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California Wildfires, Property Damage, and Mortgage Repayment*

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Abstract

This paper examines the impact of wildfires on mortgage repayment using novel data that combine property-level damages and mortgage performance. We find that 90-day delinquencies were 4 percentage points higher and prepayments were *16 percentage points* higher for properties that were *damaged* by wildfires compared to properties 1 to 2 miles outside of the wildfire perimeter, which suggests higher risks to mortgage markets than found in previous studies. We find no significant changes in delinquency or prepayment for *undamaged* properties inside a wildfire boundary. Prepayments are not driven by increased sales or refinances, suggesting insurance claims drive prepayment. Almost 40 percent of affected households receive insurance settlements lower than the estimated replacement costs that define coverage limits. This underpayment and the resulting deficits imply that households receive about $200,000 to $300,000 less than their entitled amount under California law.

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

JEL Codes: G21; G51; Q54

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1 Introduction

From 2017 to 2021, large wildfires in the United States led to $16.8 billion in damages per year, compared with $1.2 billion in damages per year during the previous 37 years.[1] Wildfires are particularly concerning in California, as 13 of the state's 20 most destructive fires (by number of structures burned) have occurred since 2017. Negative wealth shocks after these events can delay mortgage payments, restrict borrowers' access to future credit, and increase lenders' exposure to default risk. Insurance and government aid exist to mitigate this default risk, but these protections have been weakening because insurers have been reducing coverage (Dixon et al., 2018; Kaufman, 2021).[2] Several large insurers in California, totaling 55 percent of the market share in areas with high fire risk, have either stopped writing or capped new policies, citing the rising costs of insuring wildfires (Boomhower et al., 2023). Furthermore, these safeguards may increase prepayments after natural disasters because households can use insurance payouts to pay mortgages early, which may be a suboptimal use of these funds.

This paper studies the types and extent of risk that natural disasters present to borrowers and lenders by evaluating the impact of wildfires on mortgage repayment. Using a novel database of fire damage inspections geographically merged to properties with mortgages, we separately identify the effects of wildfires on properties that are burned and the effects on properties within the fire perimeter that are undamaged. Existing research finds that different perils (e.g., hurricanes, floods, tornadoes) and events (e.g., Hurricanes Harvey and Katrina) lead to small increases in delinquency, default, and foreclosure that are short-lived because of insurance, government aid, and hazard mitigation efforts.[3] Our analysis makes three key contributions regarding the economic effects of natural disasters and finds that wildfires present greater risks to mortgage markets than suggested by previous studies.

First, we show 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. These 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

[1]The median year between 2017 and 2021 had 18 natural disaster events of any peril exceed $1 billion in damages, leading to $8.9 billion in damages per event, which is substantially higher than the six "billion-dollar events" leading to $6.3 billion in damages per event in the median year during the previous 37 years (NOAA, 2022).

[2]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.

[3]See Gallagher and Hartley (2017); Kousky et al. (2020); Ratcliffe et al. (2020); Du and Zhao (2020); Issler et al. (2021); Billings et al. (2022); Panjwani (2022) and An et al. (2022, 2023).

commonly used fire perimeters; our sample shows that 56 percent of properties and 59 percent of mortgages within the perimeter remain undamaged. This measurement error is exacerbated in California, where stricter building standards under stronger wildfire codes have made newer properties significantly less likely to be destroyed from exposure to a wildfire (Baylis and Boomhower, 2021).[4] 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 mortgage markets. To the best of our knowledge, this is the first paper to analyze multiple natural disaster events using property-level damage information.[5]

Second, our paper finds that wildfires substantially increase prepayment, which can be an inefficient use of insurance funds; indicate welfare losses for households; and pose risks to lenders, servicers, and mortgage-backed securities investors. Damages from natural disasters, except for floods and earthquakes, are covered under the home insurance required by mortgage lenders.[6] 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) and Gallagher et al. (2023) find large reductions in mortgage and credit card balances after a disaster. Prepayment results in lost interest revenue for lenders, which is larger if the disaster occurs during a low prevailing interest rate period. Effectively, insurance shifts some of the default risk associated with natural disasters to prepayment risk, thereby mitigating banks' exposure by a lesser degree than expected.[7]

Third, we provide evidence that the decision to prepay is motivated by insurance settlements that are insufficient to rebuild. After a wildfire, a household may use insurance settlements toward the rebuilding of the damaged home, the payment of the mortgage balance, or the purchase of a new home. The latter two alternatives can lead to a mortgage prepayment. A large increase in prepayment indicates that many affected households do not use their insurance settlements to rebuild the damaged 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. In such cases, households

[4] 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.

[5] The previously cited papers construct disaster exposure and damage measures at the county, census tract, census block, or zip code levels. Kousky et al. (2020) use property-level flood damages from home inspections, but their analysis is restricted to Hurricane Harvey.

[6] Households may, and in some cases are required to, purchase flood insurance through the National Flood Insurance Program administered by the Federal Emergency Management Agency (FEMA).

[7] Mortgage prepayment is the primary risk for investors holding mortgages securitized by government-sponsored enterprises (GSEs).

face strong incentives to apply insurance funds toward the mortgage balance instead of rebuilding, and the observed increase in prepayment represents a symptom of broader frictions in insurance markets that leave households with large financial losses in the aftermath of a natural disaster.

Specifically, we construct a novel database linking property-level fire damage to mortgage performance and estimate the effect of 79 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 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 4 percentage points, and prepayment rates increase by as much as 16 percentage points. Before the fire, the average delinquency rate is 1.35 percent, and the average prepayment rate is 2 percent. We find no significant changes in delinquency or prepayment for undamaged properties located within a fire perimeter. Our reduced-form parameter estimates include the protective effects of insurance and government aid, which suggest an even larger risk if climate scenarios worsen and assistance programs weaken. Particularly in California, greater wildfire risk has led to an increase in policy nonrenewals by insurers and has shifted households toward more expensive Free Access to Insurance Requirements (FAIR) plans that serve as home insurers of last resort and offer basic fire insurance (Dixon et al., 2018; Kaufman, 2021).

Using policy and claims data for fire-related insurance coverage in California, we show that insurance settlements that are too low to cover rebuilding costs after fires provide strong incentives for households to prepay their mortgage with insurance funds instead.[8] Almost 40 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 28 percent lower than the anticipated rebuilding costs. A back-of-the-envelope calculation suggests

[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.

that households receive about $200,000 to $300,000 less than their entitled amount under California law. Furthermore, we find a larger increase in prepayment for homes that face greater rebuilding costs using a triple-difference design. This result supports survey findings of underinsurance in California, where reconstruction costs exceed existing coverage often because of surges in construction prices after fires (Dixon et al., 2018; United Policyholders, 2022). Public records data confirm this implication, as only 8 percent of owners with a damaged property file a construction permit in the two years following a fire. These findings suggest the increase in prepayment is a symptom of frictions in insurance markets that leave households with settlements that cover their mortgage but not a full rebuild.

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. (2021) find small increases in delinquency and foreclosure. We estimate that wildfires lead to a much larger increase in mortgage delinquency. 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] Beyond mortgage delinquency, this paper's focus on mortgage prepayment, which identifies the immediate frictions households face when determining whether to rebuild or walk away from a damaged property, complements the other studies' focus on long-run migration and home prices.

In addition to the above contributions to research on consumer finance outcomes after natural disasters, this paper is 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, 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 Taṣpinar, 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).

[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. (2021).

[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).

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 and primarily focuses on transition risks.[11] 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.

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 four 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 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 and Appendix are derived from calculations based on these four 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. MTBS delineates wildfire burn perimeters by utilizing Landsat satellite imagery to analyze changes in burned areas before and after wildfire

[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).

[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).

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 79 wildfires are plotted in Figure 1. While fires that burned under 1,000 acres are not included in our sample, the 79 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. For each parcel, damage is assessed by in-person visual inspections by teams of 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.[13] 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. 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 falling within the fire perimeter but not 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, 59 percent of our mortgage sample and 56 percent of our properties sample within burn perimeters do not sustain damage,

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

underscoring the importance of incorporating DINS data in addition to wildfire perimeters in order to identify damaged parcels.

