore requiring the Coverage A limit to be the RCV.[28] However, it is possible that the RCV estimate itself may be low or outdated (Dixon et al., 2018). In these cases, the household may think it is fully covered but the quoted replacement cost value would not be enough to replace the destroyed structure, even after accounting for extended coverage (Klein, 2023). Such a coverage gap is exacerbated by demand surges after fires in areas with a large concentration of property damage, leading to the increased cost of construction materials,

[28] In addition, for mortgages secured by government-sponsored enterprises (GSEs), the coverage limit on homeowners insurance needs to cover the lesser of the RCV and the unpaid principal balance of the mortgage. If the mortgage balance is lower than the RCV, the insurance must cover the greater of mortgage balance and 80 percent of RCV.

transportation, and labor. We examine this last mechanism of demand surges by estimating the heterogeneous impacts of fires with varying severity in Section 5.4.

5.2 Policy and Claims Data

We gather data on fire policies and claims in California from 2018 to 2021 from the California Department of Insurance (CDI).[29] The data include information on all policies in force in a given year for insurers that write $10 million or more in premiums for property or homeowners insurance. The data are repeated cross sections of policies that can be linked to the claims made on each policy and cover over 98 percent of the voluntary market. The policy data include coverage type, limits, premiums, deductibles, and start and end dates, and the claims data include the type, date, and amount of loss. Notably, the date reveals the timing of the loss but not the timing of the claim filing or payment.

We focus our sample on fire coverage policies for single units through homeowner or standalone dwelling-fire insurance.[30] For each policy in a specific month, we merge in the total dollars of claims associated with a loss incurred in that month to account for settlements received over multiple payments. Lastly, we only include fire-related claims on the primary structures (type A) that are classified as a catastrophic loss.[31]

The primary limitation of these data is the lack of geographic information. While we observe each policy's zip code, we are not able to link the policy or claim to a specific property in the damage inspection data from CAL FIRE. Therefore, we do not observe the coverage or claims for a specific damaged property. Instead, we identify the set of claims made on the set of damaged properties in a zip code in any particular month.

[29]The data are collected through Public Records Request GOVR-2023-00074. Every other year, the CDI collects policy and loss data from insurers for the previous two years through the Personal Property Experience (PPE) data call. Our data request includes two such data calls that cover information from 2018 to 2021.

[30]This restriction matches our mortgage repayment analysis sample of single-family residences.

[31]In total, we exclude 10 percent of policies. Specifically, we exclude guaranteed replacement cost coverage, which accounts for less than 4 percent of policies, and outliers in coverage limits and claim-to-limit ratios that account for the remainder of the exclusions.

First, we rank all claims from highest to lowest within zip code j and month t. Then, we keep the top N_{jt} claims, where N_{jt} is the number of properties damaged in zip code j and month t. For example, if there were 100 properties damaged in a zip code from a specific fire, we keep the 100 largest claims in that zip code in the month of the fire under the assumption that the largest fire claims result from properties damaged by wildfires.

For each claim i in this sample, we calculate underpayment and the resulting deficit as the following:

$$\text{Underpaid}_{ijt} \equiv \mathbb{1}\left(\text{Claim}_{ijt} < \text{Coverage A Limit}_{ijt}\right)$$
$$\text{Deficit}_{ijt} \equiv \text{Coverage A Limit}_{ijt} - \text{Claim}_{ijt}.$$

Underpayment measures the share of policies that received fewer claims than their estimated replacement cost value, as measured by the Coverage A limit. The deficit measures the magnitude of deviation between claims and coverage. When aggregated across our sample of claims, which approximates the set of damaged properties facing a total loss, the deficit measures the extent of the shortfall between claims and replacement cost.

Restricting the sample of claims by the number of properties damaged conservatively measures underpayment and deficits. If a fire claim due to reasons other than a wildfire exists in our sample, it replaces a claim resulting from a wildfire that is of a lower amount.[32] Therefore, any bias will overestimate the total claims paid resulting from the wildfire. Consequently, any observed underpayment in our sample will be a lower bound for the true underpayment rate. We also assume that the Coverage A limit is the actual replacement cost of a destroyed property. Studies have found the insurer-estimated RCV that dictates coverage limits is often much lower than the actual costs of rebuilding (Dixon et al., 2018;

[32]Examples of fire claims due to reasons other than a specific wildfire include a kitchen fire occurring at the same time as a wildfire, fraudulent claims, or claims on undamaged properties requiring hazardous debris removal.

Klein, 2018, 2023). Therefore, our estimate of coverage deficits would be lower than the true deficit between the insurance settlement and the costs of rebuilding.

5.3 Insurance Underpayment and Deficits

We find a high prevalence of underpayment and associated deficits. Table 3 shows that between 2018 and 2020, approximately 39 percent of claims were underpaid. The resulting deficit is $112,840, or 26 percent, of coverage limits. That is, the largest claims in zip codes where we observe fire damage received 74 cents per dollar of their respective Coverage A limits. Conditioning on underpaid claims, the deficit jumps to 82 percent. While these figures are high, they are similar to results from surveys of affected homeowners that show 42 percent to 66 percent of respondents would not be fully covered to replace or rebuild their home, with average deficits ranging from $163,000 to $375,000 (United Policyholders, 2022).

Table 3: Insurance Underpayment Prevalence and Deficit

	All	2018	2019	2020
Deficit (share)	0.258	0.208	0.615	0.389
Deficit ($)	112840	84979	365795	209481
Underpaid (share)	0.388	0.346	0.819	0.530
Deficit if Underpaid (share)	0.821	0.832	0.791	0.796
Deficit if Underpaid ($)	487450	479235	482557	510061
Number of Claims	11255	8931	155	2169
Number of Zip-Months	100	29	12	59

Note: Table reports the underpayment rates and resulting deficits. A claim is considered underpaid if the settlement is below the Coverage A limit. The deficit is the difference between the Coverage A limit and claim amount. Deficits that are represented as shares are dollar weighted by the coverage limit. We include the largest N_{jt} claims in zip code j and month t, where N_{jt} is the number of observed wildfire-damaged properties, to identify the set of claims associated with wildfire damage.

Next, we aggregate claims to the zip-code level and plot the correlation between average claim amounts and average Coverage A limits in Figure 7. Recall that California residents who intend to rebuild or purchase a new home are entitled to receive the lesser of the full coverage limit and quoted replacement costs under CA Insurance Code §2051.5, which would

suggest claims at or close to \$1 per dollar of coverage (the 45-degree solid black line). The figure shows that almost all zip codes are, on average, underpaid. Only five zip codes fall at or above \$1 of claims paid per dollar of coverage. Accounting for extended RCV, all zip codes' average payments are below the average coverage limit plus 20 percent additional coverage, as represented by the dotted line.

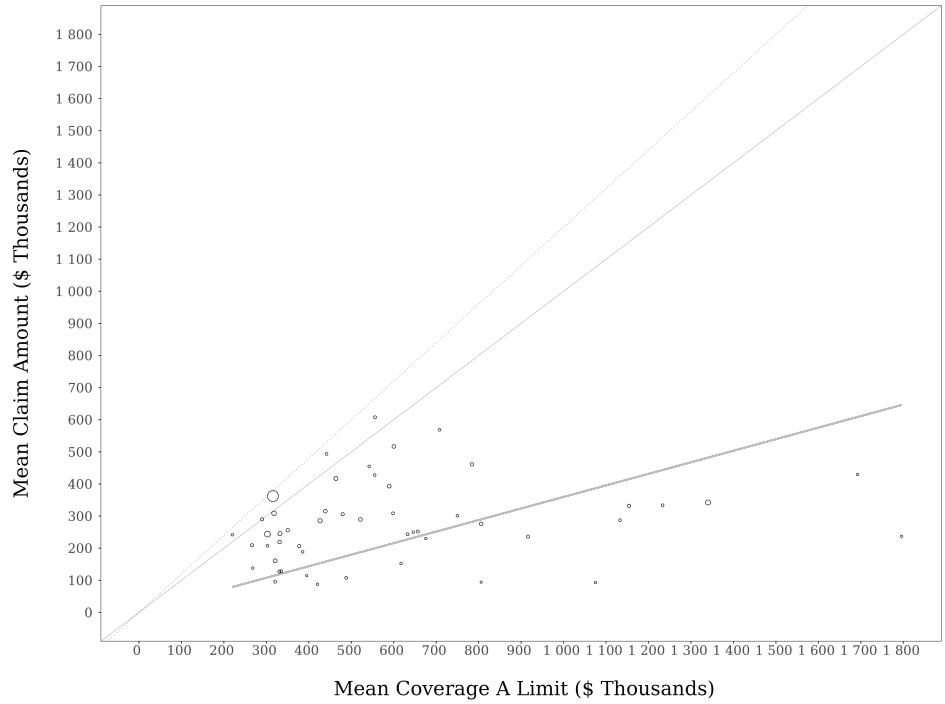


Figure 7: Zip-Code Level Coverage and Claims

Note: The solid black 45-degree line represents the counterfactual, in which claim settlements equal the Coverage A limit. The dotted line represents the counterfactual of 20 percent extended replacement cost value coverage (ERCV), in which claims equal \$1.20 per dollar of Coverage A. Over 80 percent of policyholders hold at least 20 percent ERCV coverage. We include the largest N_{jt} claims in zip code j and month t, where N_{jt} is the number of observed wildfire damaged-properties. Standard errors are clustered by zip code.

