California Wildfires, Property Damage, and Mortgage Repayment*

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Abstract

This paper examines wildfires' impact on mortgage repayment using novel data that combines property-level damages and mortgage performance data. 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, 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. We provide evidence that underinsurance may force borrowers to prepay instead of rebuild.

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 to $1.2 billion in damages per year during the 37 years prior.[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). Furthermore, these safeguards may increase prepayments after natural disasters as 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 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 due to insurance, government aid, and hazard mitigation efforts.[2] Our analysis makes two 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 delinquency rates for properties that are damaged. In contrast, 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 commonly used fire perimeters; our sample shows that 59 percent of properties 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 with exposure to a wildfire (Baylis and Boomhower,

[1]The median year between 2017 and 2021 had 18 natural disaster events of any peril exceed $1 billion of damages leading to $8.9 billion in damages per event, substantially higher than the 6 "billion-dollar events" leading to $6.3 billion in damages per event in the median year during the 37 years prior (NOAA, 2022).

[2]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); An et al. (2022, 2023).

2021).[3] 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.[4]

Second, our paper finds that wildfires substantially increase prepayment, which can be a risk for lenders and an inefficient use of insurance funds. Damages from natural disasters except for floods and earthquakes are covered under home insurance required by mortgage lenders.[5] Insurance and government aid reduce lenders' exposure to default risk caused by natural disasters, but households may use assistance to pay off mortgage and other debts. Gallagher and Hartley (2017) and Gallagher et al. (2022) 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.[6]

For households, an unconstrained choice to prepay reveals that it is preferable to walk away from a damaged home rather than to rebuild.[7] After a wildfire, the household may use insurance settlements toward the rebuild of their damaged home, 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 their damaged home. If the decision not to rebuild is driven by insufficient insurance settlements, the increase in prepayments is a symptom of broader frictions in insurance markets that leave households underinsured 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 82 wildfires in California on mortgage borrowers' likelihoods 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

[3]Fried (2021) 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.

[4]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.

[5]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).

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

[7]We do not find evidence of lenders pressuring households to use insurance funds to repay mortgages, unlike the case of Hurricane Katrina documented by media accounts and Gallagher and Hartley (2017).

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-difference 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. Then, we use a triple-difference design to estimate whether prepayment differs by borrower, loan, or fire characteristics. This exercise allows us to test the validity of proposed mechanisms driving the large observed increase in prepayment after wildfires.

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 non-renewals by insurers and has shifted households toward more expensive FAIR plans that serve as home insurers of last resort and offer basic fire insurance (Dixon et al., 2018; Kaufman, 2021).

After a fire, sales and refinances do not increase for damaged properties quickly enough to result in the immediate increase in prepayment. Therefore, the prepayment increase seems to be driven by the use of insurance funds to pay off mortgages. We find that households decide to use insurance funds to prepay rather than rebuild without interference or pressure from lenders. We also find a larger increase in prepayment for homes that face greater rebuilding costs, which supports survey results that report underinsurance for fire coverage in California. This finding suggests that insurance settlements may cover a prepayment but may not be sufficient to rebuild.

Our results show that wildfires pose a greater risk to mortgage markets than evaluated by previous research. After large wildfires, Balch 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 due to more precise measurement of property-level damages through damage inspection data 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.[8] Beyond mortgage delinquency, this paper's focus on mortgage prepayment, which identifies 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).[9] 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; Balch et al., 2021). From a banking supervision perspective, climate risk may also impact financial systems. Generally, the research on this topic utilize a stress-testing framework to assess repayment and bank losses under different climate scenarios, and primarily focus on transition risks.[10] An et al. (2022) focuses on physical risks and finds 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 the determinants of elevated prepayment after wildfires. Section 6 highlights the policy implications of our findings, and Section 7 concludes.

[8]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).

[9]See Canals-Cerdá and Roman (2021) for a comprehensive summary. 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). Bakkensen and Barrage (2021) attribute these mixed results to heterogeneous beliefs about current and future flood risk.

[10]Researchers and central bankers have conducted stress tests that evaluate transition risks in 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).

2 Data

2.1 Data Sources

We rely on four datasets. Wildfire burn perimeters are obtained from Monitoring Trends in Burn Severity (MTBS). Parcel-level wildfire damage reports (DINS data) are provided by CAL FIRE. 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 datasets unless otherwise noted. Details on the contents and usage for each of these datasets are described below.

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 events. This dataset includes all wildfires 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 burn at least 1,000 acres and damage at least one structure. These 82 wildfires are plotted in Figure 1. While fires under 1,000 acres are not included in our sample, the 82 fires included account for 98 percent of structure damaged caused by wildfires in California from 2013 through 2020.

2.1.2 DINS damage inspection data

CAL FIRE's Damage Inspection (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 dataset identifies the extent of damage (no damage, affected, minor, major, destroyed), the assessor parcel number, parcel location (latitude/longitude), parcel address, and limited structure characteristics.[11] Unaffected parcels are not included for the majority of fires. Among the parcels that sustained wildfire damage, 92 percent of them are classified as

[11]See Appendix Figure A.1 for an example damage report.

destroyed. 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 from 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 damage inspection 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 corresponding damage status for the Camp Fire, which burned in Southern California in 2018. As shown, the majority of parcels falling within the Camp Fire perimeter do not sustain damage, underscoring the importance of incorporating DINS data in addition to wildfire perimeters in order to identify damaged parcels.

