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How Does Mortgage Performance Vary Across Borrower Demographics Following a Hurricane?

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Abstract

Hurricanes cause billions of dollars in damages to the United States annually. Property damages and associated local economic impacts from hurricanes can affect homeowners' ability to pay their mortgage and in turn can harm borrowers' access to credit or decrease property values in the long term. This paper studies how hurricanes affect loan outcomes in the year following the event. With our unique dataset, we are able to consider how mortgage performance varies by severity, interventions, and low-income or minority status borrowers. We find that delinquencies, modifications, and foreclosures increase after an event and that more severe events see higher increases. For example, we find the average impact of all 28 storms on 90-day delinquencies is 0.025% over the following 12 months, increasing by another 0.013% with each inch of rain. Prepays decrease overall due to a decrease in refinances, but non-cashout and non-refinance prepays increase for a subset of the population with access to insurance and disaster assistance. Delinquencies increase more so for minority and low-income borrowers. Further, minority borrowers experience higher rates of modifications after a hurricane. These results demonstrate that hurricanes decrease borrower welfare overall and more so for vulnerable borrowers through increased negative loan outcomes.

Keywords: hurricanes · mortgage · borrower · equity · housing · disasters

JEL Classification: Q54 · R11 · R30

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1. Introduction

Hurricanes are the most damaging natural hazard recorded in United States history.[1] Scientific evidence demonstrates the damage from hurricanes will likely increase due to sea level rise, increasing rainfall rate, and increasing intensities in wind strength.[2] Destruction of property and infrastructure are two of the main components of hurricane damages and both wind strength and flooding from rain or coastal surges are main drivers of these damages. These can be short lived if rebuilding is insured and no other costs are incurred; however, damages can be longer lasting if hurricanes lead to poor mortgage performance like delinquency and default. Foreclosure can have long-term impacts on the value of the property or nearby properties and harm a borrowers access to credit. Further, if there are differences in mortgage performance by minority status or income after the disaster, these can exacerbate existing inequities in access to credit and housing. In this paper, we explore how loan characteristics vary across disaster exposure and underrepresented populations, as well as the effect of exposure to a disaster on loan performance and whether this effect occurs differentially by storm severity and borrower demographics.

There is a growing body of literature devoted to investigating the impact of natural disasters and climate related risks on housing market outcomes. This is of course due to the numerous disaster types and countless means through which they might impact the housing market. Much of the literature is focused on analyzing post-disaster lender and borrower behavior, such as overall housing transactions, migration patterns, mortgage terms, and loan performance, in addition to outcomes such as insurance market, infrastructure, and house price impacts. For researchers interested in these topics, Contat et al. (2024*a*) provide a comprehensive survey of the literature categorized by risk and outcome.

The main area of research relevant to this paper is focused on mortgage loan performance

[1] NOAA (https://coast.noaa.gov/states/fast-facts/hurricane-costs.html)
[2] NOAA (https://www.gfdl.noaa.gov/global-warming-and-hurricanes/)

after a disaster event.[3] Many of these papers focus specifically on mortgage default, delinquency, or other outcomes using one or two specific disasters in an event style analyses. Several of these papers (Gallagher and Hartley (2017), Du and Zhao (2020), Kousky, Palim, and Pan (2020), Holtermans, Kahn, and Kok (2024), Mota and Palim (2024)) have found that mortgage behavior suffers post hurricane with heterogeneous effects across several loan characteristics such as initial financial conditions, federal assistance, property damage and flood insurance. Additionally, Gallagher and Hartley (2017) estimates the impact of flooding from Hurricane Katrina on credit behavior, rather than mortgage, and find a modest and short lived spike in both borrowing and delinquency rates. These event studies focus on single large hurricane events and are therefore limited in their external validity. We add to this literature by expanding our analysis to all relevant hurricanes, and allowing our results to be heterogeneous across hurricane intensity allowing for a better understanding of the effects of hurricane across the spectrum of events.

We are not the first to look at several disaster events. Issler et al. (2020) utilize a DID estimation to show that there is a significant increase in both delinquency and foreclosure rates following wildfire events in California. They also note that these are decreasing with size of wildfire, likely due to the increased resources allocated to such events. This is plausibly similar for any natural disaster. Biswas, Hossain, and Zink (2023) builds and expand on Issler et al. (2020) results by including precise measurements of property-level damage. Rossi (2021) aims to understand the specific impacts of hurricane intensity and frequency on mortgage default. Estimating across 41 named disasters which resulted in a Disaster Declaration from the Federal Emergency Management Agency's (FEMA) they find that areas with more hurricanes will see higher default risk. Similarly, Gete, Tsouderou, and Wachter (2024) uses FEMA data on hurricanes and finds that the occurrence of a hurricane in a county increases default risk defined as 6 months or more of missed payments. Calabrese

[3] Other papers look at more broad economic impacts of hurricanes. For example, Deryugina, Kawano, and Levitt (2018) estimate the economic impact of Hurricane Katrina by constructing a panel of households using random sampling. They find that there is a small and transitory effect on labor income and total income for impacted households. Additionally, there is a spike in unemployment and non-employment following the event, but these spikes disappear by 2007 and 2009, respectively. They show that retirement account withdrawals increased throughout the post-Katrina period, implying that savings was likely a tool used to cover the losses these households faced. They also relied more on SSDI and unemployment insurance temporarily following the hurricane. For additional literature on the impact of disasters on housing markets beyond loan performance see Contat et al. (2024*a*) literature review. Published after the literature review, Contat et al. (2024*b*) consider how public data on hurricanes can be used to estimate the impact on housing prices.

et al. (2024) focus on the impacts of precipitation and wind across multiple hurricane events in Florida. Their analyses show that there is a statistically significant impact of heavy rain on areas with large exposure to flood risk on mortgage defaults, as well as a systematic increase in risk under climate change. Their results suggest it is important to account for the severity of a hurricane event when estimating these impacts.