We consider the following hypothesis that could lead to large observed underpayment rates and deficits. In an effort to reduce costs, insurers commonly send initially low settlement offers that cover only the ACV, deducting the depreciation of the house's materials from replacement costs. To calculate the ACV, insurers require several details about the structure, such as the quality of finishes and size of cabinets. When such details are not available, insurance adjusters rely on aggregated characteristics of the zip code housing the property.

Households may accept these offers because of a lack of information or unwillingness to enter the required negotiation process to secure a higher settlement based on the property's individual damages. In the event of large fires that require quick processing of claims, it is likely that the dollar amount of claims would not vary greatly within zip codes. To examine this hypothesis, we estimate the following fixed-effects regression.

$$\text{Claim}_{ijt} = \beta \text{Coverage A Limit}_{ijt} + \gamma X_{ijt} + \lambda_j + \lambda_t + \epsilon_{ijt} \tag{2}$$

In Equation 2, X_{ijt} includes additional extended replacement cost coverage and the policy premium rate per \$100,000 of coverage to account for policy quality. The fixed effects isolate the identifying variation to be as close to within-fire as our data allow by using zip code and month fixed effects. The β from this regression can be interpreted as the additional dollar of claims a household with an additional dollar of coverage receives for the same fire and same quality of policy. If claims reflect the rebuilding costs of the individual properties, as estimated by the Coverage A limits, we expect $\hat{\beta}$ to be close to 1. Moreover, the fixed-effects estimate $\hat{\beta}$ should not differ substantially from the ordinary least squares (OLS) estimate unless the property's zip code is a critical component of determining the share of the coverage limit households receive in claims.

However, both of these hypotheses are rejected. Table 4 shows that the fixed-effects estimate of the correlation between coverage limits and claims is weak, as $\hat{\beta}$ is statistically indifferent from zero. In addition, the correlation drops dramatically when introducing aggregated controls, such as extended RCV and policy price, and zip code fixed effects. These results support the hypothesis that the initial ACV settlement offer varies more by zip code characteristics than by the individual property replacement costs, as estimated by coverage limits.

Table 4: Correlation of Claims and Limits Within Zip Codes

	OLS	OLS with Controls	Fixed Effects
Coverage A ($)	0.3872	0.1920	0.0303
	(0.1537)	(0.0748)	(0.0550)
ERCV (Additional $)		-0.0037	-0.0568
		(0.0658)	(0.0293)
Policy Premium		618.2	-64.07
		(120.9)	(29.74)
Month-Year	No	No	Yes
Zip Code	No	No	Yes
Policy Type	No	No	Yes
Observations	11,430	11,430	11,430

Note: Table reports OLS and fixed-effects estimates of $\hat{\beta}$ from Equation 2. ERCV (Additional $) represents the additional dollar amount extended replacement cost value coverage provides to the specific policy beyond the Coverage A limit. Policy premium measures the annual price per $100,000 of Coverage A limit. The last column includes fixed effects for the month and year of loss, zip code, and policy type (homeowners or dwelling fire). We include the largest N_{jt} claims in zip code j and month t, where N_{jt} is the number of observed wildfire-damaged properties.

5.4 Underinsurance and Rebuilding Costs

In addition to underpayment, households may be underinsured, meaning that the actual costs of rebuilding exceed the total coverage available through the policy. As a result, even if the settlement is not underpaid, households face a coverage gap and would receive insurance settlements that do not cover the cost of rebuilding (Dixon et al., 2018; United Policyholders, 2022). In such a case, the household faces strong incentives to prepay mortgages on damaged homes instead of rebuilding. While we cannot test for all causes of underinsurance, we empirically test whether higher-than-anticipated costs of rebuilding lead households to prepay at higher rates. Since policy limits are fixed through the policy year, the coverage gap is increasing in reconstruction costs.

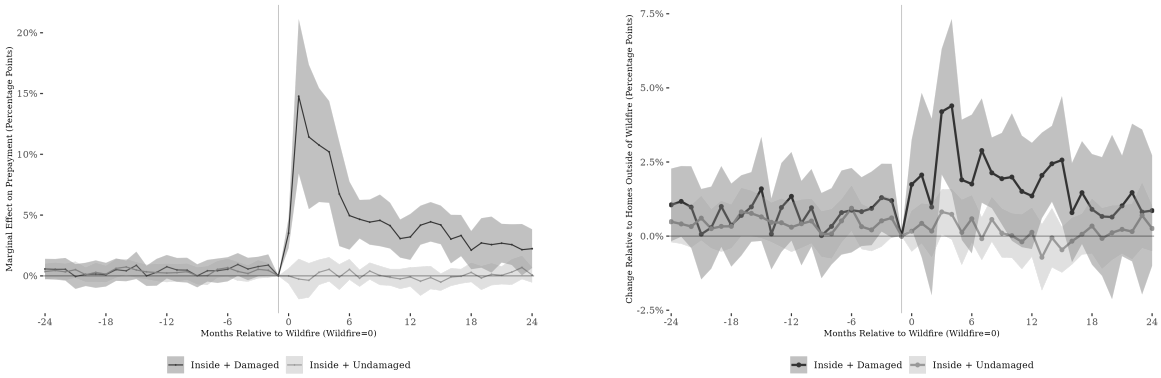
To test this mechanism, we consider a surge in demand for construction after large natural disasters. Homeowners in areas with a great concentration of fire damage should face a higher cost to rebuild. The cost to rebuild may exceed the policy limit by more than

the allowed adjustments under extended RCV. Simultaneously, insurers may be financially stressed to pay out more insurance claims, providing further incentives to negotiate lower settlements with households. Specifically, we use the triple difference design in Equation 3, where we interact property damage with the log number of damaged properties inside the fire perimeter, Z_{ift}, as a proxy of high reconstruction costs.[33]

$$
\begin{aligned}
Y_{ift} = & \sum_{t=-24;t\neq-1}^{t=24} \beta_{1t} Damaged_{ift} + \sum_{t=-24;t\neq-1}^{t=24} \beta_{2t} InsideFireZone_{ift} \\
& + \sum_{t=-24;t\neq-1}^{t=24} \gamma_{1t} Damaged_{ift} \times Z_{ift} + \sum_{t=-24;t\neq-1}^{t=24} \gamma_{2t} InsideFireZone_{ift} \times Z_{ift} \\
& + \lambda_{ft} + \lambda_{ft} \times Z_{ift} + \lambda_i + \epsilon_{ift}.
\end{aligned} \tag{3}
$$

As shown in panel (a) of Figure 8, estimates of $\hat{\gamma}_{1t}$ are positive and significant, confirming that the prepayment rates for damaged homes after a fire increase with fire severity. This result implies that prepayment rates are increasing in reconstruction costs and supports underinsurance as a determinant of the observed prepayment spikes. The role of frictions after fires does seem to be driven by the most severe fires. In panel (b), we see that the magnitude of the differential effect by fire severity is smaller but still statistically significant when we exclude the Camp Fire from our estimation sample.

[33] We standardize the values of Z_{ift} so that coefficients γ_{1t} and γ_{2t} can be interpreted as the change in the dependent variable from a 1 standard deviation increase in the Z variable. We also interact time fixed effects with our measure of heterogeneity to correct for estimation bias from multiple treatments, as discussed by de Chaisemartin and D'Haultfoeuille (2022).