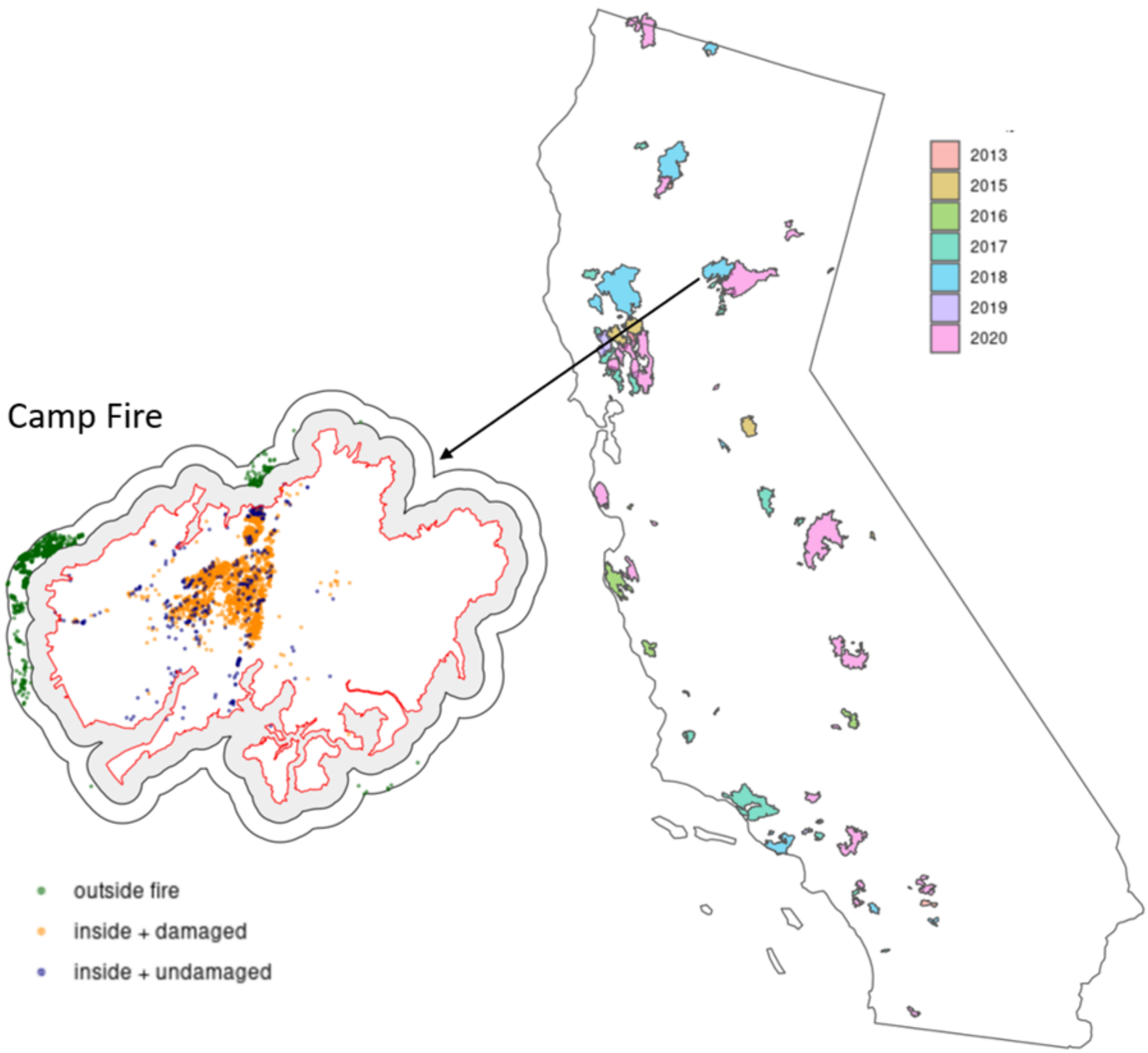
2.1.4 Federal Reserve FR Y-14M mortgage performance

We obtain monthly mortgage performance history and origination characteristics for first-lien loans from FR Y-14M. FR Y-14M data are submitted to the Federal Reserve by 24 large banks as part of the stress testing program. 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 prepaid. The borrower characteristics include credit score, debt-to-income ratio, loan-to-value 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 prior to a wildfire.

2.2 Data Construction

We combine the data above to generate a loan-fire-month dataset and a property-fire-month dataset. For the loan-level dataset, 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

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.

Table 1: Summary Statistics

	Outside Fire		Inside + Damaged		Inside + Undamaged	
	mean	sd	mean	sd	mean	sd
Credit Score	747.42	65.50	748.76	61.63	754.34	58.53
Debt-to-Income	25.77	41.57	23.46	15.90	24.72	18.40
Interest Rate	0.04	0.01	0.04	0.01	0.04	0.01
Loan Term	328.37	72.23	330.48	71.14	333.01	69.59
log(Loan Amount)	12.67	0.69	12.49	0.84	13.01	0.80
Origination 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
N	69,830		4,997		7,120	

Note: Table contains loan-level summary statistics by treatment group in the month prior to the wildfire (event time $t = -1$). Credit score, debt-to-income (DTI), loan-to-value (LTV), and loan size 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. Prepaid is equal to one if the loan is prepaid in event time $t = -1$ and zero otherwise.

months after the fire. Therefore, for each fire, we have a balanced four-year window of mortgage performance data.[12] For the property-level dataset, 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 its damage status. As shown in Table 2, our analysis sample includes 81,947 loan-fire observations, which account for 23.5 percent of the 349,396 property-fire observations.[13]

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 (we still include 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 a year after it was hit by 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-period of another fire. This does create an unbalanced panel for loans that are affected, but due to

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

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

Table 2: Sample Composition

Sample	Inside + Damaged	Inside + Undamaged	Outside Fire	Total
Total Properties	24033	88998	440199	553230
Single-Family Houses	23414	30093	295889	349396
Mortgages	4997	7120	69830	81947

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

the disastrous nature of wildfires, we view 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.

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 12,117 parcels inside a wildfire perimeter at the onset of a fire, of which only 4,997 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.[14] The bottom panel shows that prepayments increase immediately in the month of the fire and further spike in 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.

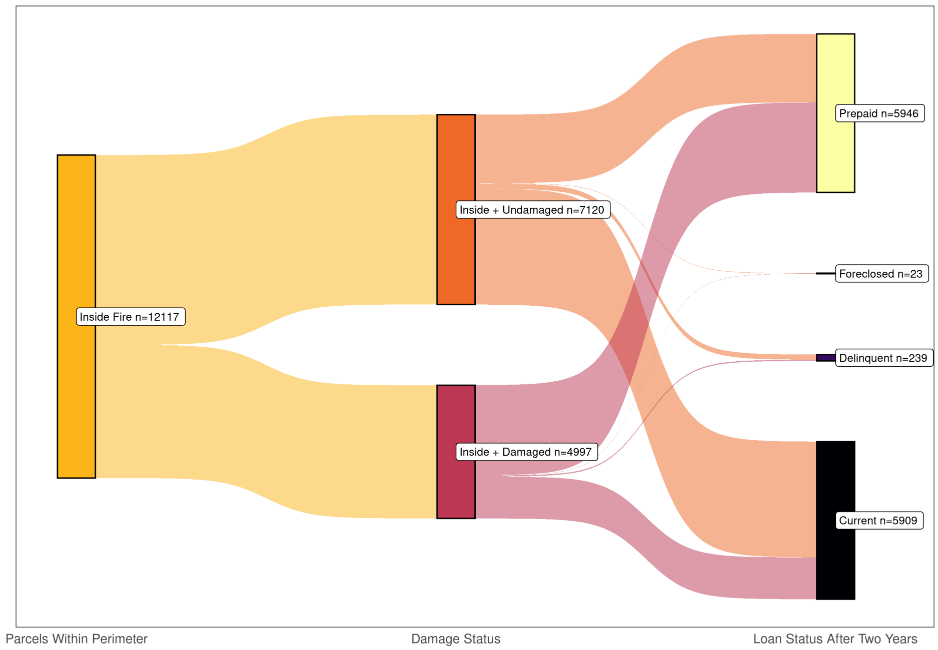
3 Analysis

Our goal is to examine the impact of wildfire damage to one's house on delinquency and prepayment risk.[15] In order to estimate the causal effect of wildfires on mortgage repayment,