We build on these papers in several ways. Given that experiencing repeated hurricanes might have compounding effects, we run our estimation for a restricted sample of residences that experience only one event in a given year, in addition to the unrestricted sample. We identify impacted regions using a broader strategy that does not require a disaster declaration. We also incorporate disaster declaration and rain intensity information into our regressions to control for the potential impact post disaster assistance availability has on mortgage performance separate from intensity and exposure. In this way, we are able to consider disaster aid, hurricane impact, and differences in storm severity. Incorporating rain intensity into the analysis further allows us to better consider the role of flooding, which is increasingly the driver of damage after a hurricane.

Studying several events also allows us to consider heterogeneity in outcomes by underlying borrower characteristics. Bakkensen and Ma (2020) investigate the incidence of sorting across flood risk by race, ethnicity, and income, they show that low-income households and minorities are more likely to move into high-risk flood zones. Similarly, Ratnadiwakara and Venugopal (2020) find that after a disaster less affluent and lower credit worthy borrowers move into the area. In addition to potentially increasing exposure to disasters, Ratcliffe et al. (2020) find that those who have lower credit scores or live in communities of color suffer worse after a disaster. Combined, this research provides some evidence that different socieconomic and demographic groups face higher risks associated with exposure to natural disasters. Understanding these heterogeneous effects across sociodemographic groups is important in order to determine the policies that will best address the inequitable distribution of risks and associated costs. Using detailed loan data from the Enterprises[4]–Fannie Mae and Freddie Mac, our paper adds to the overall literature on the impacts of hurricanes on mortgage performance by considering how loan performance varies by minority and low income status.

[4]Note that the analyses and results herein are limited to the Enterprises and may not be representative of all government loans nor of the entire mortgage market more broadly.

In this paper, we analyze the impacts of natural disasters on mortgage borrower performance. Using a stacked difference-in-differences (DID) approach, we estimate the effect of all 28 Atlantic basin hurricanes that impacted the US between 2010-2018 on post-disaster borrower behavior. To address the fact that evidence in the literature suggests vulnerable populations face higher risks of natural disaster effects, we then extend this to a triple DID. This allows us to estimate the heterogeneous effects by minority status and income to consider how underrepresented borrowers perform after a hurricane. We provide evidence of parallel trends prior to the hurricanes to lend legitimacy to the parallel trends assumption. We employ multiple specifications and different sample populations to show that the results we find are robust to various estimation conditions.

The results of this analysis suggest that natural disasters lead to an overall increase in delinquencies, modifications, foreclosures, and certain types of prepays. Severity of a hurricane increases the rates of all of these loan outcomes relative to a less severe event. We find that overall prepays decrease due to a decrease in refinance and cash out prepayments. However, non-cash out and non-refinance prepays increase for those located in SFHAs. For minority borrowers we find an additional increase in delinquencies and modifications relative to the overall populations. Whereas, for low-income borrowers, we see an additional increase in delinquencies, but no clear evidence of differential performance for the other outcomes. These results demonstrate that hurricanes have negative and significant impacts on mortgage performance. Increased delinquencies and foreclosures can harm credit scores and property values, modifications require additional costs on housing finance sector, and unexpected prepays may impact mortgage-backed security valuations. Given that the rain severity of hurricanes is predicted to increase, it is likely future storms will increase these harmful impacts.

One of the main contributions this paper provides is our inclusion of the National Oceanic and Atmospheric Administration's (NOAA) weather data which is used to measure the severity of hurricanes. We supplement our data with ZIP code level information on the hurricane paths, wind speeds, rainfall, etc. from NOAA, this allows us to determine the severity of the storm at the time a particular property was impacted. Another contribution of this paper is the estimation of effects across all relevant hurricanes in the time of interest, this allows us to estimate the impact of the average hurricane. Additionally, combining multiple events with the data on severity and aid further allows us to assess the role of severity in loan outcomes. A final notable contribution of this paper is the use of a triple DID in order to estimate the differential impact of hurricanes on mortgage performance by race and income. Our findings demonstrate that minority and low-income borrowers may be more negatively impacted by hurricanes. It is important to ascertain how these effects vary by racial and income categories in order to understand the dynamic routes through which disasters can magnify disparities. Additional work is needed to understand the mechanisms driving the differential results so that policies can better alleviate the disparate outcomes. Ultimately, the results presented here provide a better overall understanding of the impacts of hurricanes on post-disaster mortgage performance.

The remainder of the paper is as follows. In Section 2, we provide an overview of our data and stylized facts on how loans and borrower characteristics vary across hurricanes. We also provide descriptive evidence on mortgage performance before and after a hurricane. In Section 3 we walk through our estimation strategy. The results of our analyses are presented in Section 4 and we conclude in Section 5.

2. Empirical Overview

In this section, we detail our data sources, discuss our sampling strategy, and present descriptive statistics, then conclude with motivating descriptive evidence that hurricanes do impact loan performance and that there are differences across vulnerable populations.