(a) Log of Properties Damaged × Fire Damage, All Fires

(b) Log of Properties Damaged × Fire Damage, Excluding Camp Fire

Figure 8: Heterogeneous Impact on Prepayment by Damage Severity

Note: Figure illustrates the coefficients for Z_{ift} interacted with damaged (γ_{1t}) and undamaged (γ_{2t}) parcels estimated from the event study specification in Equation 3. Plot presents the differential impact on prepayment after the fire for large fires as measured by number of properties damaged. Coefficients estimate the marginal effect of a 1 standard deviation change in damage severity. Regression controls for fire-month and loan fixed effects. Shaded regions indicate 95% confidence intervals clustered by zip code.

6 Welfare Implications

6.1 Households

Our estimates of underpayment and deficits have strong welfare implications for households affected by a fire. We calculate a back-of-the-envelope change in household equity from before to after the fire based on received claims and measure any resulting shortfall relative to the amount households are entitled to under California Insurance Code §2051.5. The financial position of the household does not completely characterize household welfare, but a change in equity will underestimate total welfare losses under the assumption of a negative change in the nonmonetary components of welfare, given the stress associated with losing one's house to a fire and relocating.

Under Insurance Code §2051.5, if a household rebuilds or purchases a new home, California residents are entitled to the lesser of the full coverage limit and the quoted costs to rebuild

the damaged home in the original location.[34] The counterfactual change in equity from before to after the fire for households that receive the full payment under California law is therefore represented in Equation 4.[35] We assume that home value decreases by the amount of damage, D_{ijt}, for homeowners that do not rebuild and homeowners that do rebuild incur reconstruction costs, D_{ijt}, to restore the damaged value.

$$\Delta e^*_{ijt} = \min\{(1 + \text{ERCV}_{ijt}) \cdot \text{Coverage A Limit}_{ijt}, D_{ijt}\} - D_{ijt}. \tag{4}$$

However, households may not receive their entitled claim. Therefore, the realized changed in equity from before to after a fire for households is

$$\Delta e_{ijt} = \text{Claims}_{ijt} - D_{ijt}. \tag{5}$$

The counterfactual equity change in Equation 4 nests two possible outcomes for households: (1) the replacement cost is below the coverage limit, in which case the homeowner is made whole and suffers no loss or (2) the replacement cost is above the coverage limit and the homeowner has to cover the difference, which is their loss.

Unfortunately, we do not observe the actual replacement cost of the property. Instead we assume that insurers should pay out at least the full limit of the insurance policy. We consider this assumption to be reasonable as most coverage limits are supposed to be for full replacement cost coverage, and as seen in our data over 90 percent of damaged properties are destroyed. Additional evidence shows that these replacement cost estimates, and therefore coverage limits, may be biased downward (Klein, 2018, 2023). Under these assumptions, we calculate a household's equity shortfall as the amount of equity lost when comparing received claims to the counterfactual scenario where they receive their entitled payout of the full

[34] In the case of a new purchase, the amount entitled is also capped by the price of the new home, but we assume that a new home will be costlier than replacing the destroyed structure of the existing home.

[35] This calculation ignores deductibles, as they are very small compared with the total loss of a structure. The mean deductible is $1,878, and the median is $1,000.

coverage limit after a total loss.[36]

$$\text{Equity Shortfall}_{ijt} \equiv \min\{\Delta e_{ijt} - \Delta e^*_{ijt}, 0\} = \min\{\text{Claims}_{ijt} - \text{Coverage A Limit}_{ijt}, 0\} \quad (6)$$

This calculation assumes that, for claims that were not underpaid, households receive their entitled payout and thus do not face a shortfall. This calculation is likely underestimating the shortfall for households receiving claims exceeding limits, as we assume their settlement equals the full replacement cost. For underpaid claims, the shortfall between the actual and counterfactual equity change is simply the deficit.

We also estimate the actual change in equity from before to after a fire. Assuming that property damages lead to a total loss of structure value, we calculate the change in equity as

$$\Delta \hat{e}_{ijt} = \text{Claims}_{ijt} - \text{Structure Value}_{ijt}. \quad (7)$$

We use zip-code level structure values, as estimated by Davis et al. (2021). The household gains the claim amount, which can be applied toward the mortgage. Note that we are assuming there is no additional loss of value to the land in the case of a fire. If the land value drops further, our calculated change in equity is an upper bound.

As shown in Table 5, households are financially worse off by \$189,955 to \$283,967 than if they received their entitled payout under California law, assuming caps on the payout are either Coverage A or ERCV. For reference, the actual change in equity assuming no rebuilding is a gain of \$30,632.[37] However, this improvement in the household's equity position does not imply that the household is better off because our shortfall measure shows household equity is

[36] It is possible that the extended replacement cost coverage is more than enough to rebuild the home, so we provide two separate estimates of this shortfall comparing received claims to the Coverage A limit and the extended replacement cost coverage limit.

[37] This equity gain is entirely driven by one zip code in the Camp Fire, where total claims account for only 68 percent of damaged properties even though the insurance take up rate is 93 percent. Claims in other zip codes affected by Camp Fire account for 96 percent of damaged properties. Assuming all insured properties should file a claim in the event of fire damage, we do not observe 1,907 claims. Calculations in Table 5 do not include these properties as underpaid. If we assume these properties are underpaid because they do not receive claim payments, the average change in equity Δe_{ijt} would be a *loss* of \$7,800.

well below the counterfactual amount if insurance claims are not underpaid. While Insurance Code §2051.5 was designed to assist households with these financial stresses associated with disasters, the large shortfall implies a substantial welfare loss that households are legally protected against.

Table 5: Impacts on Household Equity

			Shortfall Relative to:	
	N	Δe_{ijt} ($)	Coverage A ($)	ERCV ($)
All	9,905	30,632	-189,955	-283,967
2018	8,667	50,190	-164,751	-250,620
2019	151	-193,863	-398,586	-560,525
2020	1,087	-94,119	-361,935	-511,442
Camp Fire Only	6,969	131,580	-72,834	-122,843
Excluding Camp Fire	2,936	-208,982	-467,959	-666,419

Note: The change in equity is calculated from Equation 7 and shortfall amounts are calculated from Equation 6. We assume that the legal entitlement under Insurance Code §2051.5 is capped by either the Coverage A limit or the ERCV. Each row provides the same calculation for different subsamples of our claims data. We include the largest N_{jt} claims in zip code j and month t, where N_{jt} is the number of observed wildfire-damaged properties. We further restrict the claims to zip codes where an estimate of structure value is available from Davis et al. (2021).

A few factors determine these large shortfalls, although it is difficult to empirically identify their relative contributions. First, households and insurers are often uninformed of the protections under Insurance Code §2051.5. To meet the demand of claims processing after large disasters, insurers rely on out-of-state adjusters who may not know the details of the state law protecting residents and instead dispute that a household would get the full coverage amount only if they rebuild. While other states have similar laws, such as valued policy laws, California is one of few states that both face large and frequent disasters and entitle residents to the full coverage amount even if they do not rebuild. Second, households may face credit constraints in purchasing a new home because their equity is illiquid in the form of burned land. As a result, lenders may be unwilling to provide credit to households for a seemingly second home. With limited access to credit, households may not be able to prove to the insurer that they will indeed purchase a new home.

Regardless of the reasons behind these shortfalls, households face large welfare losses relative to legal entitlements that have existed since 2004. Increasing insurer compliance, through information or enforcement, would largely improve households' financial condition after wildfires, which continue to increase in frequency and severity.

6.2 Local Property Tax

In addition to reducing household welfare, insurance underpayment has broader public finance implications. If insurance claims are too low and households apply these funds towards a mortgage, rebuilding in an affected area can take longer than expected. Property damage reduces the tax base, which remains low until rebuilding occurs. We quantify this tax impact by examining public records data on residential property tax revenues for damaged homes.

First, Figure 9 shows residential property tax collections for damaged homes. Relative to the year of the fire, tax revenues for damaged homes are $39.3 million to $53 million lower per year for the three years following the fire, representing a 35.3 to 47.8 percent reduction in annual tax collections for damaged homes. The reduction in tax revenues is fully explained by a decrease in assessed values as tax rates remain unchanged from before the fire to after the fire.[38] Furthermore, the drop in tax revenues collected persists for at least three years after the fire. The large and prolonged drop in tax revenue for damaged properties is consistent with the previously discussed lack of rebuilding.