2.1.4 Federal Reserve FR Y-14M Mortgage Performance

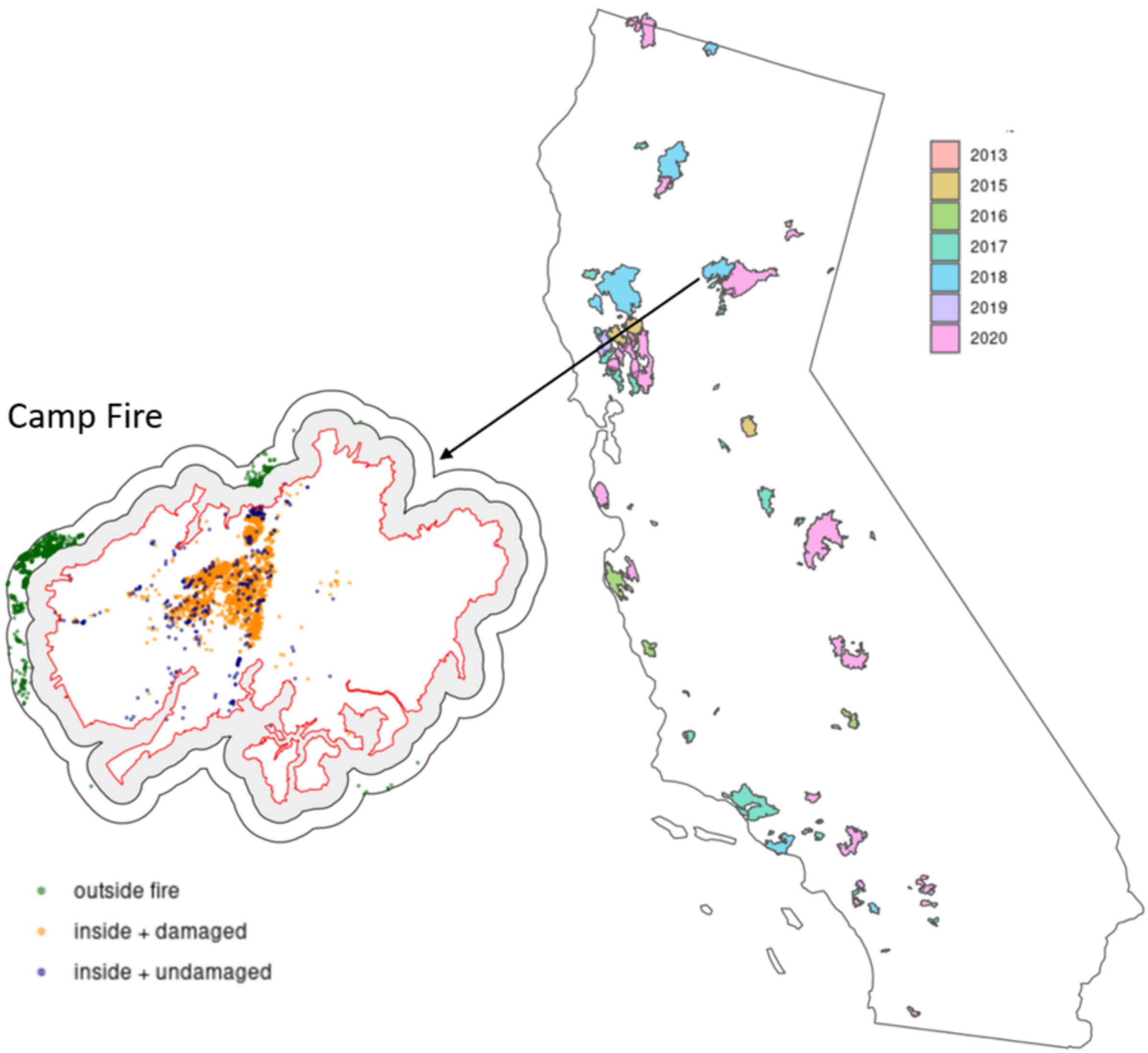
We obtain monthly mortgage performance history and origination characteristics for first-lien loans from FR Y-14M. Large banks submit these data to the Federal Reserve as part of the stress testing program, with our sample including 24 institutions. These data are collected monthly starting in June 2012 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. Table 1 contains borrower-level summary statistics by treatment group in the month before a wildfire.

Table 1: Summary Statistics

	Outside Fire		Inside + Damaged		Inside + Undamaged	
	mean	sd	mean	sd	mean	sd
Credit Score	747.42	65.50	748.77	61.67	754.34	58.53
Debt-to-Income	25.77	41.57	23.45	15.92	24.72	18.40
Interest Rate	0.04	0.01	0.04	0.01	0.04	0.01
Loan Term	328.36	72.23	330.52	71.13	333.03	69.57
log(Loan Amount)	12.67	0.69	12.49	0.84	13.00	0.80
LTV	0.64	0.22	0.66	0.24	0.61	0.21
Delinquency Rate	0.01	0.12	0.01	0.10	0.01	0.09
Prepayment Rate	0.02	0.13	0.01	0.11	0.01	0.11
Building Square Footage	2,130.57	1,049.57	2,158.83	1,122.48	2,852.04	1,509.40
Year Built	1977.48	19.70	1980.15	17.76	1984.95	15.77
N	69,831		4,983		7,126	

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.

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.

2.2 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.[14] 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 2, our analysis sample includes 81,940 loan-fire observations, which account for 23.5 percent of the 349,252 property-fire observations.[15]

Table 2: Sample Composition

Sample	Inside + Damaged	Inside + Undamaged	Outside Fire	Total
Single-Family Houses	23,233	30,124	295,895	349,252
Mortgages	4,983	7,126	69,833	81,940

Note: The first row of the table decomposes the number of unique property-fire observations we match by combining our property data on single-family houses with fire damage information. "Outside Fire" indicates that a property is within 1 to 2 miles of a fire perimeter. The second row restricts the sample to single-family houses that have a mortgage in the FR Y-14M database and makes up the sample for our mortgage performance analysis.

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

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

[15]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).

observations as pre-fire controls for another fire would incorrectly identify those loans as "unaffected" by a wildfire at that point in time.

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 12,109 parcels inside a wildfire perimeter at the onset of a fire, only 4,983 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.[16] 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 minimal loans entering foreclosure.

3 Analysis

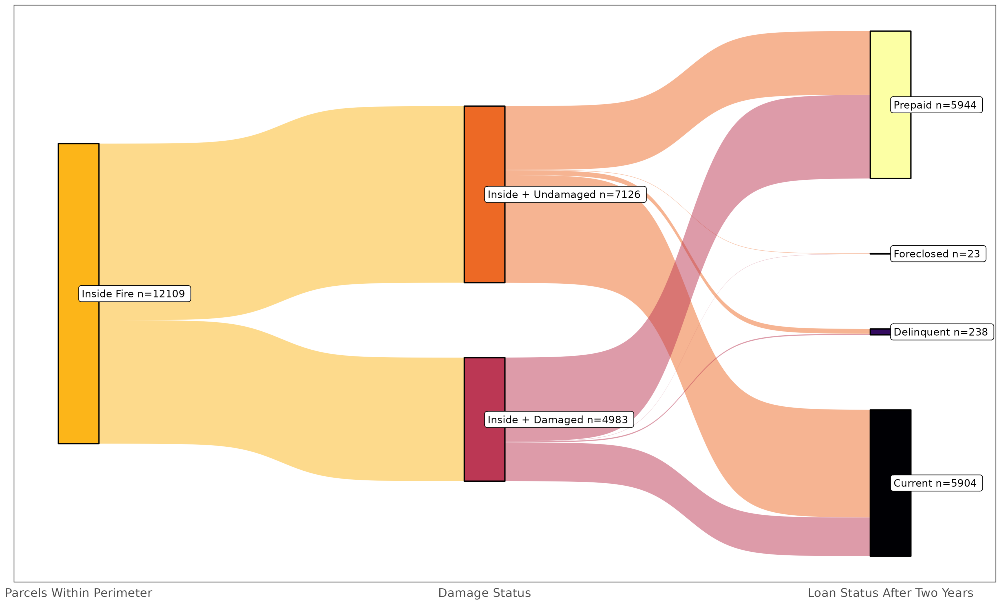
Our goal is to examine the impact of wildfire damage to one's house on delinquency and prepayment risk.[17] In order to estimate the causal effect of wildfires on mortgage repayment, we use a difference-in-differences (DiD) framework with varying treatment intensities. We use quasi-experimental variation 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.[18]

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

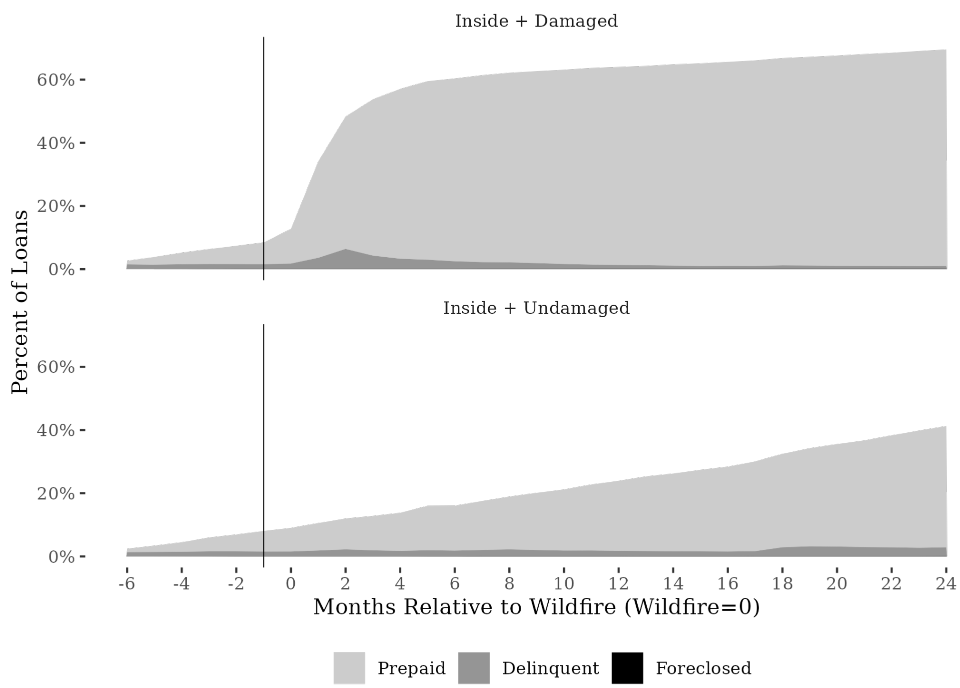
[17] Throughout this paper, we use "loan" and "home" interchangeably because it is too cumbersome to write "whether loan i was secured by a property that was damaged by a wildfire." We prefer to refer to homes being affected or damaged by wildfires, while loans become delinquent or are prepaid.

[18] Issler et al. (2021) 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.

Figure 2: Loan Status Flows After Wildfires



(a) Loan Status Two Years After Fire



(b) Monthly Loan Status

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.