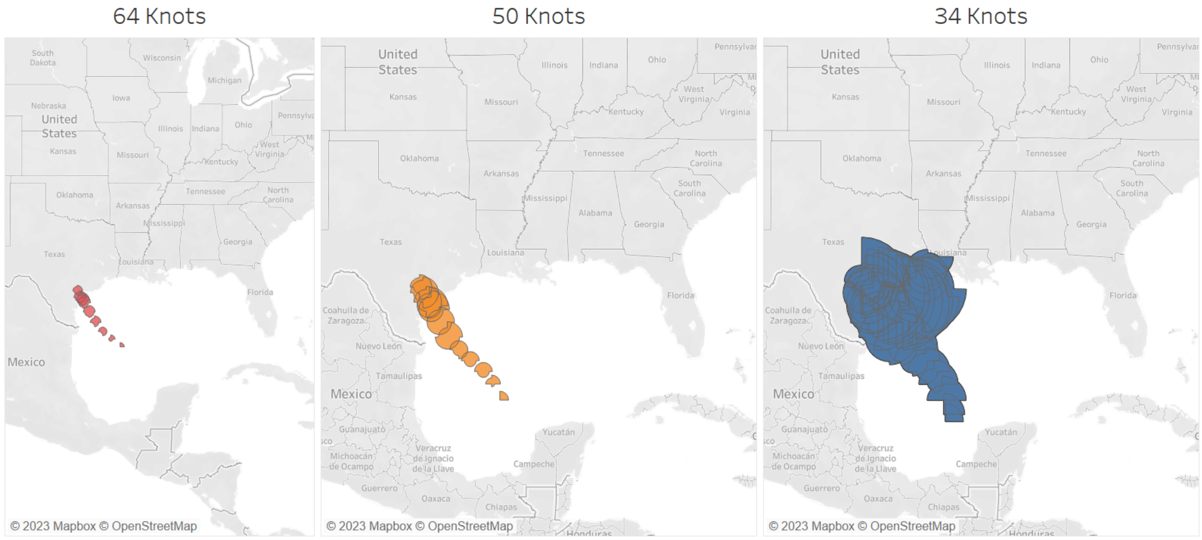
2.1 Data

2.1.1 Hurricanes and Weather

To identify hurricanes and tropical storms we use NOAA's HURDAT2 dataset on tropical cyclones. HURDAT2 provides observations of location, maximum winds, central pressure, and size of all known tropical cyclones. The best track data from HURDAT2 is available in GIS format and reports the track of hurricanes by type on Saffir-Simpson Hurricane Wind Scale, wind speed, and wind radii which represent the maximum possible extent of a given wind speed within particular quadrants around the tropical cyclone. Figure 1 presents example radii data for Hurricane Harvey.

For every Atlantic basin hurricane with an archived best track between 2010-2018, we check if the estimated wind-radii overlaps with any United States ZIP codes. From a total of 146 NOAA reported storms in the relevant time frame, we identify 28 relevant hurricanes. These

Figure 1: Hurricane Harvey - HURDAT2 Radiis



Note: Visual representations of the Hurricane Harvey wind radiis at 64, 50, and 34 knots respectively.

are listed in Table1 and the number of events in each ZIP code is displayed in Figure 2.

In addition to wind data, we capture precipitation data to measure potential severity in damage from flooding. For every relevant hurricane and affected ZIP code, we merge in NOAAs Daily Accumulations data provided by the Advanced Hydrological Prediction Service from the National Weather service. The precipitation data include daily accumulations and are estimated using multiple sensors (radar and rain gauge) from the National Weather Service River Forecast Centers. The data is mosaicked by the National Centers for Environmental Predictions. For our analysis, we do a land-weighted average over daily accumulation within the geographical bounds of the ZIP code for everyday that ZIP code is being "affected" by a hurricane (in a wind radii). We then average the average daily accumulations for each ZIP code over the days the hurricane is active. Figure 3 displays precipitation for Hurricane Harvey.

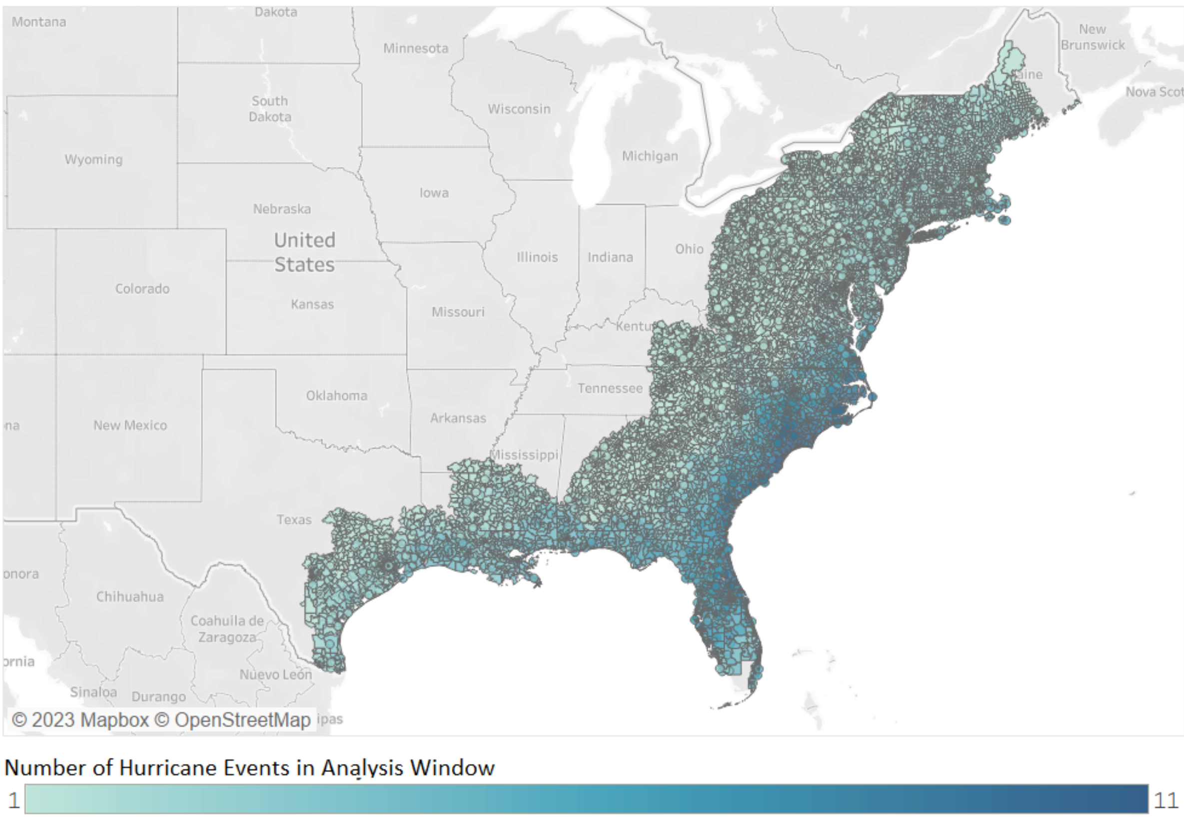
In addition to weather variables, we include disaster declaration data from the Federal Emergency Management Administration (FEMA). When either a Major or Emergency disaster is declared, FEMA is able to offer additional aid to impacted areas including their individual assistance programs. In our dataset, we create an indicator variable for "assistance