Tax revenue losses from damaged properties in the year after the fire represent 1.3 percent and 9.4 percent of total residential single-family property tax collections in the year of the fire for tax code areas (TCA) with any properties inside the fire perimeter and TCAs with more than 50 percent of properties inside the fire zone, respectively.[39] Some tax losses are offset by increasing tax revenues from undamaged homes, due to increasing property assessments.

[38]The average annual tax rate for damaged properties is between 1.13 to 1.17 percent of assessed value from three years before to three years after the fire.

[39]Tax code areas group properties that pay the same statutory tax rate to a common local government entity and receive the same set of publicly funded services (Amornsiripanitch, 2024).

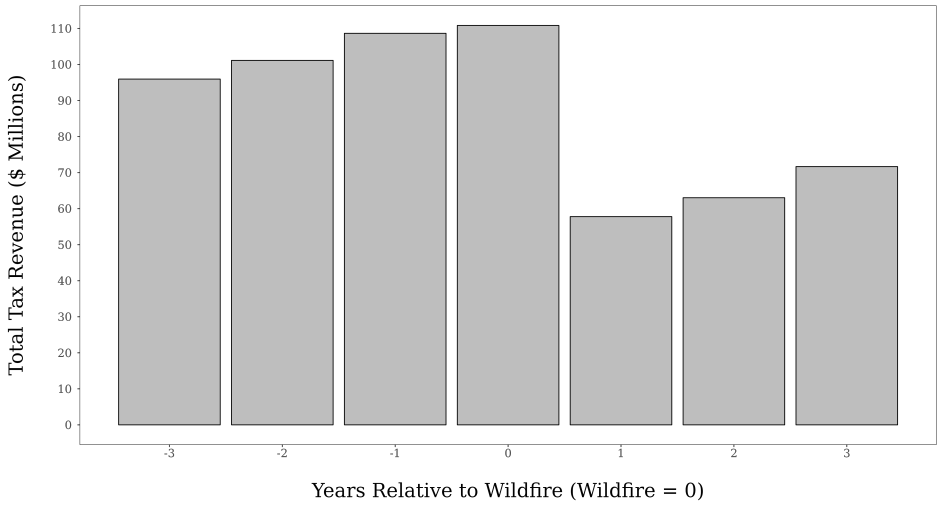


Figure 9: Property Tax Revenue for Homes Damaged by Wildfires

Note: Figure illustrates the total residential property tax collected for our sample of damaged properties.

Total tax revenues in TCAs containing damaged homes are still increasing after a fire, but the annual growth rate of tax revenue per property is 1.8 percentage point lower in the year after the fire relative to the year before the fire.[40]

Second, we show that insurance underpayment drives the drop in tax revenue among damaged homes. We estimate a zip code level regression (Equation 8) to test whether tax revenue from damaged homes varies after a fire by the percentage of claims in zip code j being underpaid, relative to the coverage limit. We include zip code fixed effects and a zip code specific time trend to account for factors such as local house price appreciation. The time variable is measured in years relative to the fire and β_s can be interpreted as the marginal increase in residential property tax revenue per damaged property associated with a marginal increase in rate of underpaid claims.

$$\ln(\text{Property Tax}_{jt}) = \sum_{s=-5;s\neq-1}^{t=4} \beta_s \text{Percent Underpaid}_j \times \delta_{jt}^s + \lambda_j + \lambda_j t + \epsilon_{jt} \tag{8}$$

[40]Proposition 13, passed in 1978, limits California localities' ability to increase taxes to recover lost tax revenue from damaged properties. Annual assessement value increases are capped at 2 percent, except for changes in ownership or new construction, which prompts reassessement at market value.

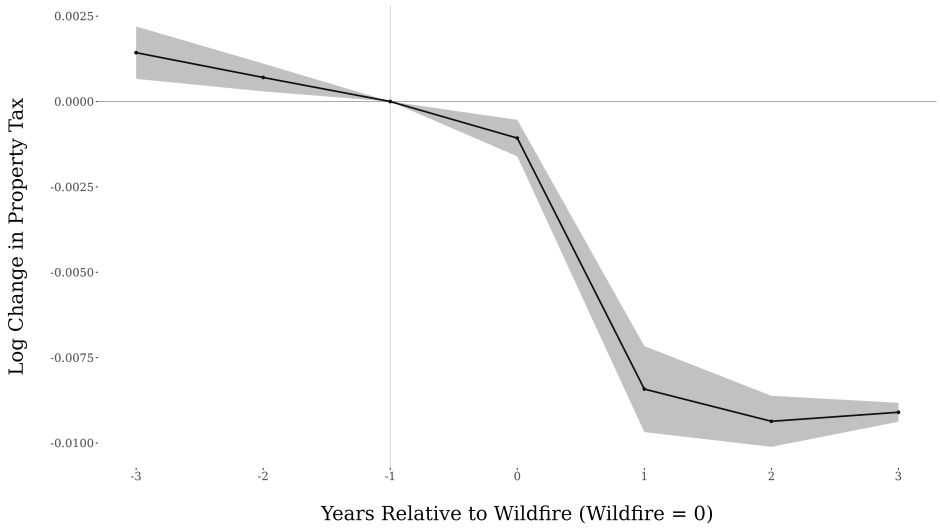


Figure 10: Impact of Insurance Underpayment on Tax Revenues

Note: Figure illustrates the coefficient β_s from Equation 8, with log tax revenue per property as the outcome variable. Regression controls for zip code fixed effects and zip-specific time trends. Shaded regions indicate 95% confidence intervals clustered by zip code.

Figure 10 shows that zip codes with higher rates of insurance underpayment face a larger decrease in tax revenues per property. In the three years following the fire, a one percent higher rate of claims being underpaid is associated with a 0.84 to 0.94 percent decrease in tax revenues per year. These elasticities imply that the average underpayment rate of 39 percent is associated with a 24.8 percent reduction in tax revenues for damaged homes in the year after the fire relative to the counterfactual of no underpayment.

6.3 Lenders, Servicers, and Investors

While we show large welfare losses for households, other agents in the mortgage market face potential losses as well. For lenders, servicers, and investors in mortgage-backed securities, insurance effectively shifts the default risk associated with natural disasters toward prepayment risk. Even if damaged properties rarely default after a wildfire in our loan sample, the increase in prepayment can lead to losses. In the case of a prepayment, lenders lose anticipated interest revenue and servicers lose recurring servicing fees. Moreover, the temporary reduction in housing supply due to fire damage would impact the lender's ability to replace the mortgage

in its portfolio. While investors in mortgage-backed securities are protected by the geographic diversification of their portfolios, a prepayment leads to a loss in the security's cash flow as the GSEs repay investors at par instead of the anticipated return.[41] Lenders and servicers also face operational costs to verify whether their collateral was indeed damaged.

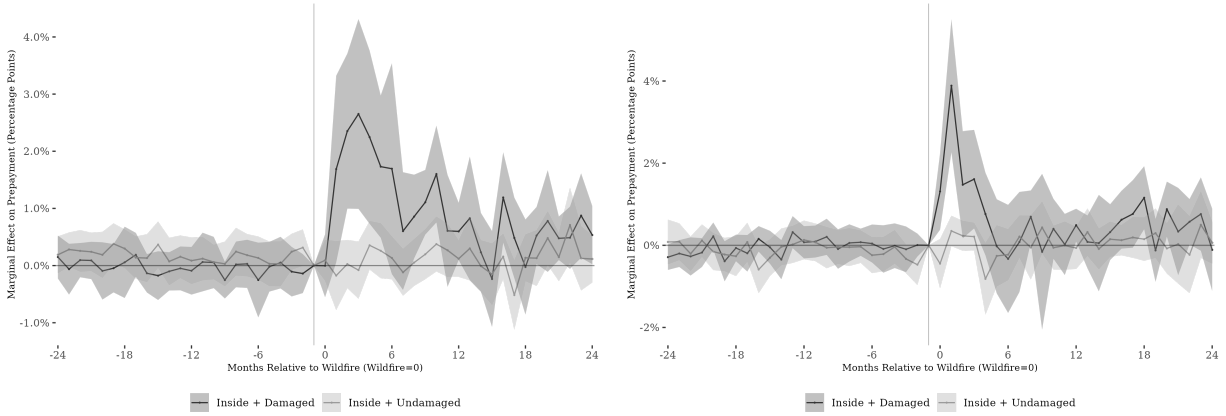
However, total losses to lenders may be modest given the small number of mortgages affected by wildfires relative to the lender's portfolio. While we cannot explicitly calculate the total losses lenders, servicers, and investors face, we do test whether the marginal damaged home in a mortgage portfolio would increase the loss of interest revenue. We estimate heterogeneous effects on prepayment using the specification in Equation 3 with the loans' origination interest rates as Z_{ift}. Banks would prefer borrowers with lower interest rates prepay to minimize lost interest revenue and to potentially add a new mortgage with a marginally higher interest rate. The estimate of $\hat{\gamma}_{1t}$ in panel (a) of Figure 11 opposes bank preferences, as loans with higher interest rates have higher likelihoods of prepayment after a fire. Loans with a 1 standard deviation higher interest rate have a 2.7 percentage point higher likelihood of prepayment.