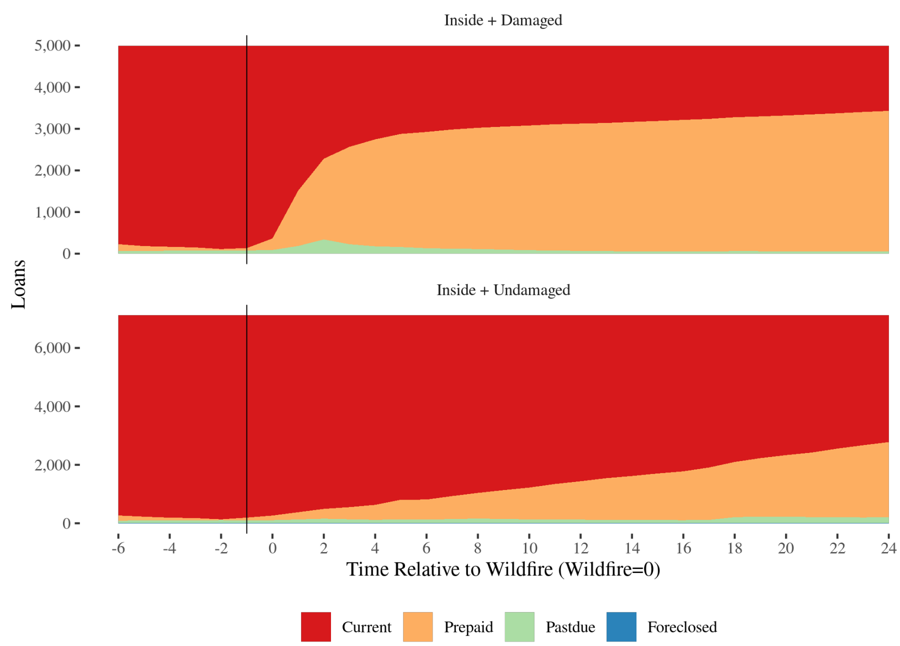
[14]Figure A.2 in Appendix A provides snapshots of loan performance in three and six months after a fire.

[15]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.

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 or past due, foreclosed, or prepaid), while the bottom panel tracks monthly loan status.

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.[16]

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.[17] λ_{ft} consists of fire-year-month fixed effects so that we can control for different time paths for different fires (i.e., separately capture the behavior of non-damaged 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 holds in the pre-treatment periods, we estimate an event study specification:

[16] 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 externalties of the wildfires on these homes.

[17] 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 et al., 2022; Roth et al., 2022).

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

Several recent studies have documented 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 contain no never-treated groups, which can lead to underidentification. To address these concerns, we follow a "stacked regression" design where 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.

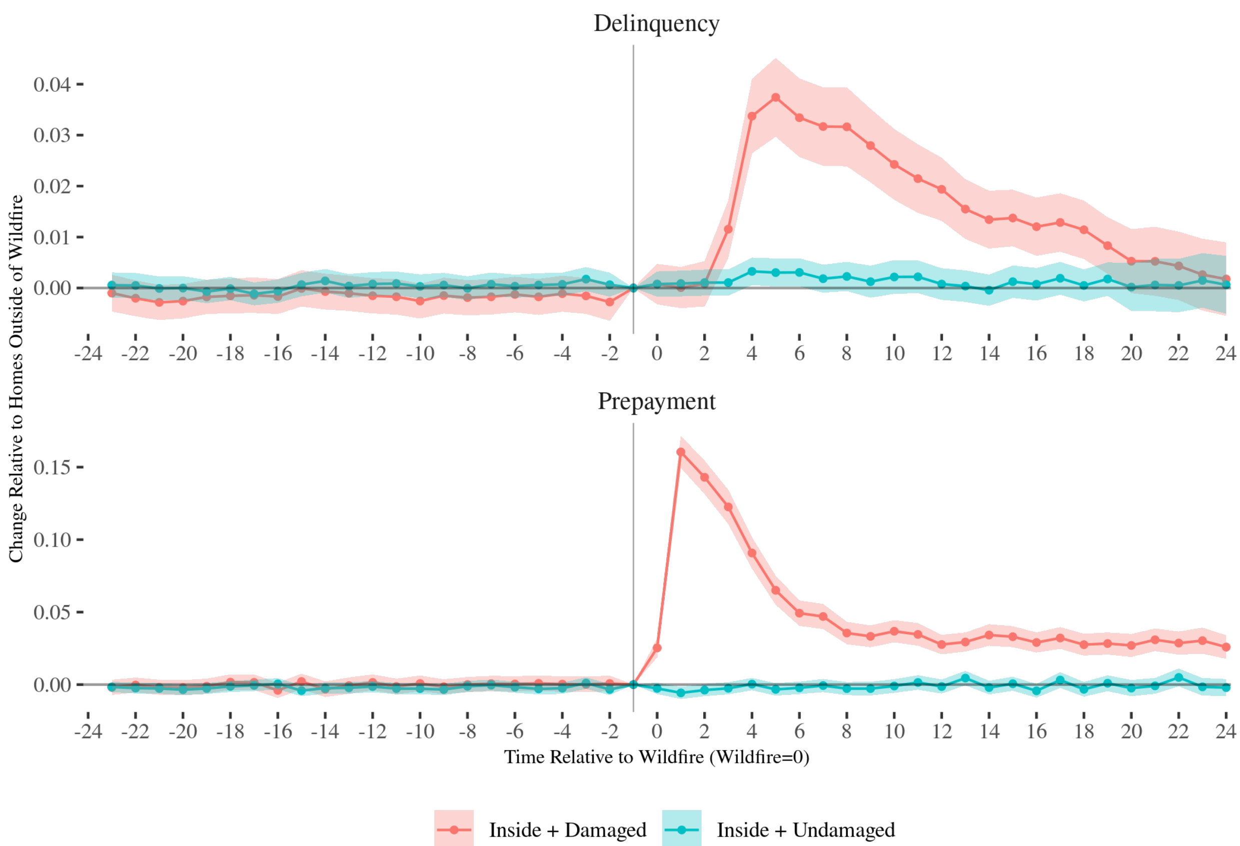
4 Results

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). After the fire, we see a dramatic increase in delinquency starting three months after the fire and peaking at 4 percentage points in the four to six months after the fire.[18] The increase then gradually declines in the six to 24 months after the fire, likely due to either 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

[18] 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.