Table 1: Identified Relevant Hurricanes

Event Name	**Event Year**	**Event Number**
Subtropical Storm ALBERTO	2018	al012018
Hurricane FLORENCE	2018	al062018
Tropical Storm GORDON	2018	al072018
Hurricane MICHAEL	2018	al142018
Tropical Storm CINDY	2017	al032017
Tropical Storm EMILY	2017	al062017
Hurricane HARVEY	2017	al092017
Hurricane IRMA	2017	al112017
Hurricane JOSE	2017	al122017
Hurricane MARIA	2017	al152017
Hurricane NATE	2017	al162017
Tropical Storm COLIN	2016	al032016
Hurricane HERMINE	2016	al092016
Tropical Storm JULIA	2016	al112016
Hurricane MATTHEW	2016	al142016
Tropical Storm ANA	2015	al012015
Tropical Storm BILL	2015	al022015
Tropical Storm ANDREA	2013	al012013
Tropical Storm BERYL	2012	al022012
Tropical Storm DEBBY	2012	al042012
Hurricane ISAAC	2012	al092012
Hurricane SANDY	2012	al182012
Hurricane IRENE	2011	al092011
Tropical Storm LEE	2011	al132011
Hurricane ALEX	2010	al012010
Tropical Storm BONNIE	2010	al032010
Hurricane EARL	2010	al072010
Tropical Storm HERMINE	2010	al102010

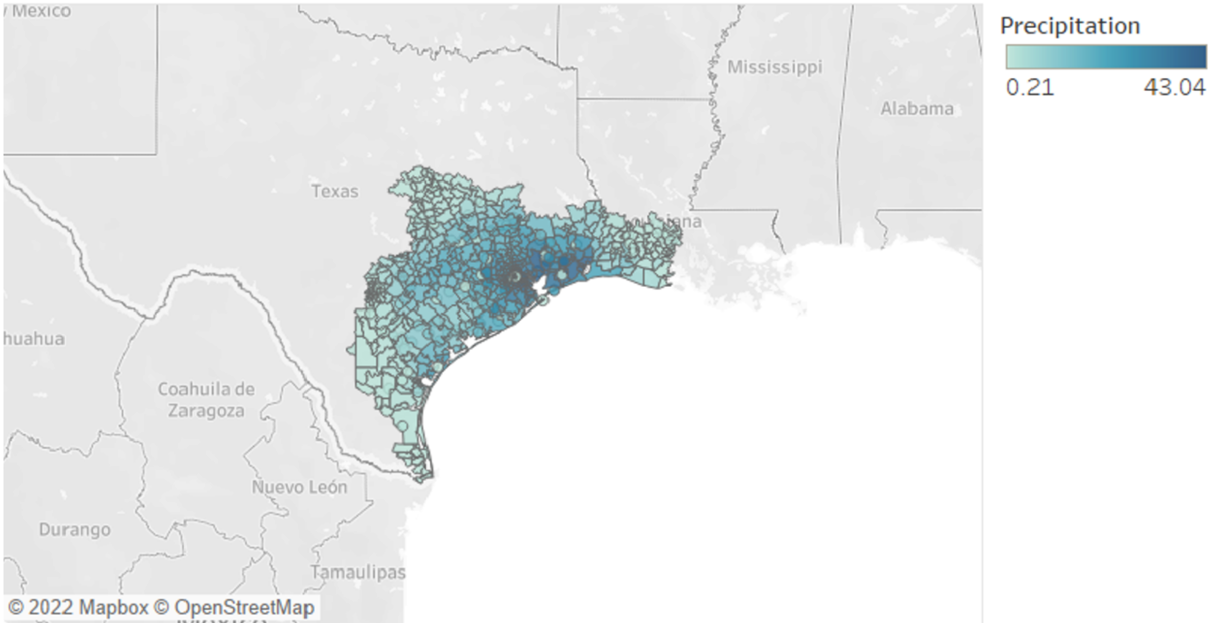
Notes: A table naming the 28 relevant hurricanes used in the study. Additional information given in the table is the hurricane year, and the event number as given by NOAA

Figure 2: Number of Events by Affected ZIP Codes



Note: A map of the the East Coast of the United States depicting how many times each zip code is affected by one of the 28 relevant storms. Maximum number of hurricane events in a single zip code is 11.

Figure 3: Hurricane Harvey - Average Daily Rain Accumulations



Note: A map of Texas overlaid with the precipitation by zip code as calculated by the authors using precipitation data.

county" if the county received individual assistance for the relevant hurricane event. A disaster declaration can be considered a measure of severity, but it is also a measure of aid and interventions available.