This pattern could still be beneficial to lenders, servicers, and investors if higher interest rates are correlated with borrower risk, which would result in a borrower pool with lower risk after high-interest mortgages prepay. Panel (b) of Figure 11 does not support this hypothesis and shows that there is no heterogeneous effect in prepayment across borrower risk, as measured by credit score. In fact, less risky borrowers with higher credit scores are slightly more likely to prepay, resulting in a borrower pool with higher risk.[42]

These results suggest that prepayment after wildfires is not beneficial for lenders, servicers, and investors, as they face losses in interest revenue. Taken together with the implications for

[41] Furthermore, a share of the GSE losses get borne by private investors in credit risk transfer securities associated with the reference mortgage pool underlying the mortgage-backed securities.

[42] We estimate the same heterogeneous effects for the delinquency outcome, as shown in Figure A.7. Borrowers with higher interest rates and lower credit scores are more likely to be past due by 90 days or more.



(a) Interest Rate × Fire Damage

(b) Credit Score × Fire Damage

Figure 11: Differences in Prepayment by Interest Rate and Credit Score

Note: Figure illustrates the coefficients for Z_{ift} interacted with damaged (γ_{1t}) and undamaged (γ_{2t}) parcels estimated from the event study specification in Equation 3. Both plots present the differential impact on prepayment after the fire for loans with different interest rates (top panel) and borrowers with different credit scores (bottom panel). Coefficients estimate the marginal effect of a 1 standard deviation change in Z_{ift}. Regression controls for fire-month and loan fixed effects. Robust 95% confidence intervals are indicated by the shaded regions.

household welfare, wildfires and insurance market frictions that lead to prepayment suggest the potential for financial loss for all agents in mortgage markets.[43]

7 Conclusion

We construct a novel database that merges property-level damage inspections from 81 California wildfires with mortgage performance and evaluates the impact of wildfires on mortgage repayment. This paper finds that 90-day delinquency rates and prepayment rates increase significantly for damaged properties soon after a fire. In contrast, repayment trends for undamaged properties, including those inside the fire's perimeter, remain unchanged. The timing and magnitude of the increase in home sales or refinances after a fire do not explain the immediate 16 percentage point increase in prepayment. Using detailed home insurance policy

[43]Kahn et al. (2024) show that mortgage lenders and investors in mortgage-backed securities exposed to wildfire areas do suffer strictly positive losses. However, they also demonstrate that the Sharpe-ratio maximizing portfolio would still have exposure to wildfire-prone areas because other characteristics of these mortgages make them attractive to include in a portfolio.

and claims data, we find high levels of insurance underpayment – properties destroyed by fires on average receive settlements that are much lower than the insurer-estimated replacement costs that determine coverage limits. We conclude that insurance payouts drive the large increase in prepayments for damaged properties as underpayment incentivizes households to apply insurance funds toward the mortgage balance because the claims would not cover rebuilding costs.[44]

Our results imply that wildfires present a larger risk to mortgage markets than the previous research finds and highlight insurance underpayment as a novel mechanism leading to elevated mortgage prepayment, reduced rebuilding, and financial losses for households and local governments. Measurement of fire damages at the property level shows that the direct effects of fire damage on repayment dwarf any spillover effects on undamaged homes inside the fire perimeter. As we estimate a reduced-form parameter that includes any protective effects of insurance and government aid, these risks for mortgages on damaged homes are potentially larger if safeguards weaken. Our findings of damaging physical risks combined with weaker insurance protections than expected in the immediate aftermath of wildfires have implications for several stakeholders.

For households, the large increase in prepayment is an indicator for the lack of insurance coverage leading to financial losses. Substantial insurance underpayment, where the insurance settlement is lower than costs of rebuilding, implies that households are less financially resilient to natural disasters as they bear large negative wealth shocks from property damage. Even if households receive the full coverage limit, demand surges drive up the reconstruction cost and lead to higher prepayment, as households find rebuilding costs to exceed those estimated by their existing coverage. We calculate that insurance market frictions leave households with large financial shortfalls relative to their entitlements under California law.

For lenders, servicers, and investors, insurance effectively shifts the default risk associated with natural disasters toward prepayment risk. Even if damaged properties rarely default

[44] Gallagher and Hartley (2017) also attribute higher levels of prepayment after Hurricane Katrina to insurance payments.

after a wildfire in our loan sample, the increase in prepayment can lead to lost interest revenue. In fact, we observe that, among damaged properties, mortgages with higher interest rates are more likely to be prepaid.

For researchers, this study emphasizes the need to incorporate strength of insurance protections in analyses of household finances after natural disasters. Moreover, this study highlights the benefits of precise measures of physical climate risks. As 55 percent of properties and 58 percent of mortgages within the fire perimeter in our sample remain undamaged, the use of larger geographic areas, such as fire perimeters, to proxy for property damage introduces substantial measurement error. Such measurement error and assumptions of full insurance protections would attenuate resulting estimates and understate the true impact of fires.

Last, for policymakers, our findings indicate that damage mitigation efforts before fires may effectively reduce the risks wildfires present to the mortgage market. Stronger wildfire codes for building standards largely reduce the likelihood of property destruction, and we estimate negative impacts on mortgage repayment only among damaged properties (Baylis and Boomhower, 2021).[45] Prepayment can also indicate a long-term reduction in housing supply if insurance payments are not used to restore damaged properties after a disaster as intended. After a fire, we observe persistently low rebuilding activity that leads to a reduced tax base and lower property tax revenues. We also find that areas with the highest rates of insurance underpayment face the largest decreases in property tax revenues from damaged homes. Our results imply that policies that strengthen insurance protections and reduce complexities in the claims process after natural disasters would mitigate losses for homeowners, lenders, investors, and governments.

[45] del Valle et al. (2022) show that damage mitigation efforts may also substitute for post-disaster spending, at least in the case of Hurricane Harvey.