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 239 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 and then gradually declining (but still elevated) for the 24 months post-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 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 36 percent and 34 percent, respectively.

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 sample, representing 86 percent of homes inside its fire perimeter and 40 percent of all damaged homes in our sample. Figure A.3 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.4 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.

5 Prepayment After Wildfires

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 transaction. Only 34 percent of damaged properties that prepay are sold within two years of a fire. In comparison, 46 percent of undamaged properties and 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 for our estimation of the impact on mortgage repayment. Results from both samples confirm that sales activity for damaged parcels do 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 do not differ from unaffected properties until at least 10 months after a fire, when we see refinancing among damaged properties decline.[19] An increase in sales occurring later 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 those of properties that are undamaged or outside the fire zone.

Both the sale of a damaged property or the use of insurance funds to pay off a mortgage after a fire similarly imply that borrowers opt to walk away from a damaged property rather than rebuild. While households may face a large financial loss from selling their home in a damaged condition, it may still be optimal to sell if proceeds from the sale and insurance claims sufficiently cover payment of any remaining mortgage balance and 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 the remainder of this section, we provide further background on the role of insurance after wildfires and investigate mechanisms that lead to such a large increase in prepayment.

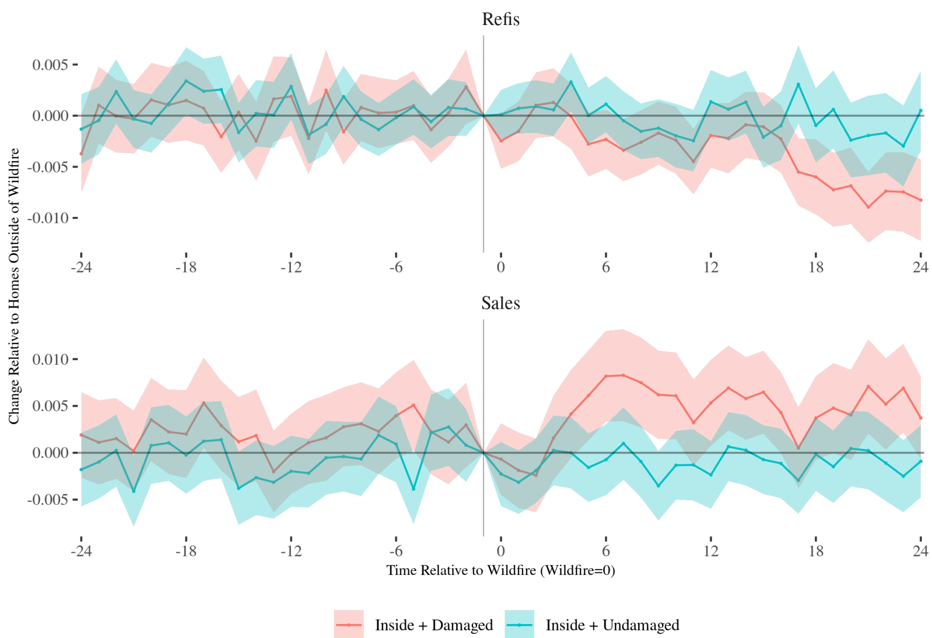
5.1 Background: Home Insurance and Wildfire Coverage

Damages from wildfires are generally covered under homeowners insurance policies. Typical policies include coverage for the replacement cost value (RCV) of the dwelling and additional structures of the residence, personal property, living expenses during loss of use of the

[19]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.

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 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.

residence, personal liability, and medical payments to others.[20] For mortgages secured by government-sponsored enterprises (GSEs), the coverage limit on homeowners insurance needs to cover the lesser of RCV and the unpaid principal balance of the mortgage.[21]

In the aftermath of a fire, the homeowner and insurance adjuster negotiate a settlement. California homeowners commonly hold Extended RCV coverage, under which replacement cost includes the current cost of labor and the cost of compliance with local building codes. Extended RCV also allows the settlement to exceed the policy limit, normally up to 125 percent or 150 percent of the original limit. 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.

However, many homeowners do not receive settlements that are sufficient to rebuild. A survey of homeowners after six large California wildfires since 2013 shows that 42 percent to 66 percent of respondents are underinsured and would not be fully covered to replace or rebuild their home (United Policyholders, 2022). Underinsurance can result from an initially low or outdated estimate of RCV that partially determines the coverage limit and an increase in rebuilding costs due to a demand surge in areas where several structures are damaged by a fire (Dixon et al., 2018). Therefore, there may be many cases where the insurance settlement would cover a full prepayment but not a rebuild. In addition, even if the settlement covers a rebuild, delays in construction timing and the transition costs associated with finding temporary housing may further incentivize households to use insurance funds for mortgage prepayment rather than rebuilding a damaged home.

5.2 Frictions in Insurance Markets Leading to Prepayment

Households may receive insurance settlements that do not cover the cost of rebuilding due to frictions in insurance markets (Dixon et al., 2018; United Policyholders, 2022). We now empirically consider to what extent these frictions lead households to prepay mortgages on damaged homes instead of rebuilding. We use a triple difference design with the following specification in Equation 1, where we interact property damage with measures of underinsur-

[20] Each of these coverages is limited to a share of the dwelling coverage unless the homeowner opts to purchase additional coverage. For example, in California, living expenses during loss of use of the residence is normally limited to 20 percent of the coverage for the dwelling (California Department of Insurance, 2021).

[21] If the mortgage balance is lower than the RCV, insurance must cover the greater of mortgage balance and 80 percent of RCV.

ance, Z_{ift}. Estimates of γ_{1t} and γ_{2t} help us understand whether homeowners' likelihoods of prepayment increase by the extent of underinsurance.[22]

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

First, a common example of insurance market frictions is a surge in demand for construction 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 2 with the number of damaged properties inside the fire perimeter as Z_{ift}. As shown in the top panel of Figure 5, estimates of $\hat{\gamma}_{1t}$ are positive and significant, confirming that the prepayment rates for damaged homes after a fire increase in 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.6).