2.1.2 Mortgage Performance and Loan Characteristics

Observations on mortgage performance come from the Enterprises' historical loan portfolios. We use Mortgage Loan Information System (MLIS) data, a confidential and proprietary regulatory dataset that contains portfolio data from both Fannie Mae and Freddie Mac. It is a historical loan-level database of mortgage, property, and borrower characteristics. Some of the key variables in this dataset for our research include race of the borrower, loan to value (LTV) ratios, credit score, income, and first-time home buyer (FTHB) status. This dataset also has information on loan performance and outcomes including if it is current, i.e. performing, or if it has missed payments, i.e. delinquent. We limit our analysis to single-family loans during 2010 to 2019. Restricting the sample to 2010 and later limits some of the potential impact of the recession. By stopping the sample at the end of 2019, we avoid picking up the impacts of COVID-19 in our estimates as the Enterprises implemented significant forbearance options during the pandemic. To calculate whether or not a loan is a low income loan, we use HUD data on area median income and the borrower income at origination of the loan included in the historical loan database.

2.2 Creating the Sample

Combining the weather and mortgage performance datasets enables this research to study how loan performance varies with hurricane events and across different groups. Due to the size of the mortgage performance data and since non-performing outcomes are relatively rare, a sample of observations is used. Further, to ensure that treated loans are similar to control loans, a matching strategy is used.

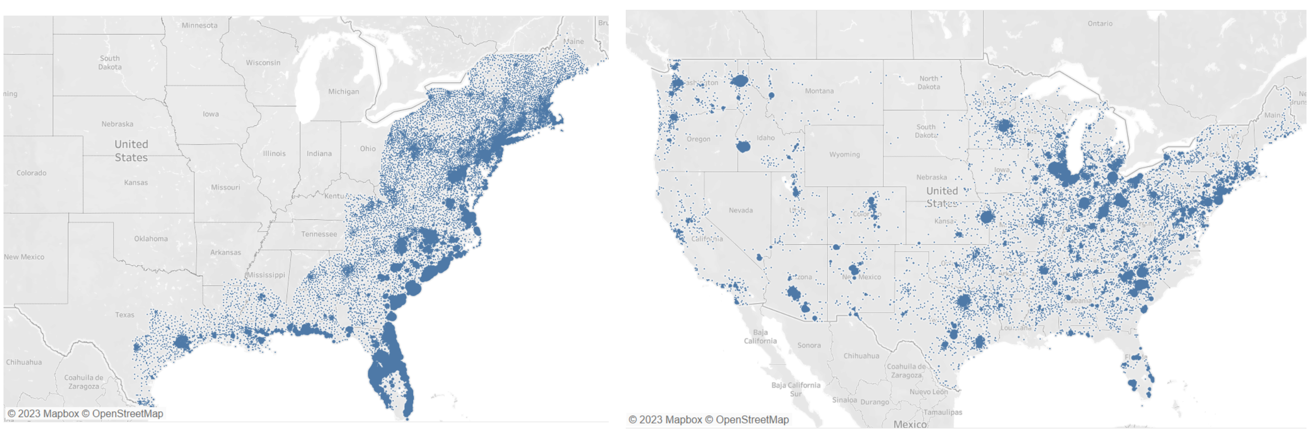
2.2.1 Treatment and Matching

The treatment group of loans affected by an event is created using a random 5% sample of all MLIS performing loans that are in any of the ZIP codes that overlap with the relevant hurricanes, as well as all of the loans in those ZIP codes that are ever one of the following states within the analysis window: Delinquent, Pre-Payed, Foreclosed, Modified, Note Sale. Observations are over-sampled for the non-performing categories to ensure we have a sufficient number of non-performing observations for estimation. We then use a nearest neighbor matching technique to create the control dataset. We use the 10 nearest neighbors to reduce noise around rare events. For each affected loan, we find the loans with the smallest Euclidian distance across several normalized variables, credit score, starting month-to-month LTV (MTMLTV), debt ratio, first-time home buyer status, original unpaid balance (UPB), starting unemployment rate, starting home price appreciation (HPA), higher education, minority status. Starting variables refer to variable as observed the month before the start of the analysis window. The control loans are found within a set of nearest-neighbor-matched unaffected ZIP codes which are found by matching the affected ZIP codes on the following normalized variables: percent with higher education, percent minority, unemployment rate, non-MSA, HPA, average original UPB, population, and whether the ZIP code is in a judicial state. One loan may be sampled multiple times in the affected population if it was affected by more than one of the relevant events. One loan may be sampled many times in the unaffected sample as it may be one of the ten nearest neighbor loans for several affected loans. All ZIP-code variables are defined using the observation period preceding the start of the analysis window. ZIP codes are defined as unaffected for a specific event if no hurricane occurs in that ZIP code within the analysis window and the twelve months preceding the analysis window, and if no FEMA disaster event with individual assistance occurs within the analysis window and the twelve months preceding the analysis window. In Figure 4, we present maps of the affected (treated) ZIP codes and the unaffected (control) ZIP codes. Table A1 presents the number of observations by ZIP code type for each event. As expected our affected ZIP codes are only in hurricane impacted regions including the Gulf and East Coasts. Our control ZIP codes are frequently pulled from the East Coast, but because they cannot be impacted by the same events we also have more inland and West Coast ZIP codes. To demonstrate the similarities of our affected and unaffected ZIP codes we present Table 2, which presents the mean and standard deviations for our key variables for both our affected and unaffected samples. The summary statistics for all dynamic variables were calculated at the start of the analysis window (six month prior to the event date). We discuss the similarities in our samples more fully when we discuss identification in our estimation section.

Figure 4: ZIP Codes included in Affected and Unaffected Samples

(a) Affected Sample

(b) Unaffected Sample



Note: Two maps of the United States. The left map shows the zip codes included in the affected sample, while the right shows the zip codes included in the unaffected sample.