We use the following framework,

$$Y_{ift} = \beta_1 Damaged_{ift} + \beta_2 InsideFireZone_{ift} + \beta_3 X_{ift} + \lambda_{ft} + \lambda_i + \epsilon_{ift},$$

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. The vector X_{ift} includes time-varying borrower and loan characteristics, such as current interest rate, credit score, and the share of balance remaining.[19] 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 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:

$$Y_{ift} = \sum_{t=-24;t\neq-1}^{t=24} \beta_{1t} Damaged_{ift} + \sum_{t=-24;t\neq-1}^{t=24} \beta_{2t} InsideFireZone_{ift} + \beta_3 X_{ift} + \lambda_{ft} + \lambda_i + \epsilon_{ift}. \quad (1)$$

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;

[19] Our results are similar if we exclude X_{ift}, alleviating 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).

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.

4 Results

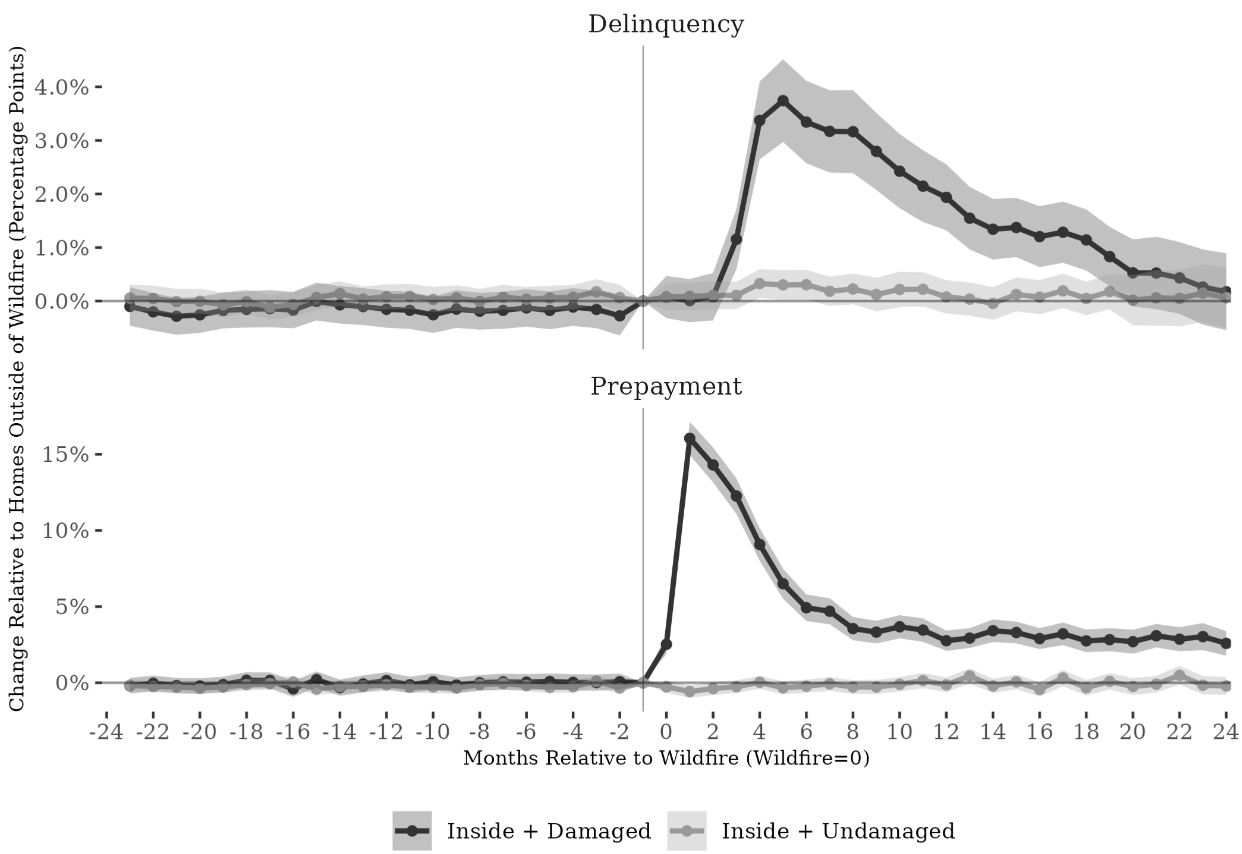
The top panel of Figure 3 shows that there is little evidence of pre-trends in delinquency for loans within the wildfire perimeter (whether damaged or not). We see a dramatic increase in delinquency starting three months after the fire and peaking at 4 percentage points within four to six months after 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 4 percentage point increase in delinquency is almost *three times* the average delinquency rate of 1.35 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 23 properties are foreclosed and 238 remain delinquent after two years.

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 delinquency is *eight times* the average prepayment rate of 2 percent. Accumulating these impacts over

[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. Robust 95% confidence intervals are indicated by the shaded regions.

time, we find that 67 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 35 percent and 32 percent, respectively.

4.1 Robustness

To test the robustness of our results, we reestimate our event study specification on two different samples. 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 2,563 homes in our mortgage sample, representing 40 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. We can infer which of these three channels are driving our prepayment results by observing if the properties associated with prepaid loans in our sample are sold after a fire and the timing of the transactions. Only 34 percent of damaged properties that prepay are sold within two years of a fire. In comparison, 46 percent of undamaged properties and 49 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.[21] 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. 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.

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.

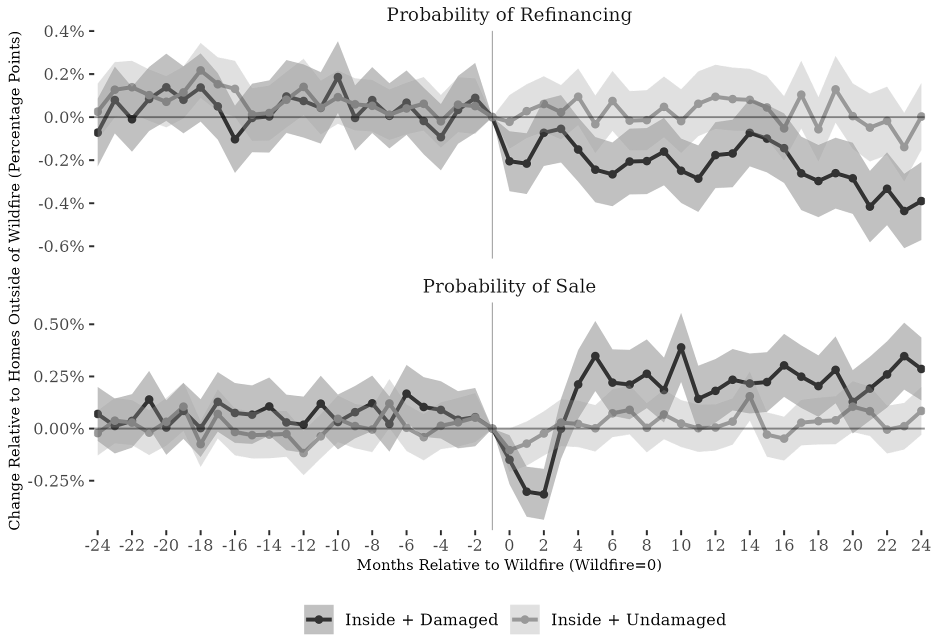
5.1 Background

Damages from wildfires are generally covered under homeowners insurance policies.[22] 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

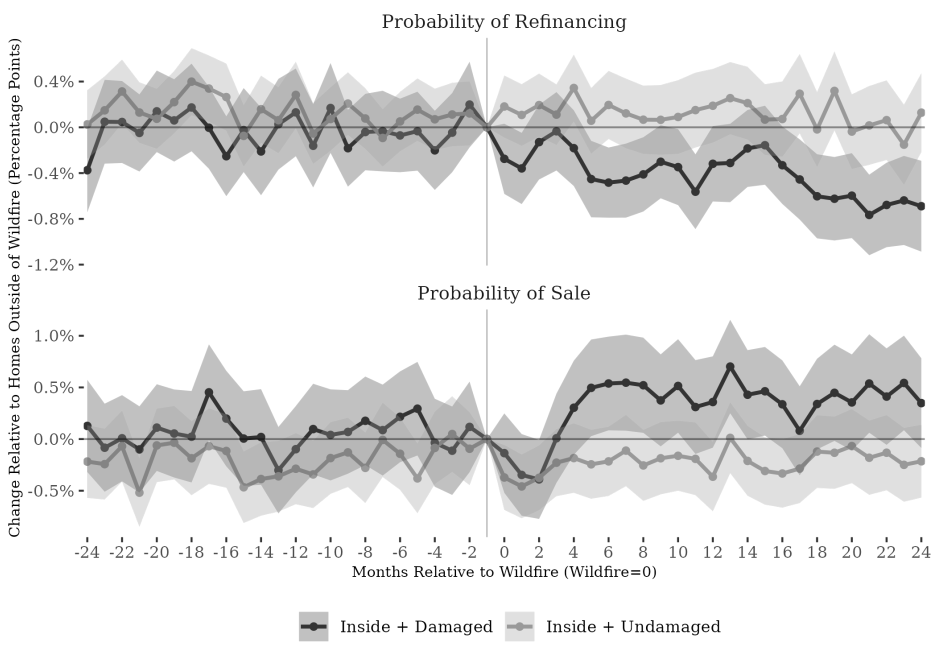
[21] The long-term decline in refinance may be explained by the higher sales rate for these properties. It is less likely that these newly purchased homes would be immediately refinanced. A decline in refinancing further rejects the hypothesis that prepayments are driven by refinancing.