Second, we estimate whether prepayment rates differ by the year the home was built. This test is motivated by substantial changes to wildfire standards in California's building codes during the 1990s and in 2008 (Baylis and Boomhower, 2021). These building code 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). As a result, a majority of new homes built after these regulations in California were required to comply with the stronger wildfire standards. For older homes built before these regulations, owners are required to comply with current wildfire standards during reconstruction, such as a roof replacement. Therefore, we hypothesize that the cost to rebuild an older home will be substantially higher than a newer home; the replacement costs will include additional costs to comply with new wildfire standards. Incentives to prepay should then be greater for older homes than newer homes as it is less likely that the insurance

[22] 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).

settlement will fully cover the higher cost of rebuilding. Estimates of $\hat{\gamma}_{1t}$ and $\hat{\gamma}_{2t}$ where Z_{ift} indicates whether the property was built before 1991 confirm this story. As expected, the bottom panel of Figure 5 shows that homes built before 1991, when stricter wildfire codes were first introduced, are more likely to prepay than newer homes built after 1991.

6 Implications

Our findings of higher prepayment rates after a fire have implications for both borrowers and lenders. First, we try to understand whether the borrower's choice to prepay is unconstrained after a fire. It is possible that lenders induce affected borrowers to pay down mortgage debt to limit exposure to future default risk (Gallagher and Hartley, 2017). If this is the case, the increase in prepayment does not provide any information about borrowers' preferences to rebuild or prepay. However, if borrowers are making an unconstrained choice, our prepayment findings inform us that the net benefits of prepayment exceed the net benefits of using insurance funds to rebuild.

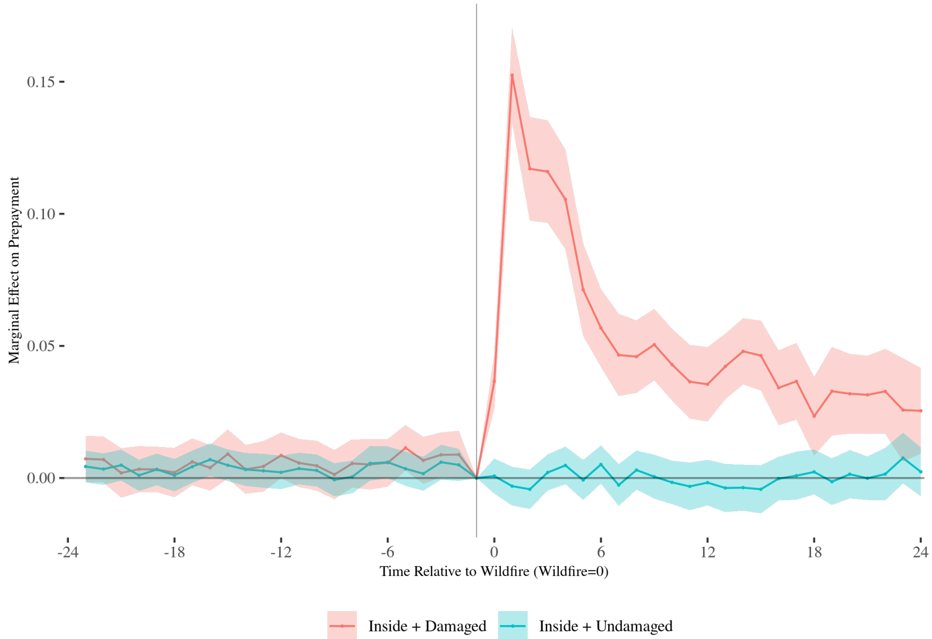
We test this hypothesis by estimating heterogeneous effects on prepayment for loans with different interest rates (Equation 2). Borrowers with higher interest rates face greater incentives to prepay as they would forgo larger interest payments over the term of the loan. Conversely, banks would prefer borrowers with lower interest rates to prepay to minimize lost interest revenue. The top panel of Figure 6 shows that loans with higher interest rates have higher likelihoods of prepayment after a fire. The chart plots estimates of $\hat{\gamma}_{1t}$ and $\hat{\gamma}_{2t}$ where Z_{ift} is the loan's interest rate standardized to have a mean of 0 and standard deviation of 1. Loans with interest rate 1 standard deviation higher have a 3 percentage point higher likelihood of prepayment. This result suggests that higher prepayment after fires is driven by borrower incentives.

However, this result could still be consistent with lender incentives because banks may want to reduce exposure to borrower risk, which is positively correlated with interest rates. The bottom panel of Figure 6 shows that there is no heterogeneous effect in prepayment across borrower risk, as measured by credit score. If lenders were inducing high-risk borrowers, who also have higher interest rates, to prepay, we would expect that low credit score borrowers would have higher prepayment rates than other affected borrowers.[23] Since this is not the case, we conclude that borrower prepayment decisions are unconstrained by bank preferences.

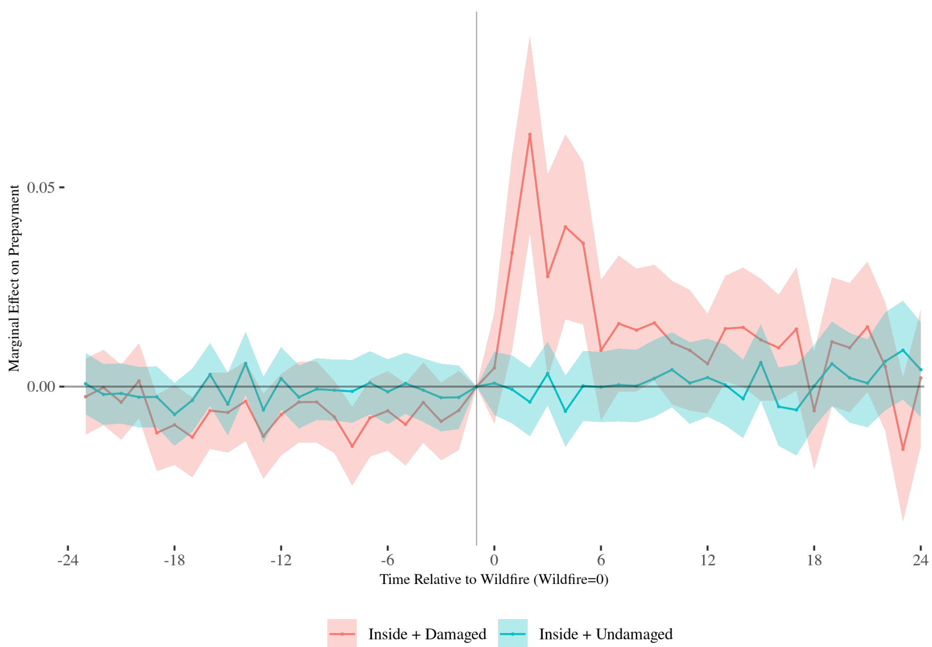
For lenders, this result suggests the potential for greater financial losses after wildfires. The cost of prepayment, which includes the loss of future interest revenue, increases if higher

[23] We estimate the same heterogeneous effects for the delinquency outcome, as shown in Figure A.5. Borrowers with higher interest rates and lower credit scores are more likely to be past due by 90 days or more.