2.3 Motivating Evidence

Before discussing our estimation strategy, we provide evidence that hurricanes do impact loan performance and that the impact may vary by borrower heterogeneity. To do this, we look at the underlying rates of different loan outcomes before and after an event and by minority and low-income status. Figures 5, 6, and 7 present clear evidence that delinquencies increase after a hurricane event and that these increases might differ for minority and low-income borrowers. In the appendix, we provide additional motivating evidence for 180 day delinquencies, modifications, and foreclosures. Similar to the 90 day figures, we see clear breaks from the trends in modification and 180 day delinquencies, but the foreclosure figures are not as telling. These figures do not control for other differences across these loans, and we discuss how we do that using our estimation strategy next.

Figure 5: Rate of 90 Day Delinquencies by Time From A Hurricane Event

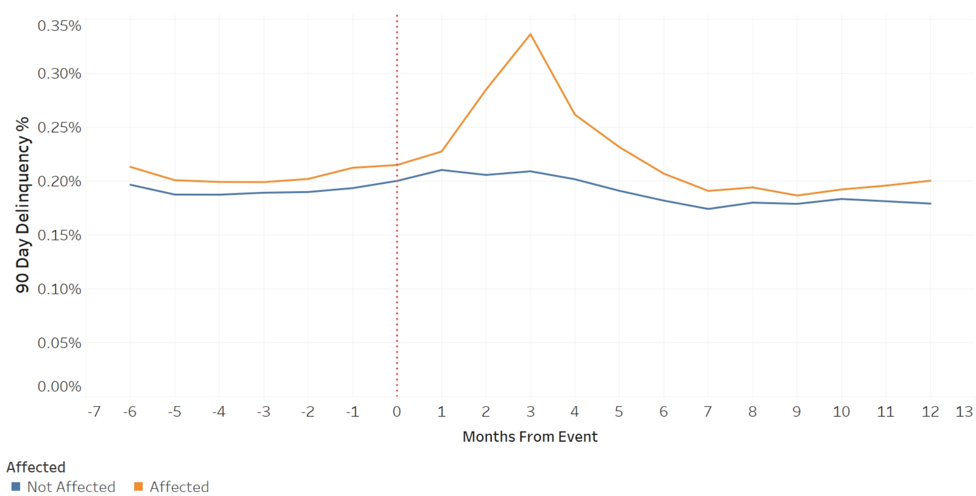


Table 2: Descriptive Statistics for Affected and Unaffected Samples

Variable	**Affected**		**Unaffected**	
	Mean	Std.	Mean	Std.
Previous Delinquent	8.96%	28.55%	8.02%	27.16%
Previosuly Modified	4.36%	20.43%	4.44%	20.60%
MTMLTV	65.17%	32.30%	65.12%	30.41%
Credit Score	732	58	733	57
Debt Ratio	38.62%	878.25%	37.76%	731.22%
Loan Age in Month	61	45	61	45
Judicial State	56.95%	49.51%	56.64%	49.56%
Origination UPB Amount	177,714	99,794	175,526	97,328
Monthly Income	8,151	9,554	8,033	8,279
Unemployment Rate	6.86%	2.13%	6.75%	2.09%
24 Month House Price Appreciation	0.89%	12.74%	0.72%	11.79%
ZIP Code Level Bachelor+ Attainment Rate	32.84%	15.68%	32.47%	15.30%
ZIP Code Level Minority Population Rate	32.20%	22.75%	31.34%	21.92%
Weighted Observations	32,495,259		324,962,060	

Notes: This table contains the summary statistics for all loans used across the twenty-eight events included in our difference-in-difference estimation. The summary statistics are separated for the Affected and Unaffected population.

Figure 6: Rate of 90 Day Delinquencies by Time From A Hurricane Event and by Minority Status

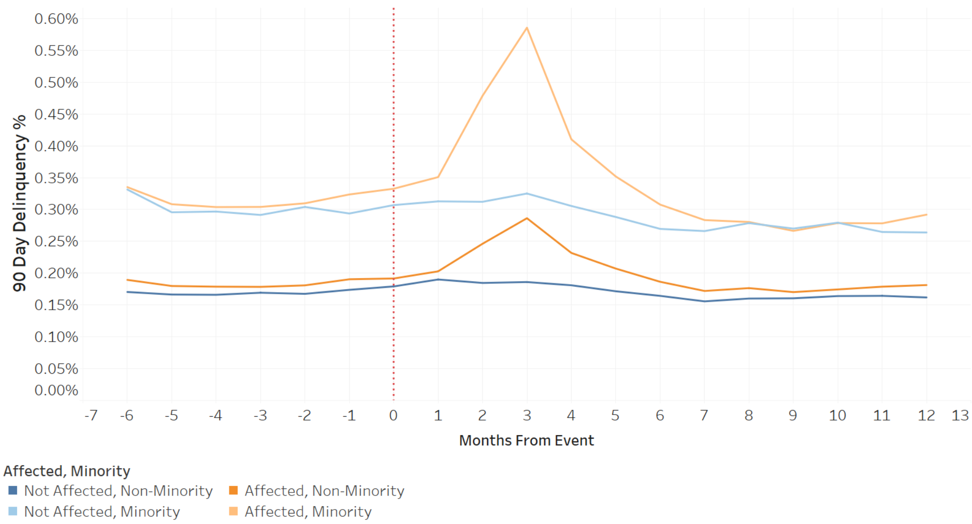
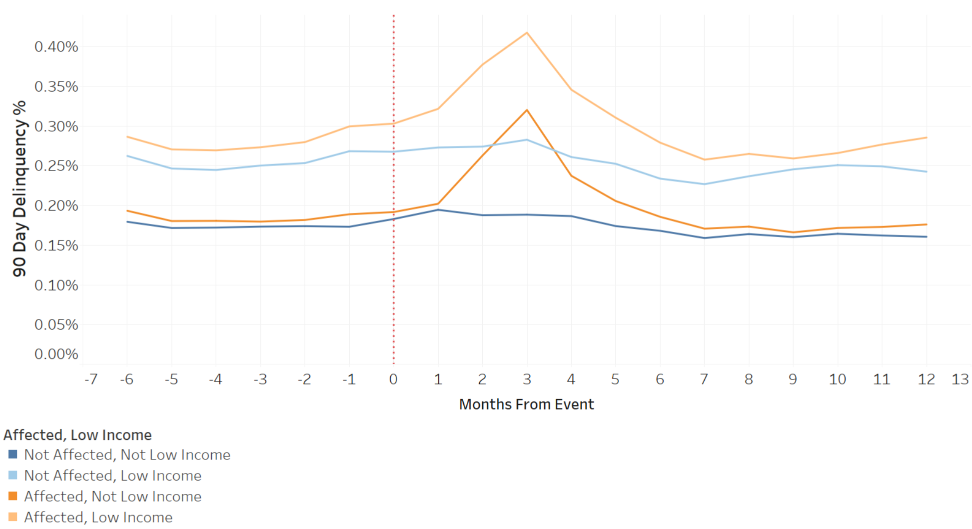