[22] 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.

Figure 4: Home Sales and Refinancings Around Wildfire Events



(a) Sample of properties affected by wildfire



(b) Sample of FR Y-14M mortgages affected by wildfire

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. Robust 95% confidence intervals are indicated by the shaded regions.

opts to purchase additional coverage.[23] Over 88 percent of California homeowners insurance 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.[24] 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 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

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

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

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.[25] 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). Lastly, 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, transportation, and labor. We examine this last mechanism of demand surges by estimating the heterogeneous impacts of fires in cases with high rebuilding costs 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).[26] 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

[25] 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.

[26] 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.

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.[27] 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.[28]

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.

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:

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

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

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

[28]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.

exists in our sample, it replaces a claim resulting from a wildfire that is of a lower amount.[29] 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; 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 40 percent of claims were underpaid. The resulting deficit is $122,912, or 28 percent, of coverage limits. That is, the largest claims in zip codes where we observe fire damage received 72 cents per dollar of their respective Coverage A limits. Conditioning on underpaid claims, the deficit jumps to 83 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

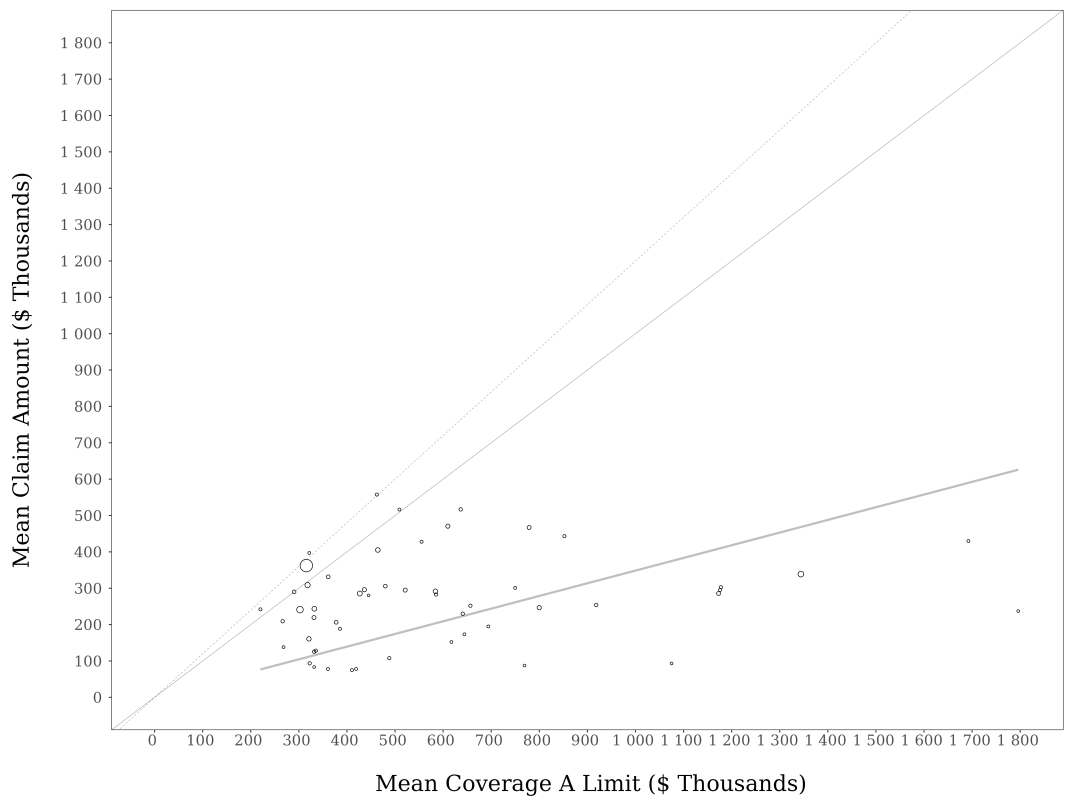
	All	2018	2019	2020
Deficit (share)	0.278	0.208	0.654	0.444
Deficit ($)	122,912	85,298	411,990	244,812
Underpaid (share)	0.398	0.344	0.836	0.568
Deficit if Underpaid (share)	0.828	0.833	0.807	0.818
Deficit if Underpaid ($)	497,485	482,344	524,734	529,458
Number of Claims	11,430	8,914	171	2,345
Number of Zip-Months	105	31	12	62

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.

[29] 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.

Next, we aggregate claims to the zip-code level and plot the correlation between average claim amounts and average Coverage A limits in Figure 5. 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 six zip codes fall at or above $1 of claims paid per dollar of coverage. Accounting for extended RCV, only two zip codes' payments would exceed the coverage limit plus 20 percent additional coverage, as represented by the dotted line.

Figure 5: 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.

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.

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

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.

at higher rates. Since policy limits are fixed through the policy year, the coverage gap is increasing in reconstruction costs. Specifically, we use the triple difference design in Equation 3, where we interact property damage with proxies of high reconstruction costs, Z_{ift}.[30] A positive estimate of γ_{1t}, in which the prepayment rate is increasing in reconstruction costs, supports underinsurance as a determinant of our observed prepayment spikes.

$$
\begin{aligned}
Y_{ift} = & \sum_{t=-24;t\neq-1}^{t=24} \beta_{1t} Damaged_{ift} + \sum_{t=-24;t\neq-1}^{t=24} \beta_{2t} InsideFireZone_{ift} \\
& + \sum_{t=-24;t\neq-1}^{t=24} \gamma_{1t} Damaged_{ift} \times Z_{ift} + \sum_{t=-24;t\neq-1}^{t=24} \gamma_{2t} InsideFireZone_{ift} \times Z_{ift} \\
& + \beta_3 X_{ift} + \lambda_{ft} + \lambda_{ft} \times Z_{ift} + \lambda_i + \epsilon_{ift}.
\end{aligned} \tag{3}
$$

[30] For continuous variables, such as log damaged properties, we standardize the values so that coefficients can be interpreted as the change in the dependent variable from a 1 standard deviation increase in the Z variable. We interact time fixed effects with our measures of heterogeneity to correct for estimation bias from multiple treatments, as discussed by de Chaisemartin and D'Haultfoeuille (2022).

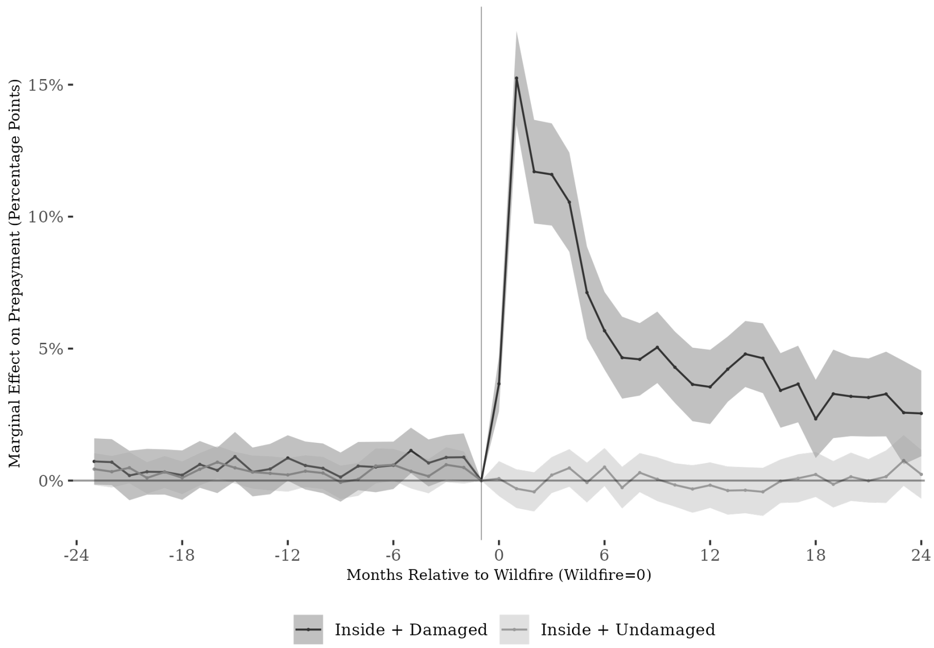
First, a surge in demand for construction is common after large natural disasters. Homeowners in areas where the concentration of fire damage is greater should face a higher cost to rebuild. The cost to rebuild may exceed the policy limit by more than the allowed adjustments under extended RCV. Simultaneously, insurers may be financially stressed to pay out more insurance claims, providing further incentives to negotiate lower settlements with households. We estimate Equation 3 with the log number of damaged properties inside the fire perimeter as Z_{ift}. As shown in the top panel of Figure 6, estimates of $\hat{\gamma}_{1t}$ are positive and significant, confirming that the prepayment rates for damaged homes after a fire increase with fire severity. The role of frictions after fires does seem to be driven by the most severe fires. We see that the magnitude of the differential effect by fire severity is smaller but statistically significant when we exclude the Camp Fire from our estimation sample (Figure A.8).