Figure 5: Differences in Prepayment by Damage Severity



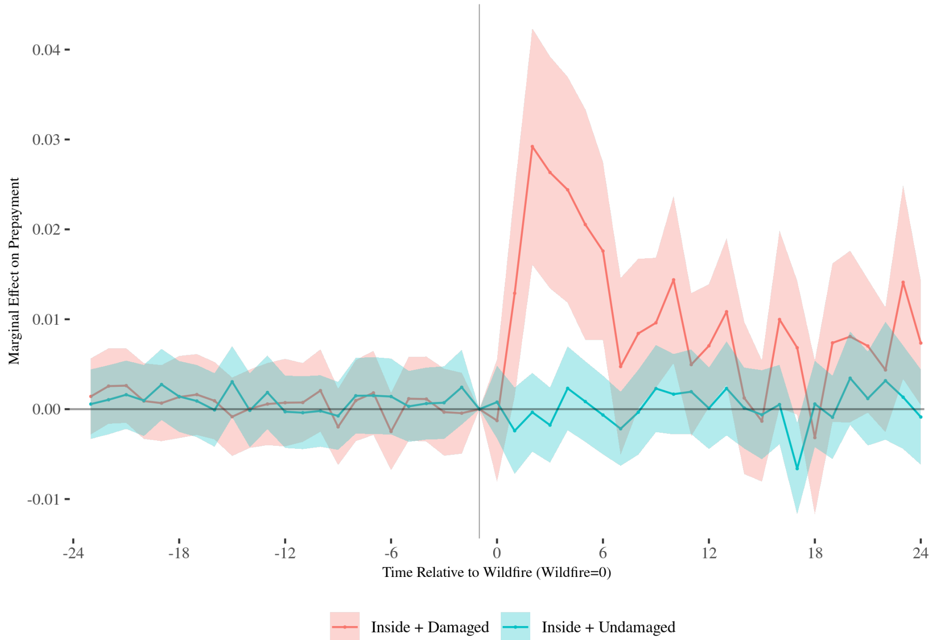
(a) Log of Properties Damaged × Fire Damage



(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 2. 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.

Figure 6: 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 2. 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.

interest-rate loans prepay more frequently. Moreover, the temporary reduction in housing supply due to fire damage would impact the bank's ability to replace the mortgage in its portfolio. Future versions of this paper will conduct a loss calculation to better understand the impact of fires on lenders.

7 Conclusion

We construct a novel database that merges property-level damage inspections from 82 California wildfires with mortgage performance and evaluate 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 what previous research finds. Measurement of fire damages at the property level shows that 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, frictions in insurance markets may reduce welfare if mortgage borrowers would prefer to rebuild but cannot due to underinsurance. Higher prepayment rates for damaged homes with higher rebuilding costs indicate that insurance settlements are insufficient to rebuild after a fire. Thus, households use insurance funds to pay off mortgage debts instead.

For policymakers, our findings imply that damage mitigation efforts prior to 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).[24] 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

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

intended. Therefore, additional research is necessary to understand prepayment risks and the use of insurance funds after disasters.

For lenders and investors, insurance effectively shifts some of 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 prepay. This finding implies greater losses for lenders and investors, and we plan to estimate these losses to better understand protections from insurance after wildfires in future research.

Last, for researchers, our work emphasizes the need to obtain more precise measures of physical climate risks. As 59 percent of the properties within the fire perimeter in our sample remain undamaged, the use of larger geographic areas, such as a 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.

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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 ☐ 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

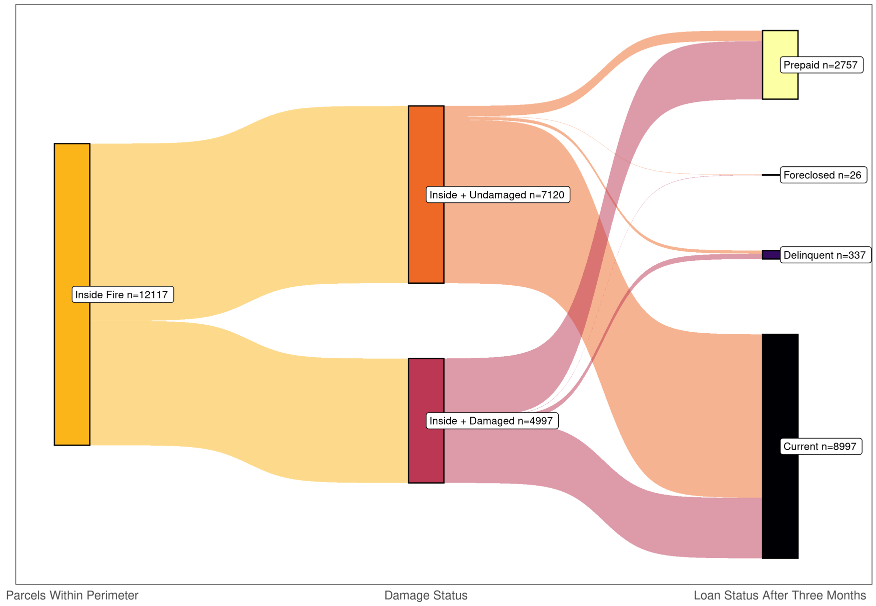
Decking Details: ☐ Top Side ☒ Posts ☐ Bottom Side ☐ Wood ☐ Composite ☐ Other

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

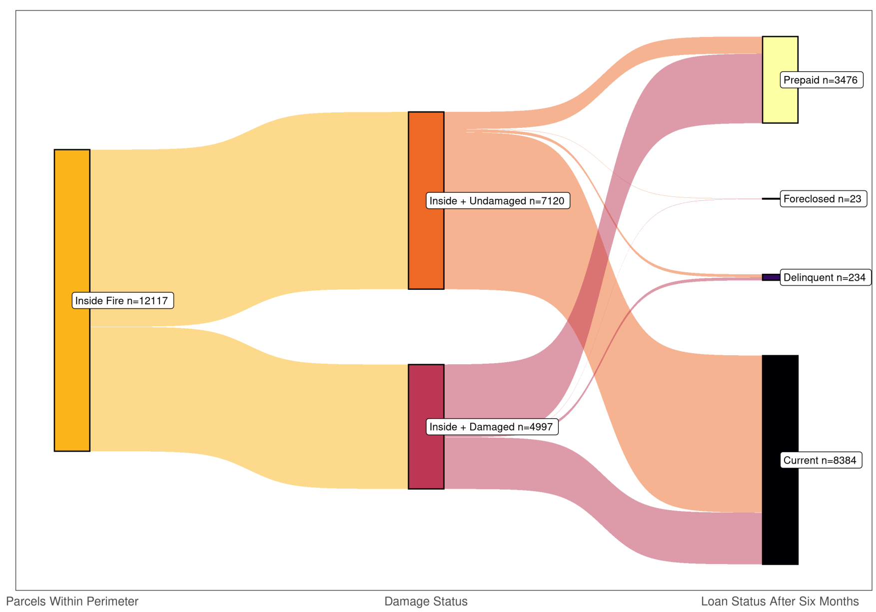
- defended
- many cracked windows, some with both panes
- many different ignitions on all sides of home
- shed burned out behind
- houses on 4 sides burned out