Figure 7: Rate of 90 Day Delinquencies by Time From A Hurricane Event and by Low Income Status



3. Estimation Strategy

We analyze the effect of 28 hurricane events that occur from 2010-2018 using a stacked difference-in-differences (DID) approach where the treatment populations are from affected ZIP codes based on wind data from hurricane best track data. The control populations are non-affected ZIP codes. As described above, we use nearest neighbor matching to match treated loans to control loans in order to control for underlying loan and area characteristics that may impact performance and to ensure parallel trends. The outcomes of interest are various levels of delinquency, prepayment, foreclosure, and modification. Additionally, we use precipitation data, flood plain status, and whether the county was declared a disaster county and enabled to receive assistance from FEMA to measure different levels of intensity and post disaster aid. We begin by discussing our overall estimation strategy. We then provide evidence that we are identifying the impact of hurricanes on mortgage performance by examining the parallel trends assumption as well as demonstrating that our impacted and control loans are correctly identified.

3.1 Stacked Differences in Differences

We use a stacked DID to estimate the effect of hurricanes on mortgage performance across 28 hurricanes. Following Cengiz et al. (2019), we use a stacked DID along with carefully defining our treatment and control loans to alleviate concerns about identification when locations are treated at different times across the analysis. See Roth et al. (2023) and Baker, Larcker, and Wang (2022) for further discussion and review of best practices for staggered DID analyses. For our stacked DID approach, we begin with the following baseline specification.

$$Y_{itg} = \alpha_{ig} + \lambda_{tg} + \delta_0 + \delta_1(\mathit{affected} \times \mathit{post})_i + \epsilon_{itg} \tag{1}$$

Where i represents a specific loan, t is a time representing months prior to and following the event, and g represents each relevant hurricane event. We include multiple fixed effects, α are event-specific fixed effects for affected and unaffected loans, and λ are event-specific pre and post fixed effects. Lastly, δ_1 represents the effect of interest and is the coefficient on the interaction of *affected* and *post*, where *affected* and *post* are defined across all the events. This coefficient is the estimated average change in the post-disaster period differential between the affected groups and the control groups.

We run the estimation using 8 different variables of interest regarding loan performance–5 categories of delinquency, prepayment, foreclosure, and modification. We use the standard definition of *Delinquent*, occurring when a loan is one payment late where the previous month was zero payments late. $Delinquent_{60}$ is defined as a loan being two-months late on payments where the previous month was less than two payments late, the second part of the definition means that we are capturing loans that are actively missing payments. The same set of rules are used to define $Delinquent_{90}$,$Delinquent_{180}$ and $Delinquent_{270}$. *Prepay* indicates that a loan is prepaid, *Foreclosed* indicates a loan was foreclosed on, and *Modification* indicates a loan was modified. Due to the nature of 0/1 variables of interest, we estimate a binary outcome model. While a logit is the typical choice for a binary variable model, we believe its multiplicative interpretation may result in a mis-specification for the Hurricane impact effect. Specifically, we believe the impact of a hurricane is additive not multiplicative; this is an especially important point for the minority triple-difference since, in general, minority populations have higher base levels of delinquencies and foreclosures. This is such that the relative risk may be lower but the difference in risk higher. A natural solution to this problem is to estimate a linear probability model. We weight the regression by loan so that the estimate of δ_1 represents the impact on the average loan.

We then extend this specification to the following equation, allowing us to analyze variation in these effects by minority status and income level.

$$Y_{itg} = \alpha_{ig} + \lambda_{tg} + \delta_0 + \delta_1(affected \times post) + \sigma(affected \times post \times minority)_i + \epsilon_{itg} \tag{2}$$

Here, *minority* is an indicator that is 1 when the holder of a loan falls into a minority race category and 0 when the holder is White. Similarly, we run the same specification with a low income indicator instead of the minority indicator. A loan classified as low income is a loan where the borrowers income is less than or equal to 80% of the area median income.

3.2 Identification

The following sections discuss the three main threats to the identification of our estimated effects: parallel trends, within ZIP-code treatment variation, and overlapping events.

3.2.1 Parallel Trends

The main assumption for the results of the DID approach to be interpreted as causal effects is that the trends of the treatment groups would have otherwise followed the same trajectory as the control group. First, in Figure 8 we present evidence of the similarities for key variables across loans in the affected and unaffected ZIP codes before an event occurs.