Second, we estimate whether prepayment rates differ by the reconstruction costs based on the year the home was built. California substantially changed its wildfire standards in building codes during the 1990s and in 2008, such that these reforms require the use of fire resistant materials throughout the structure (e.g., roof, doors, windows, decks) and maintenance of the home's defensible space (e.g., vegetation around the home) that reduce the likelihood of damage given fire exposure (Baylis and Boomhower, 2021). As a result, the majority of new homes built after these regulations in California were required to comply with the stronger wildfire standards. Owners of older homes built before these regulations are required to comply with current wildfire standards during any substantial reconstruction, such as a roof replacement. Therefore, the cost to rebuild an older home will be substantially higher than the cost for a newer home, as the replacement costs will include additional costs to comply with new wildfire standards. We hypothesize that incentives to prepay are stronger for older homes than newer homes, as it is less likely that the insurance settlement will fully cover the higher cost of rebuilding. Estimates of $\hat{\gamma}_{1t}$ where Z_{ift} indicates whether the property was built before 1991 confirm this story. The bottom panel of Figure 6 shows that homes built before 1991, when stricter wildfire codes were first introduced, are more likely to prepay than homes built after 1991.

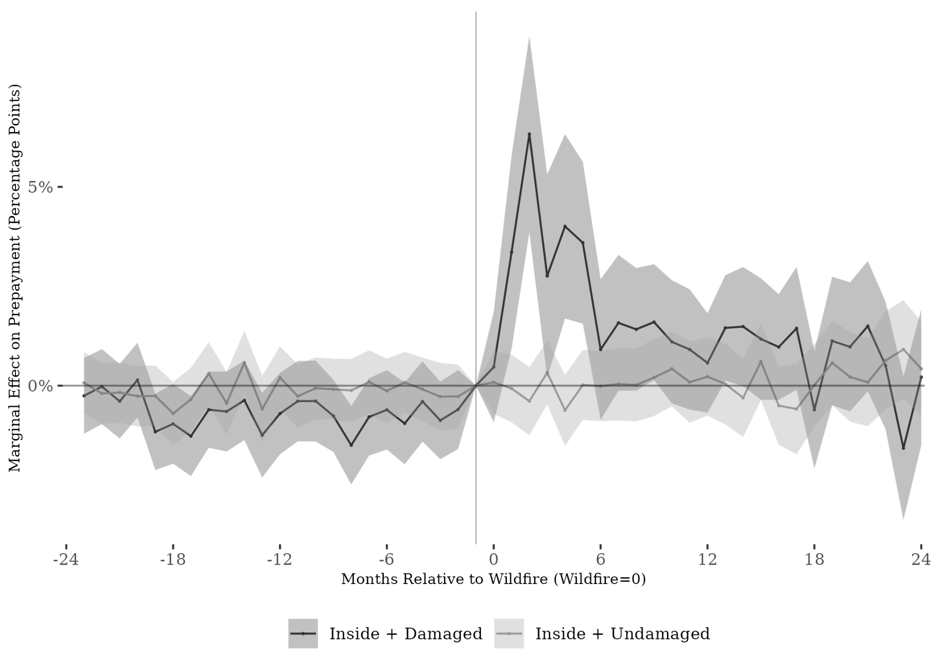
6 Welfare Implications

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

Figure 6: Differences in Prepayment by Damage Severity



(a) Log of Properties Damaged × Fire Damage



(b) Built pre-1991 × 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 prepayment after the fire for large fires as measured by number of properties damaged (top panel) and for loans on properties built before 1991 when stronger wildfire building codes were introduced (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.

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.[31] The counterfactual change in equity from before to after the fire for households that receive the full payment under California law is therefore the following:[32] If the household rebuilds, owners pay p^R_{ijt} in reconstruction costs. If the household opts to purchase a new home instead, the value of the existing property drops by the amount of damage incurred.

$$\begin{aligned}\Delta e^*_{ijt} = &\min\{(1+\text{ERCV}_{ijt})\cdot \text{Coverage A Limit}_{ijt}, p^R_{ijt}\}\\ &- \mathbb{1}(\text{Rebuild}_i)\cdot p^R_{ijt} - \mathbb{1}(\text{New Purchase}_i)\cdot \text{Damages}_{ijt}.\end{aligned}$$

Unfortunately, we do not observe all the components to calculate the above. Instead, we estimate the shortfall between the actual change in equity, Δe_{ijt}, and counterfactual change in equity as

$$\Delta e_{ijt} - \Delta e^*_{ijt} = \text{Claim}_{ijt} - \max\{\text{Coverage A Limit}_{ijt}, \text{Claim}_{ijt}\}. \tag{4}$$

Intuitively, 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 assuming there is no rebuilding. This assumption is not as strong as it seems because very few households rebuild. Only 8 percent of the damaged properties file a construction permit in the two years following the fires between 2018 and 2020. Assuming that property damages lead to a total loss of structure value, we calculate the change in equity when a household does not rebuild as

$$\Delta e^{NR}_{ijt} = \text{Claims}_{ijt} - \text{Structure Value}_{ijt}.$$

[31] 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.

[32] 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.

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 \$199,290 to \$296,318 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 \$21,998.[33] However, this improvement in the household's equity position does not imply that the household is better off. The household still has to purchase new housing and pay off any existing debt or tax obligations on the damaged house. 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: Equity Shortfall Relative to Legal Entitlement

		Entitlement Limit		
	N	Coverage A	ERCV	Δe_{ijt}
All	10,106	-199,290	-296,318	21,998
2018	8,697	-165,863	-251,867	48,602
2019	165	-433,958	-604,739	-209,706
2020	1,244	-401,858	-566,173	-133,264
Camp Fire Only	6,998	-73,841	-124,130	130,183
Excluding Camp Fire	3,108	-481,754	-684,018	-221,592

Note: Shortfall amounts as calculated from Equation 4. We show the calculations assuming that the legal entitlement under Insurance Code §2051.5 is capped by either the Coverage A limit or the ERCV. The change in equity in the last column assumes the household does not rebuild. 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

[33]This equity gain is entirely driven by the Camp Fire, which is a unique case in which we observe at least 2,000 fewer claims than properties damaged. We assume this difference is due to homeowners not holding insurance (United Policyholders, 2022). If instead those properties did hold insurance and did not receive claim payments, the underpayment would imply a larger equity loss due to the Camp Fire than we calculate.

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.

Lenders, Servicers, and Investors While we show large welfare losses for households, other agents in the mortgage 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.[34] 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 for loans with different interest rates (Equation 3). 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 the top panel of Figure 7 opposes bank preferences, as loans with higher

[34]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.

interest rates have higher likelihoods of prepayment after a fire. Loans with a 1 standard deviation higher interest rate have a 3 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. The bottom panel of Figure 7 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.[35]

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

7 Conclusion

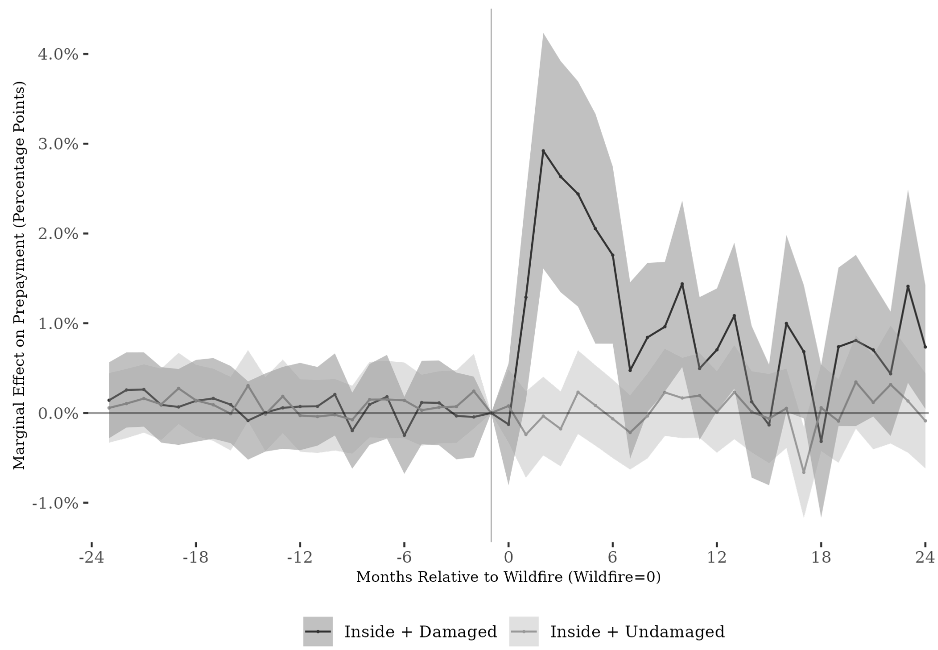
We construct a novel database that merges property-level damage inspections from 79 California wildfires with mortgage performance and evaluates the impact of wildfires on mortgage repayment. This paper finds that 90-day delinquency rates and prepayment rates increase significantly for damaged properties 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. We conclude that insurance payouts drive the large increase in prepayments for damaged properties after a wildfire, similar to the case of Hurricane Katrina (Gallagher and Hartley, 2017).

Our results highlight that wildfires present a larger risk to mortgage markets than the previous research finds. 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. These findings regarding the immediate aftermath of wildfires have implications for several stakeholders.