Source: Fire Research Division, National Institute of Standards and Technology, https://www.nist.gov/el/fire-research-division-73300/wildland-urban-interface-fire-73305/nist-investigation-california-1.

Figure A.2: Post-Wildfire Loan Status Flows: Three and Six Months After Fire



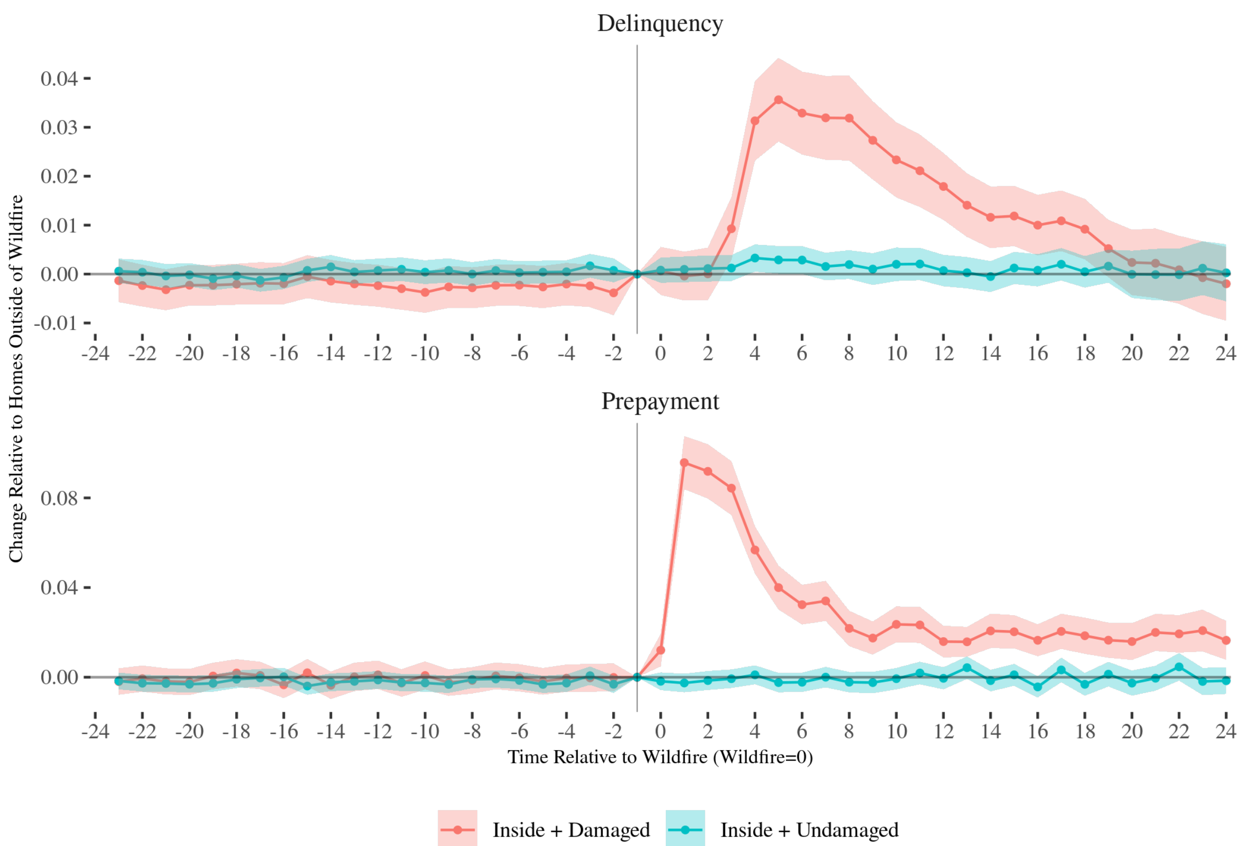
(a) Loan Status Three Months After Fire



(b) Loan Status Six Months After Fire

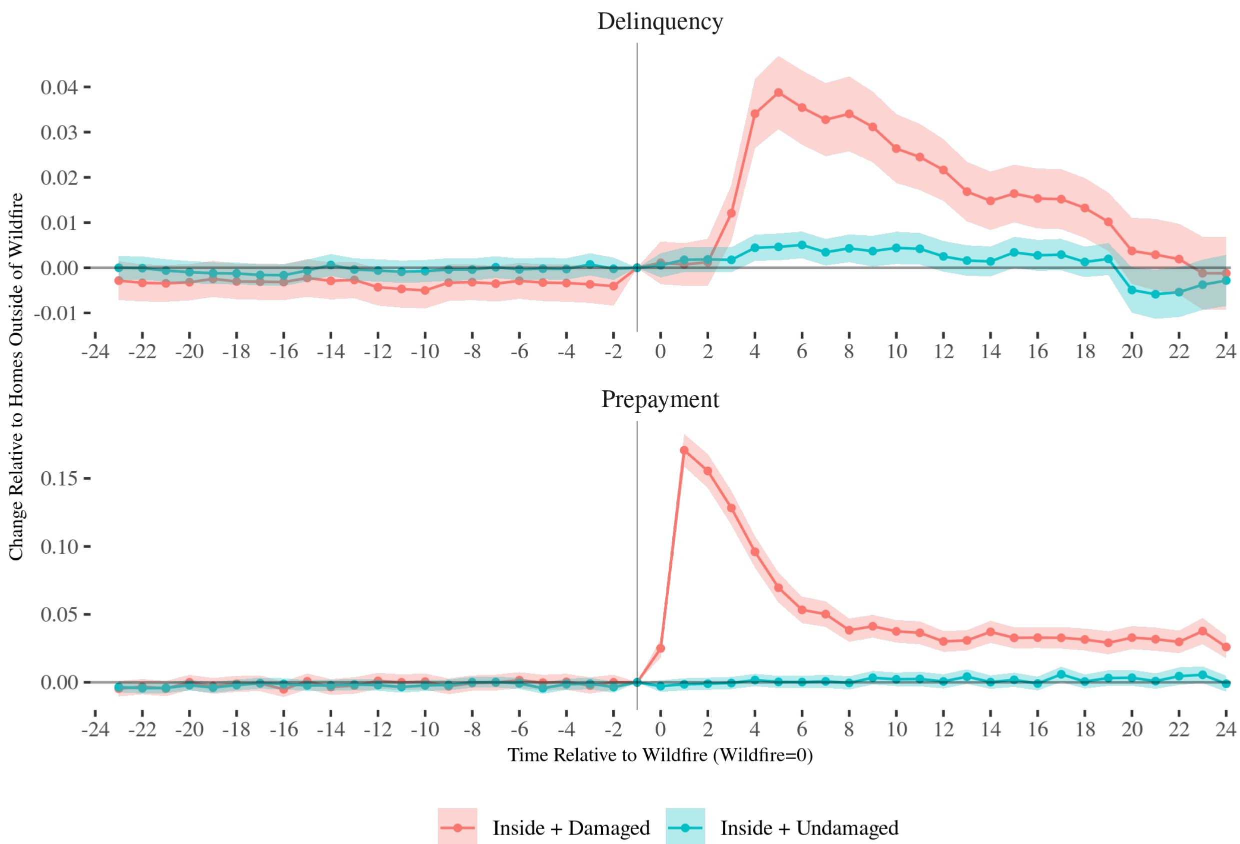
Note: Figure illustrates the decomposition of loans within wildfire boundaries based on whether or not the home was damaged by the wildfire. The top panel shows mortgage status three months post-fire (current, delinquent, foreclosed, or prepaid) while the bottom panel shows mortgage status six months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