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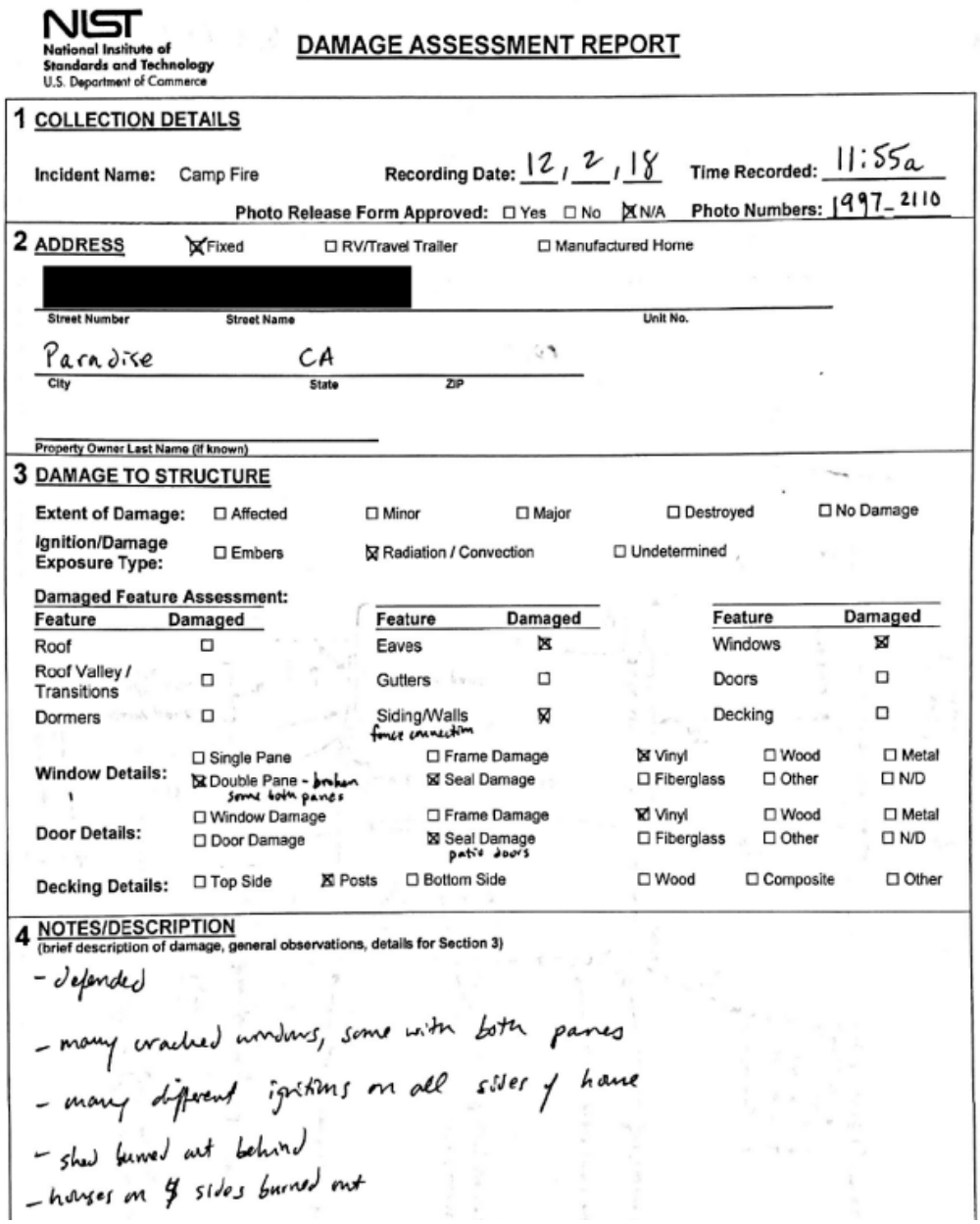
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A Online Appendix

All results presented in the figures and tables of this section are derived from calculations based on the data described in Section 2 of the paper unless otherwise noted.

Figure A.1: Example Damage Report for Camp Fire



NIST
National Institute of Standards and Technology
U.S. Department of Commerce

DAMAGE ASSESSMENT REPORT

1 COLLECTION DETAILS

Incident Name: Camp Fire Recording Date: 12/2/18 Time Recorded: 11:55a

Photo Release Form Approved: ☐ Yes ☐ No ☒ N/A Photo Numbers: 1997-2110

2 ADDRESS ☒ Fixed ☐ RV/Travel Trailer ☐ Manufactured Home

[redacted]
Street Number Street Name Unit No.

Paradise CA
City State ZIP

Property Owner Last Name (if known)

3 DAMAGE TO STRUCTURE

Extent of Damage: ☐ Affected ☐ Minor ☐ Major ☐ Destroyed ☐ No Damage

Ignition/Damage Exposure Type: ☐ Embers ☒ Radiation / Convection ☐ Undetermined

Damaged Feature Assessment:

Feature	Damaged	Feature	Damaged	Feature	Damaged
Roof	☐	Eaves	☒	Windows	☒
Roof Valley / Transitions	☐	Gutters	☐	Doors	☐
Dormers	☐	Siding/Walls (fence connection)	☒	Decking	☐

Window Details:	☐ Single Pane ☒ Double Pane - broken some both panes	☐ Frame Damage ☒ Seal Damage	☒ Vinyl ☐ Fiberglass	☐ Wood ☐ Other	☐ Metal ☐ N/D
Door Details:	☐ Window Damage ☐ Door Damage	☐ Frame Damage ☒ Seal Damage patio doors	☒ Vinyl ☐ Fiberglass	☐ Wood ☐ Other	☐ Metal ☐ N/D
Decking Details:	☐ Top Side ☒ Posts ☐ Bottom Side		☐ Wood	☐ Composite	☐ Other

4 NOTES/DESCRIPTION
(brief description of damage, general observations, details for Section 3)

- defended
- many cracked windows, some with both panes
- many different ignitions on all sides of home
- shed burned out behind
- horses on 4 sides burned out

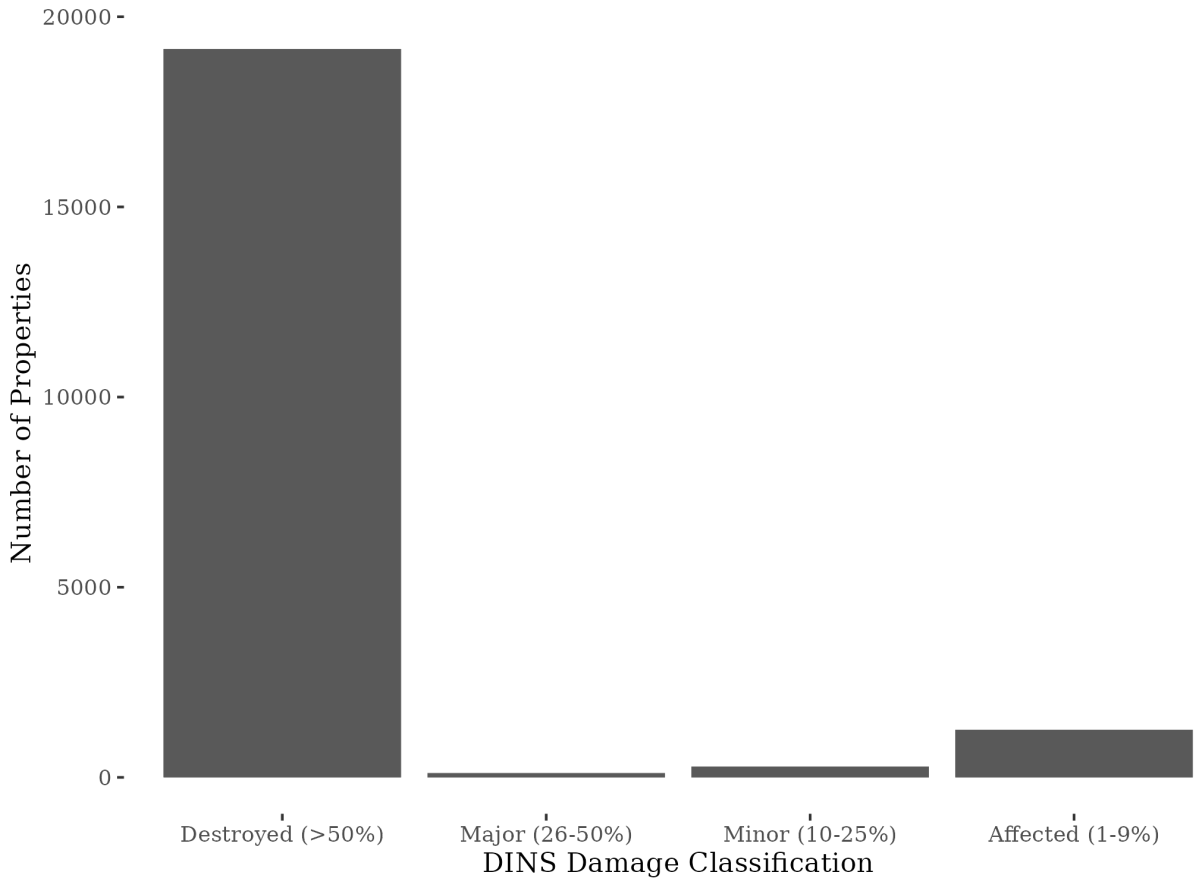
Source: NIST Investigation of the California Camp Fire, Fire Research Division, National Institute of Standards and Technology.