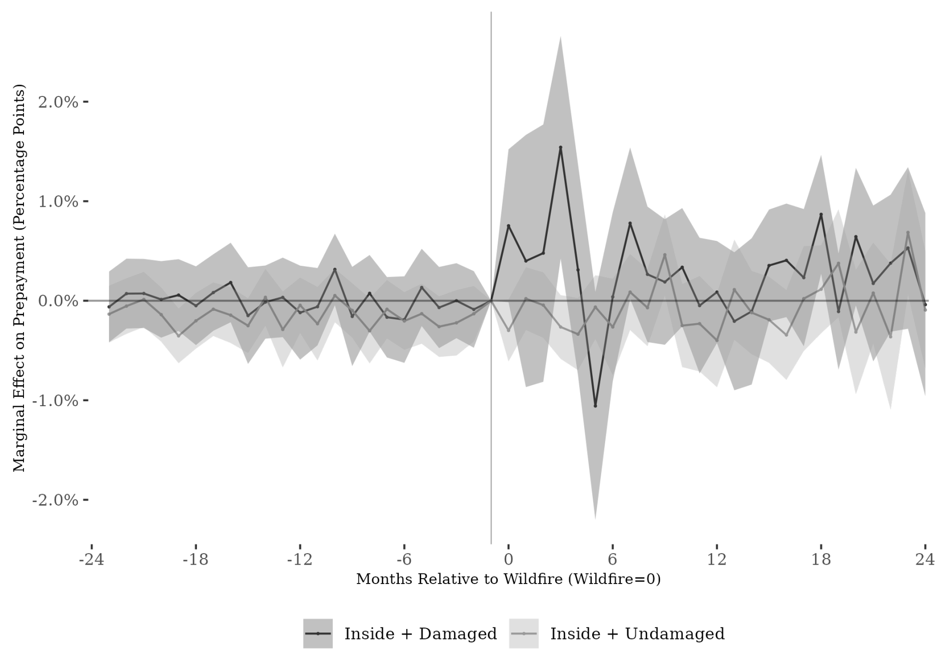
For households, the large increase in prepayment is an indicator for the lack of insurance coverage. We find substantial underpayment rates and deficits, in which the insurance settlement is lower than coverage limits, which are meant to proxy the costs of rebuilding.

[35]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.

Figure 7: Differences in Prepayment by Interest Rate and Credit Score



(a) Interest Rate $\times$ Fire Damage



(b) Credit Score $\times$ 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 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.

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. Such insurance market frictions lead households to experience 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 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 policymakers, our findings imply 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).[36] 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. Therefore, additional research is necessary to understand prepayment risks and the use of insurance funds after disasters.

Last, for researchers, this study emphasizes the need to obtain more precise measures of physical climate risks. As 56 percent of properties and 59 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. Resulting estimates would be attenuated and may understate the true impact of fires on mortgage repayment. Our research motivates a greater focus on the local effects of natural disasters to fully understand the consequences of physical climate risks.

[36] 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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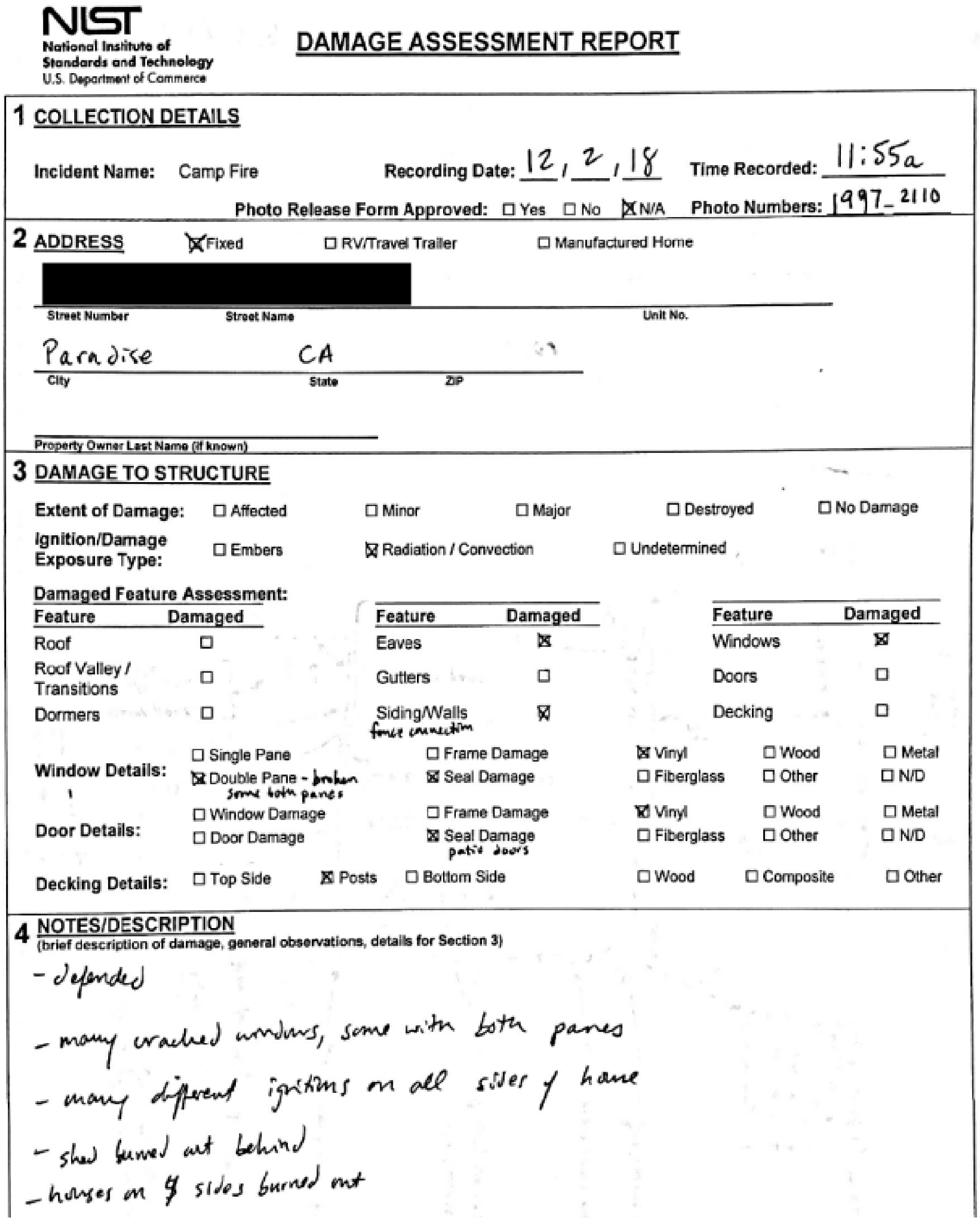
A Appendix

All results presented in the figures and tables of this Appendix 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 ☐ Wood ☐ Metal ☐ Fiberglass ☐ Other ☐ N/D

Door Details: ☐ Window Damage ☐ Door Damage ☐ Frame Damage ☒ Seal Damage (patio doors) ☒ Vinyl ☐ Wood ☐ Metal ☐ Fiberglass ☐ Other ☐ 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
- houses on 4 sides burned out

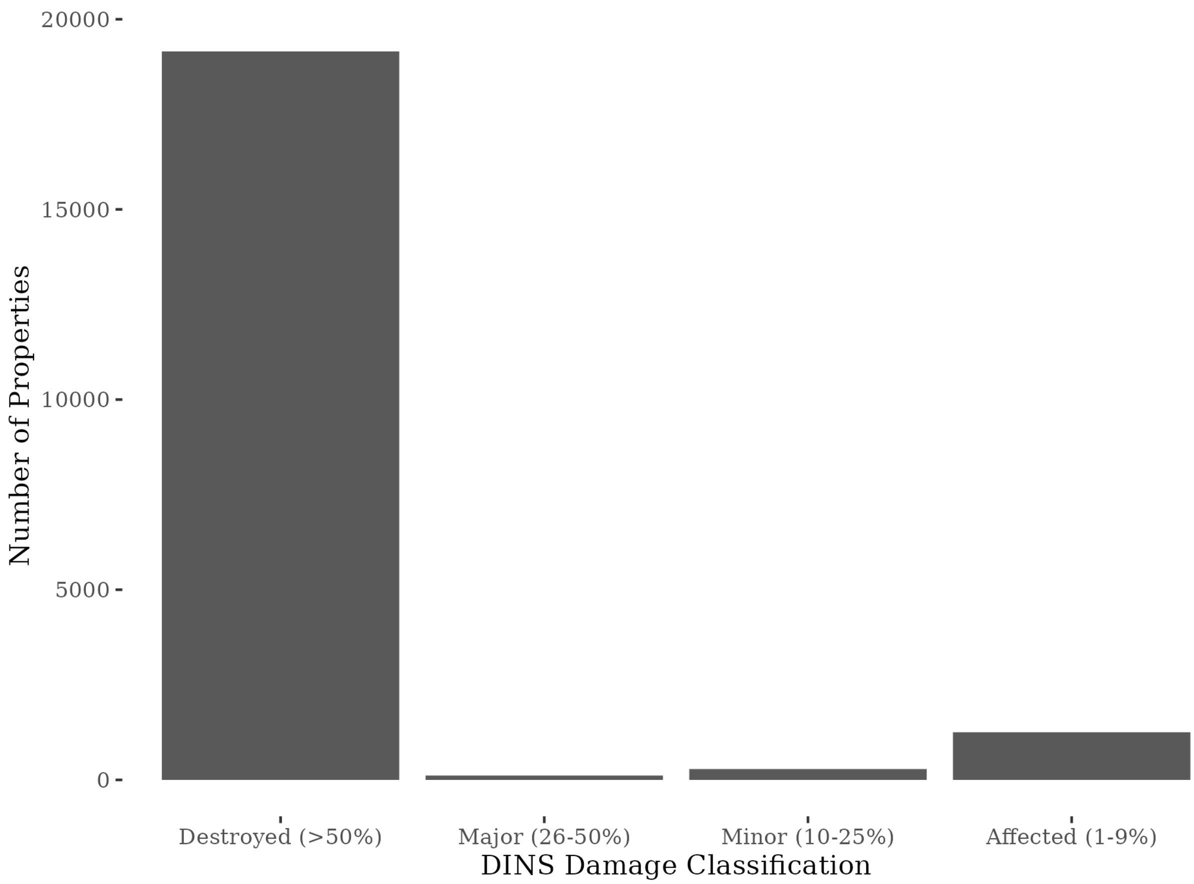
Source: NIST Investigation of the California Camp Fire, Fire Research Division, National Institute of Standards and Technology.