Figure A.3: Robustness to Omitting Camp Fire



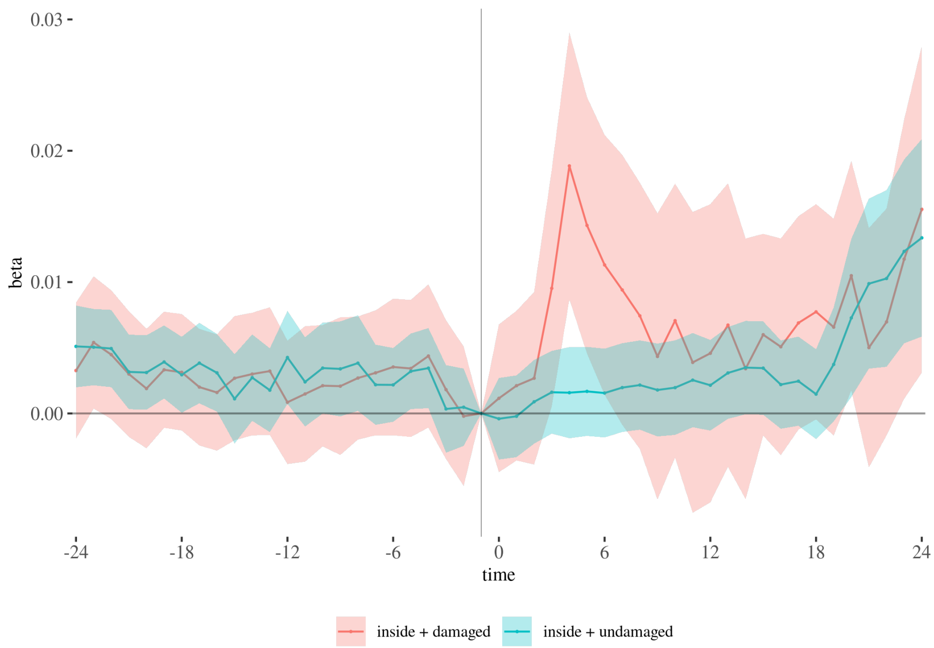
Note: Figure illustrates the coefficients for damaged (β_{1t}) and undamaged (β_{2t}) parcels estimated from the event study specification in Equation 1 after excluding the Camp Fire in 2018. The top panel presents results for delinquency and the bottom panel presents results for prepayment. Regression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

Figure A.4: Robustness to Choice of Control Group: Properties 5 to 6 Miles Outside Fire Perimeter

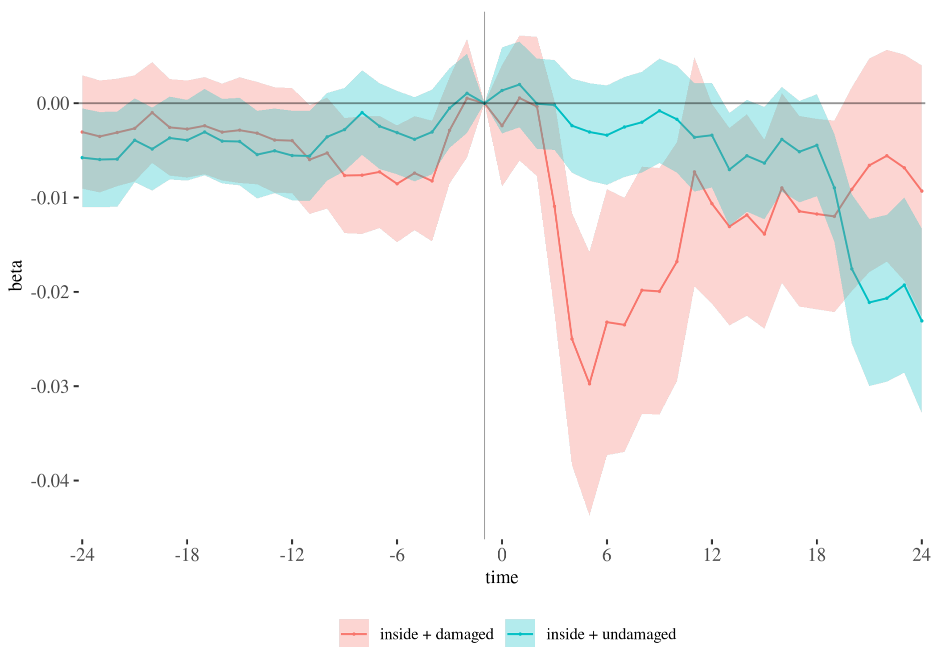


Note: Figure illustrates the coefficients for damaged (β_{1t}) and undamaged (β_{2t}) parcels estimated from the event study specification in Equation 1 using homes in the 5- to 6-mile ring outside the fire perimeter as the control group. The top panel presents results for delinquency and the bottom 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.5: 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 2. 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.6: 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 2. 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.