Figure A.2: Classification of Damage Categories

Category of Damage	Definition	Examples
Affected (1-9%)	Minimal damage to the exterior and/or contents of the building. Building is habitable/usable and requires mostly cosmetic repairs.	Partially damaged shingles or siding, but roof structure is intact. Cosmetic damages such as paint discoloration, blistering or melted siding. Broken windows. Gutter damage. Damage to an attached structure like a deck, porch, carport, or patio cover.
Minor (10-25%)	Encompasses a wide range of damage that does not affect the structural integrity of the building. Building is not habitable/usable.	Nonstructural damage to roof components (e.g. roof covering, fascia board, soffit, flashing, and skylight). Nonstructural damage to the interior wall components to (e.g. drywall and insulation). Nonstructural damage to exterior components (e.g. door and windows. Substantial damage to exterior covering (e.g. siding, vinyl or stucco). Damage to mechanical components (e.g. furnace, boiler, water heater, HVAC, etc.).
Major (26-50%)	A building that has sustained significant structural damage and requires extensive repairs. Building is not habitable/usable.	Failure or partial failure of structural elements to include rafters, ceiling joists, ridge boards, etc. Failure or partial failure to structural elements of the walls to include framing, sheathing, etc.
Destroyed (>50%)	The building is a total loss, or damaged to such an extent that repair is not feasible.	Complete failure to major components (foundation, walls, roof, etc.). Two or more walls destroyed and roof substantially damaged. Only the foundation remains. The building will have to be torn down and rebuilt as it is unsafe.

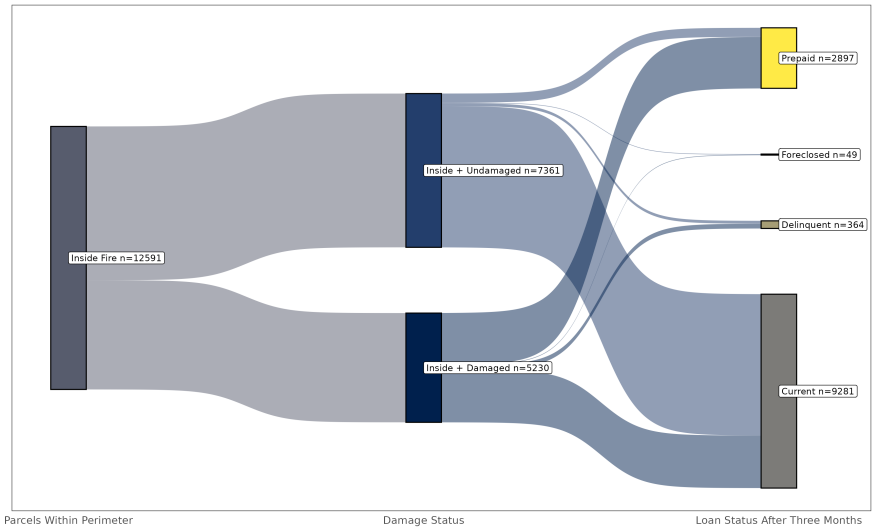
Source: Camp Incident Damage Inspection Report CABTU 016737

Figure A.3: Distribution of Damage Severity

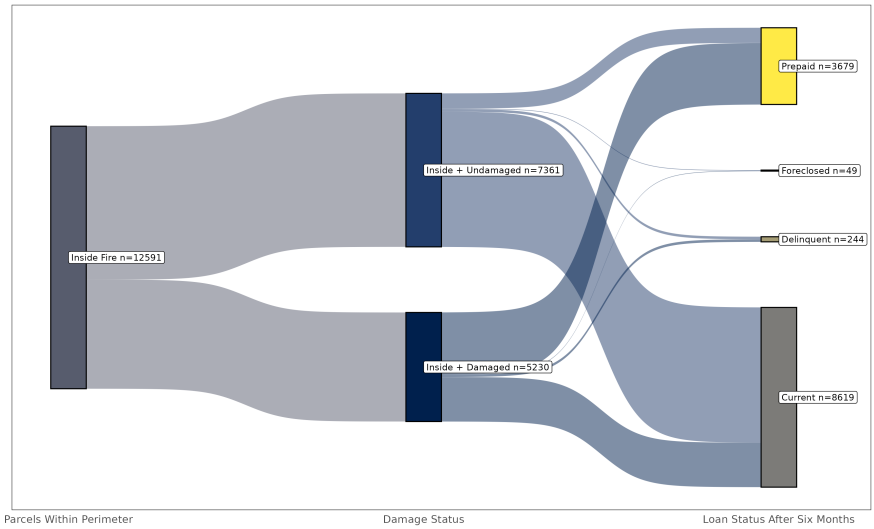


Note: Figure plots the distribution of damage categories reported in the DINS database.