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.

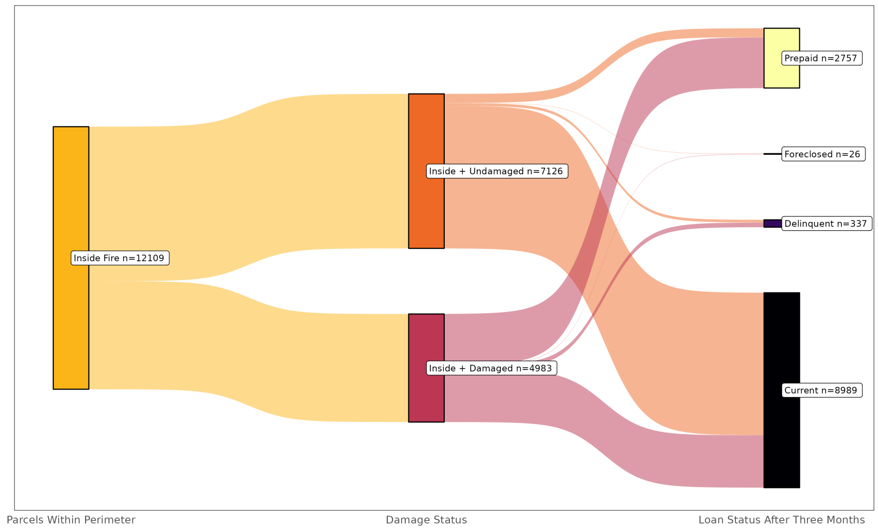
Source: Camp Incident Damage Inspection Report CABTU 016737

Figure A.3: Distribution of Damage Severity

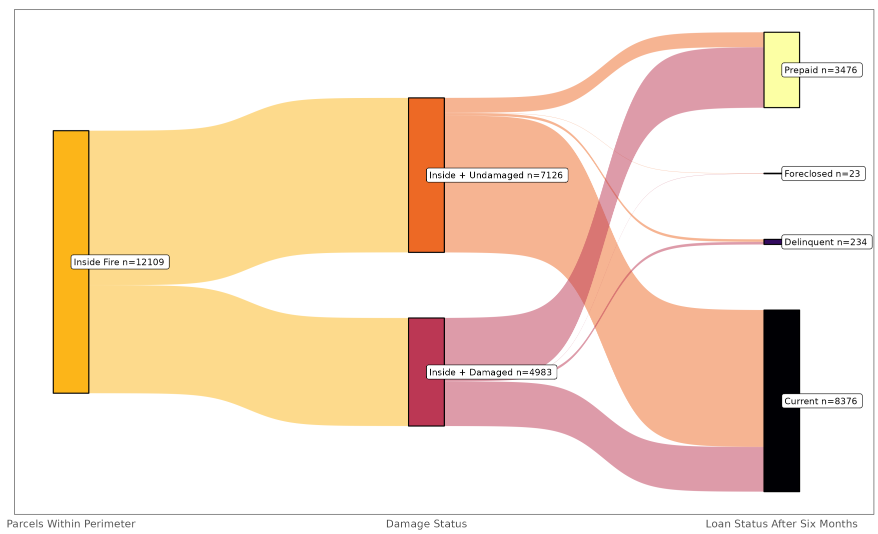


Note: Figure plots the distribution of damage categories reported in the DINS database.

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



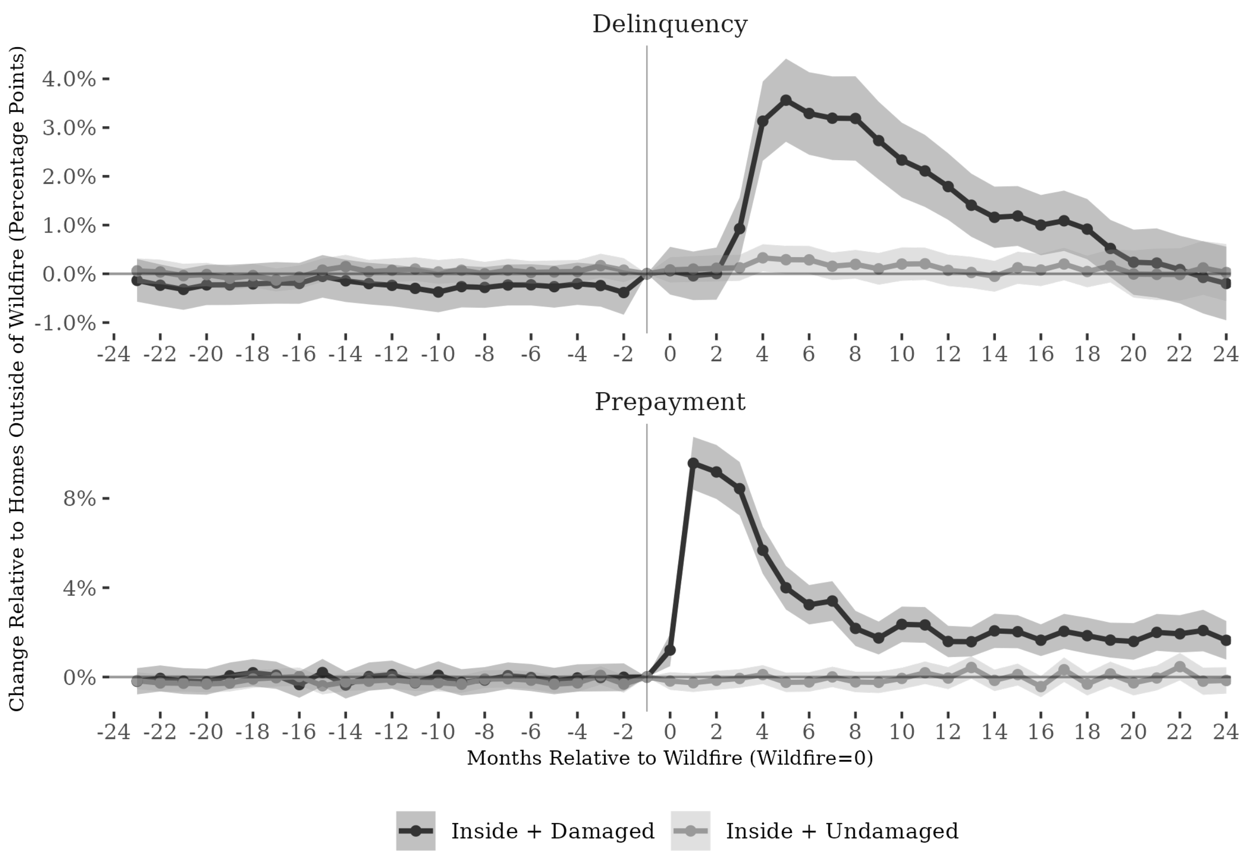
(a) Loan Status Three Months After Fire



(b) Loan Status Six Months After Fire

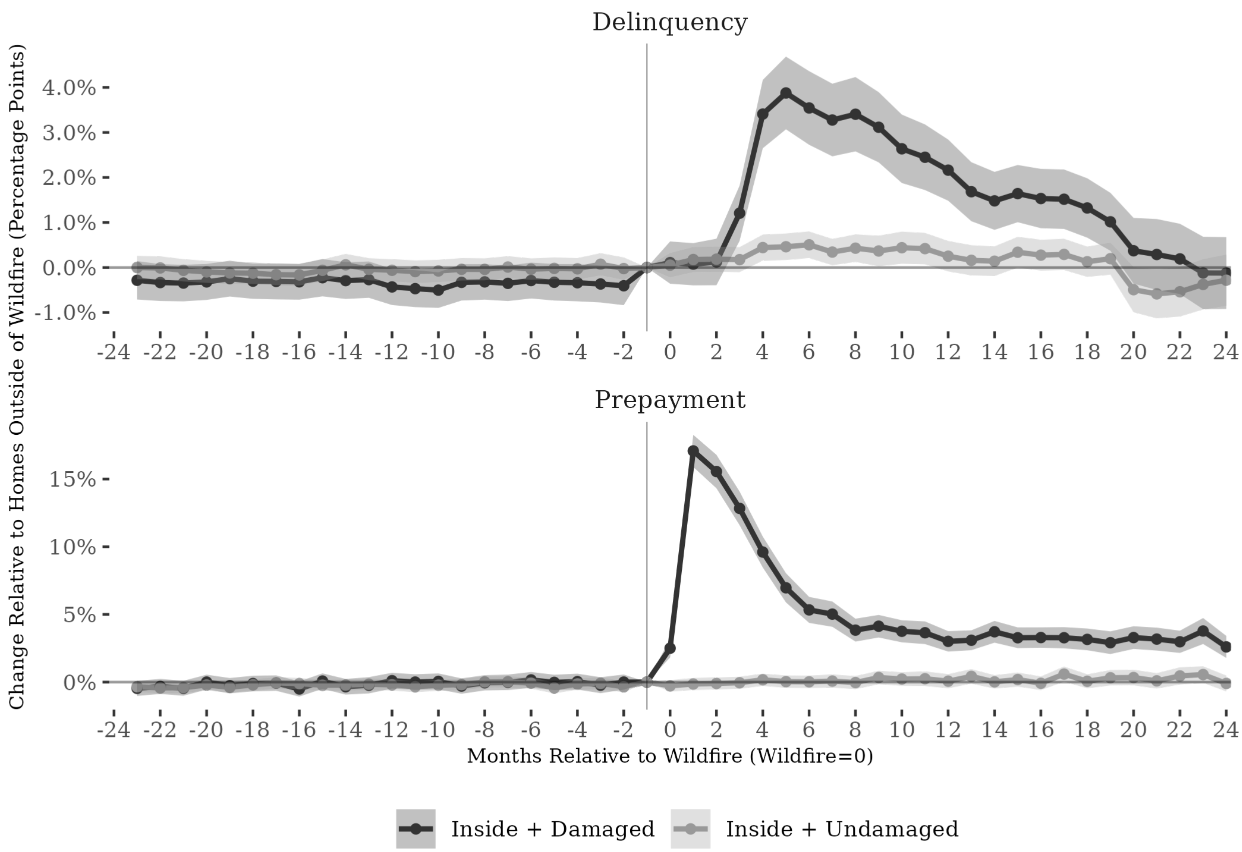
Note: Figure illustrates the decomposition of loans within wildfire boundaries based on whether or not the home was damaged by the wildfire. The top panel shows mortgage status three months post-fire (current, delinquent, foreclosed, or prepaid) while the bottom panel shows mortgage status six months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