Figure A.4: Post-Wildfire Loan Status Flows: Three and Six Months After Fire



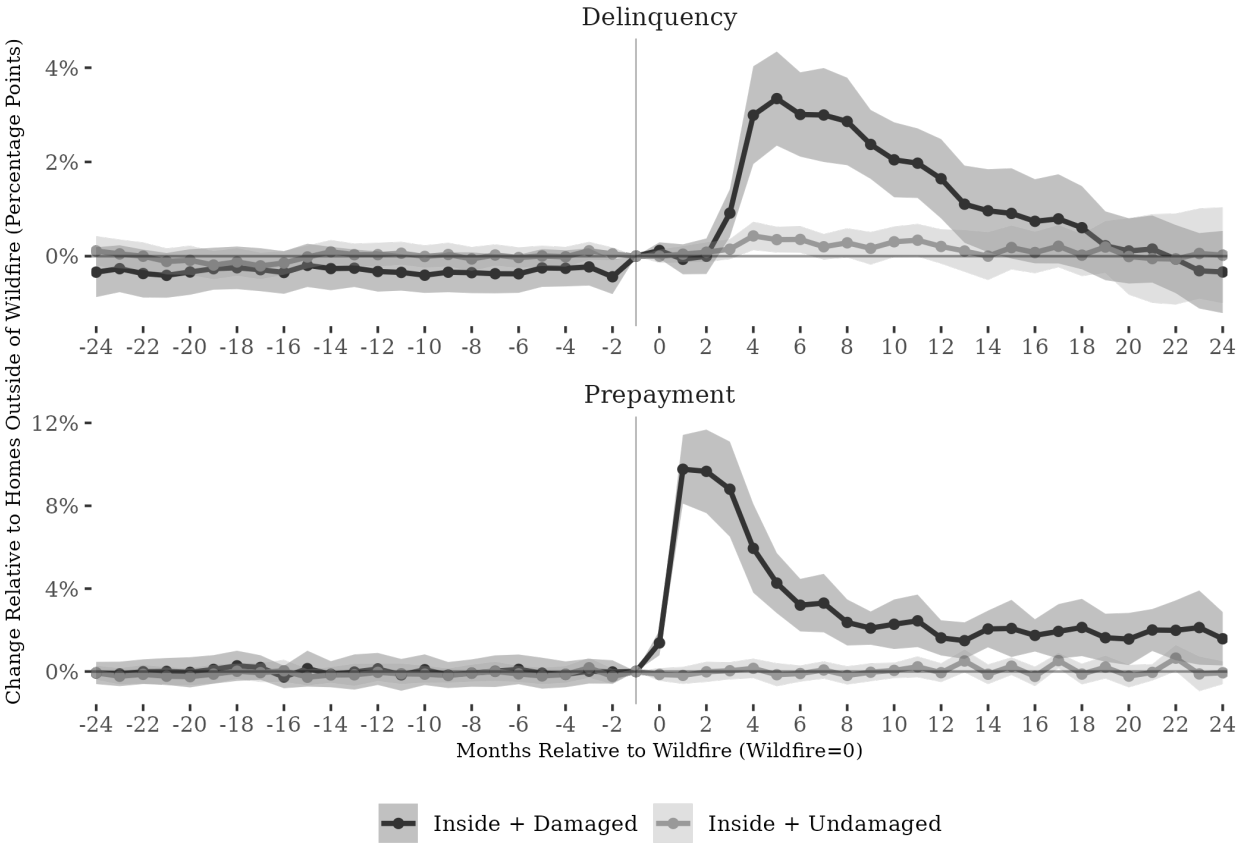
(a) Loan Status Three Months After Fire



(b) Loan Status Six Months After Fire

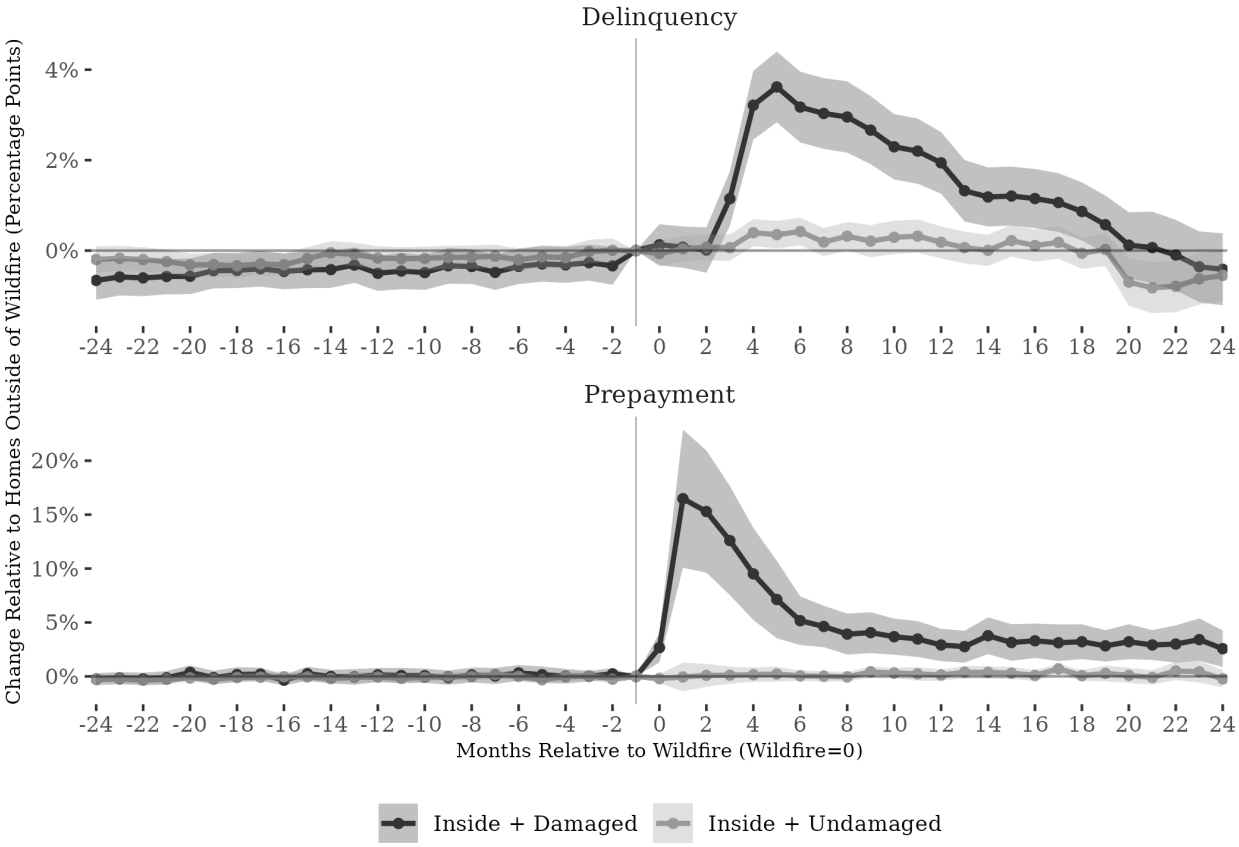
Note: Figure illustrates the decomposition of loans within wildfire boundaries based on whether or not the home was damaged by the wildfire. The top panel shows mortgage status three months post-fire (current, delinquent, foreclosed, or prepaid) while the bottom panel shows mortgage status six months post-fire.

Figure A.5: Robustness to Omitting Camp Fire



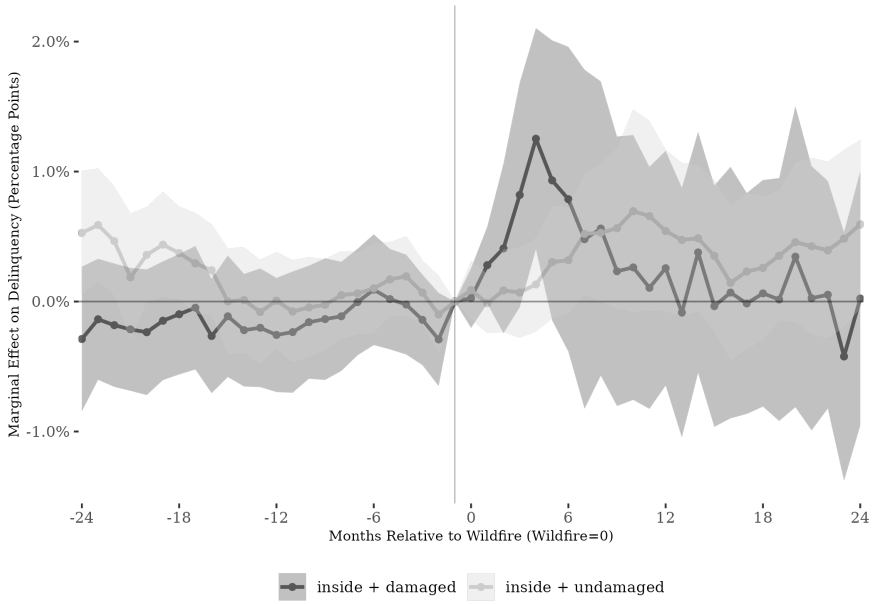
Note: Figure illustrates the coefficients for damaged (β_{1t}) and undamaged (β_{2t}) parcels estimated from the event study specification in Equation 1 after excluding the Camp Fire in 2018. The top panel presents results for delinquency and the bottom panel presents results for prepayment. Regression controls for fire-month and loan fixed effects. Shaded regions indicate 95% confidence intervals clustered by zip code.

Figure A.6: Robustness to Choice of Control Group: Properties 5 to 6 Miles Outside Fire Perimeter

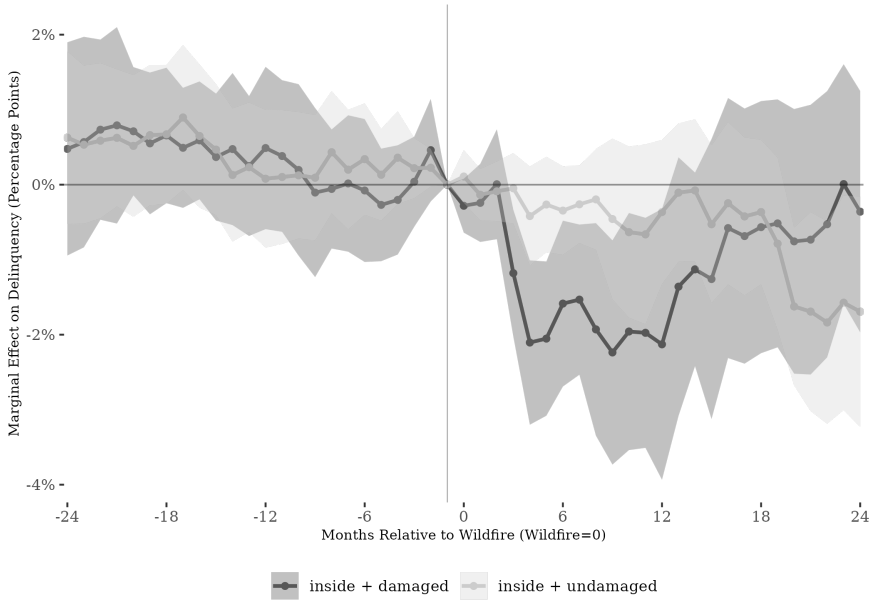


Note: Figure illustrates the coefficients for damaged (β_{1t}) and undamaged (β_{2t}) parcels estimated from the event study specification in Equation 1 using homes in the 5- to 6-mile ring outside the fire perimeter as the control group. The top panel presents results for delinquency and the bottom panel presents results for prepayment. Regression controls for fire-month and loan fixed effects. Shaded regions indicate 95% confidence intervals clustered by zip code.

Figure A.7: Differences in Delinquency by Interest Rate and Credit Score



(a) Interest Rate × Fire Damage



(b) Credit Score × Fire Damage

Note: Figure illustrates the coefficients for Z_{ift} interacted with damaged (γ_{1t}) and undamaged (γ_{2t}) parcels estimated from the event study specification in Equation 3. Both plots present the differential impact on delinquency after the fire for loans with different interest rates (top panel) and borrowers with different credit scores (bottom panel). Coefficients estimate the marginal effect of a 1 standard deviation change in Z_{ift}. Regression controls for fire-month and loan fixed effects. Shaded regions indicate 95% confidence intervals clustered by zip code.