Figure A.5: Robustness to Omitting Camp Fire



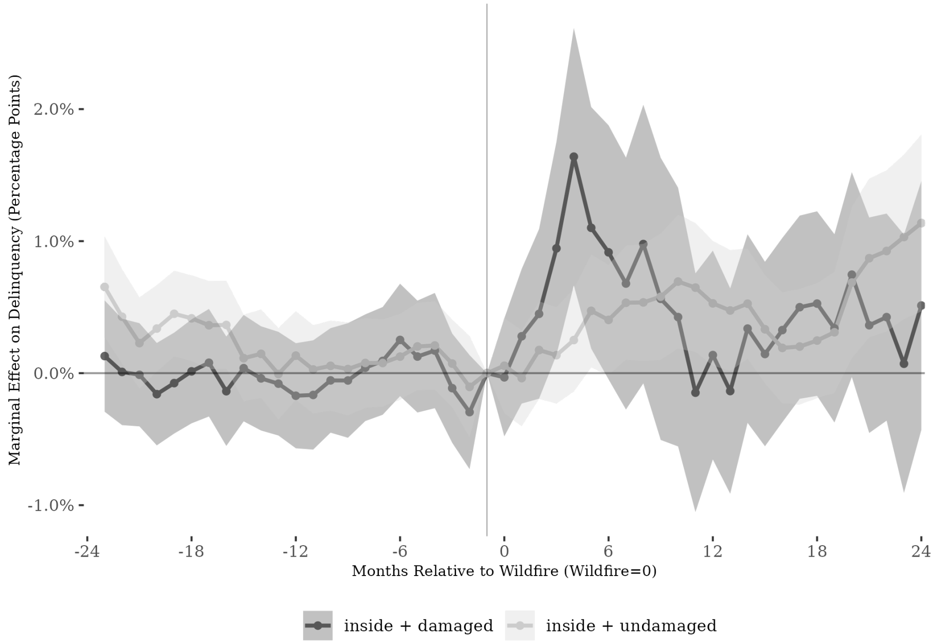
Note: Figure illustrates the coefficients for damaged (β_{1t}) and undamaged (β_{2t}) parcels estimated from the event study specification in Equation 1 after excluding the Camp Fire in 2018. The top panel presents results for delinquency and the bottom panel presents results for prepayment. Regression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

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

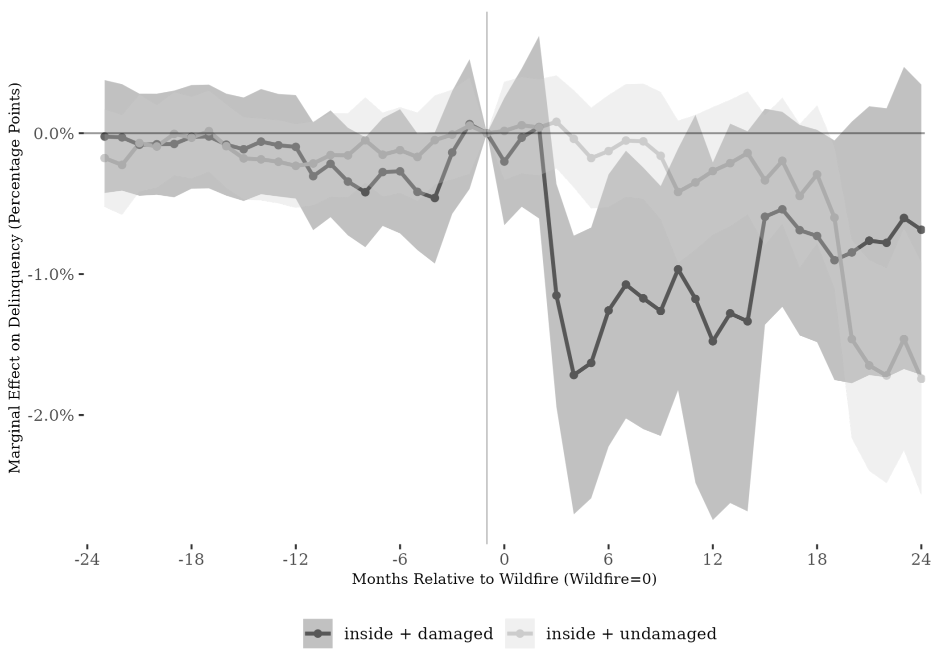


Note: Figure illustrates the coefficients for damaged (β_{1t}) and undamaged (β_{2t}) parcels estimated from the event study specification in Equation 1 using homes in the 5- to 6-mile ring outside the fire perimeter as the control group. The top panel presents results for delinquency and the bottom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

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



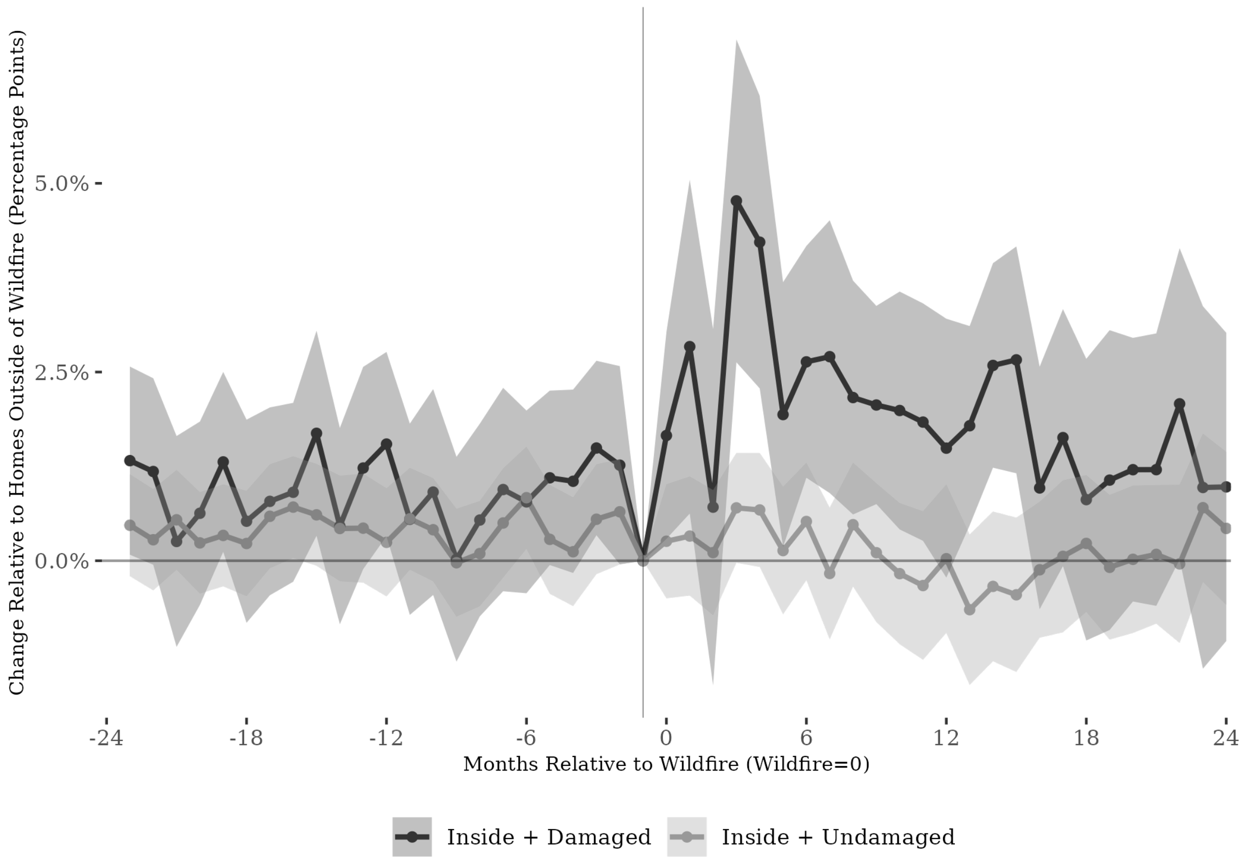
(a) Interest Rate $\times$ Fire Damage



(b) Credit Score $\times$ 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. Robust 95% confidence intervals are indicated by the shaded regions.

Figure A.8: Log Damages Heterogeneity: Robustness to Omitting Camp Fire



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. The plot presents the differential impact on prepayment after the fire for large fires as measured by number of properties damaged after excluding the Camp Fire in 2018. 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.