Second, In order to provide visual evidence that the parallel trends assumption is satisfied, we plot the rates of 30 day's delinquency between affected and control areas over the analysis window for each included event. Visually we can see that the rates of delinquencies look similar pre-impact for most event. We can also see that some events have large delinquency increases that occur after the expected time frame, including in event al012018, al062017, al142016, and al122016. These increases are from other events that were not controlled for through our "some overlap" sampling scheme.While these events might slightly bias our results, the use of severity data and event study analysis should ease these biases. In addition to visual evidence of the parallel trends we run an event study type analysis which shows the pre-impact estimates between the control and affected groups.

3.2.2 Relying on ZIP Codes

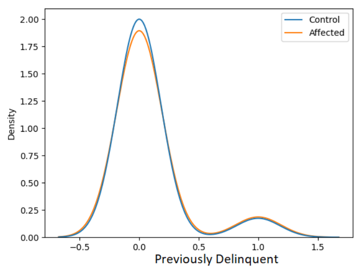
Since we rely on ZIPs codes for our samples, one might be concerned about within ZIP code variation of treatment (severity of the hurricane) since ZIP codes vary in size. If, for example, minority borrowers tend to live in smaller ZIP codes with less variation in precipitation, then the errors on our precipitation variable might be correlated with our group of interest making it difficult to get a clean estimate of borrower heterogeneity. To identify whether using ZIP codes is an issue for identification we look at the distribution of rain within a ZIP code and consider how that distribution varies across the two examples discussed here: 1.) education or 2) minority populations. Figures 10, 11, and 12 demonstrate that there is no clear relationships between education or minority populations with rainfall variation within a ZIP code.

3.2.3 Overlapping Events

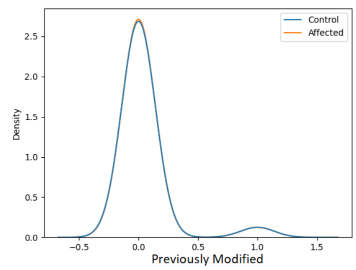
Hurricane damages in the United States are concentrated on the Gulf and East Coasts. Hurricane season runs from June to November *each year*, since we only analyze the effects of a hurricane up to one year post event it may be difficult to identify affected loans that were not also affected both the preceding and subsequent years. In order to address these overlapping events we consider three types of treated (affected loans) samples. First, we

Figure 8: Pre-Event Loan Characteristic Matching between Affected and Control loans

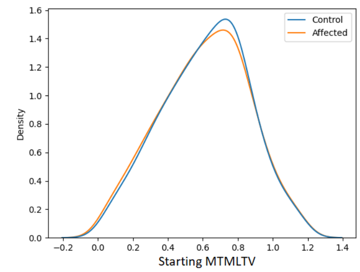
(a) Previously Delinquent



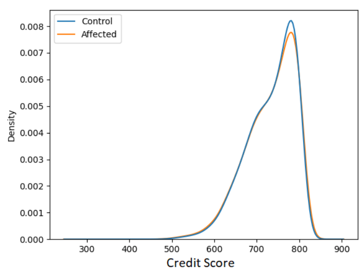
(b) Previously Modified



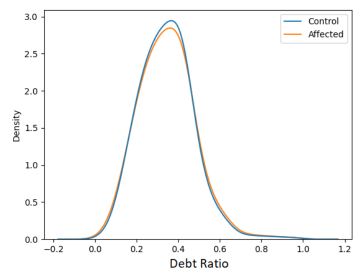
(c) Starting MTMLTV



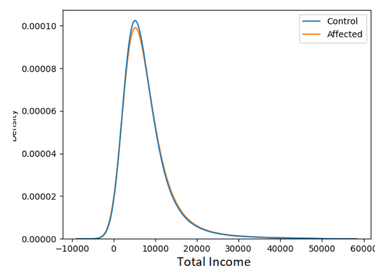
(d) Credit Score



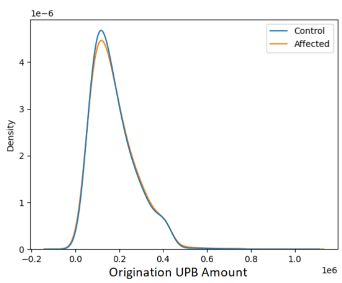
(e) Debt Ratio



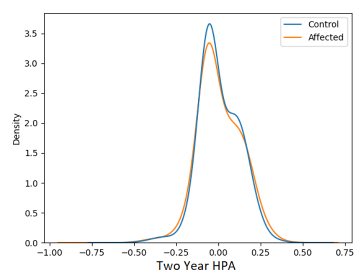
(f) Total Income



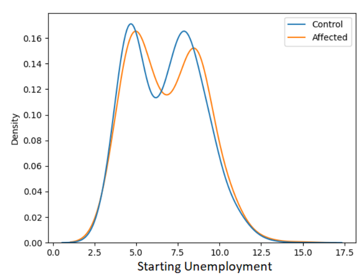
(g) Origination UPB Amt.



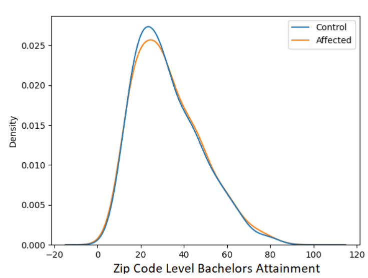
(h) Two Year HPA



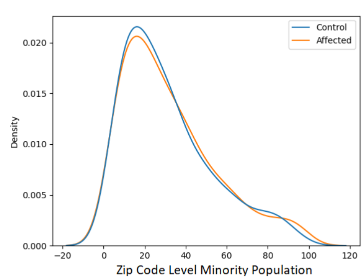
(i) Starting Unemployment



(j) Zip Code Level Bachelor Attainment

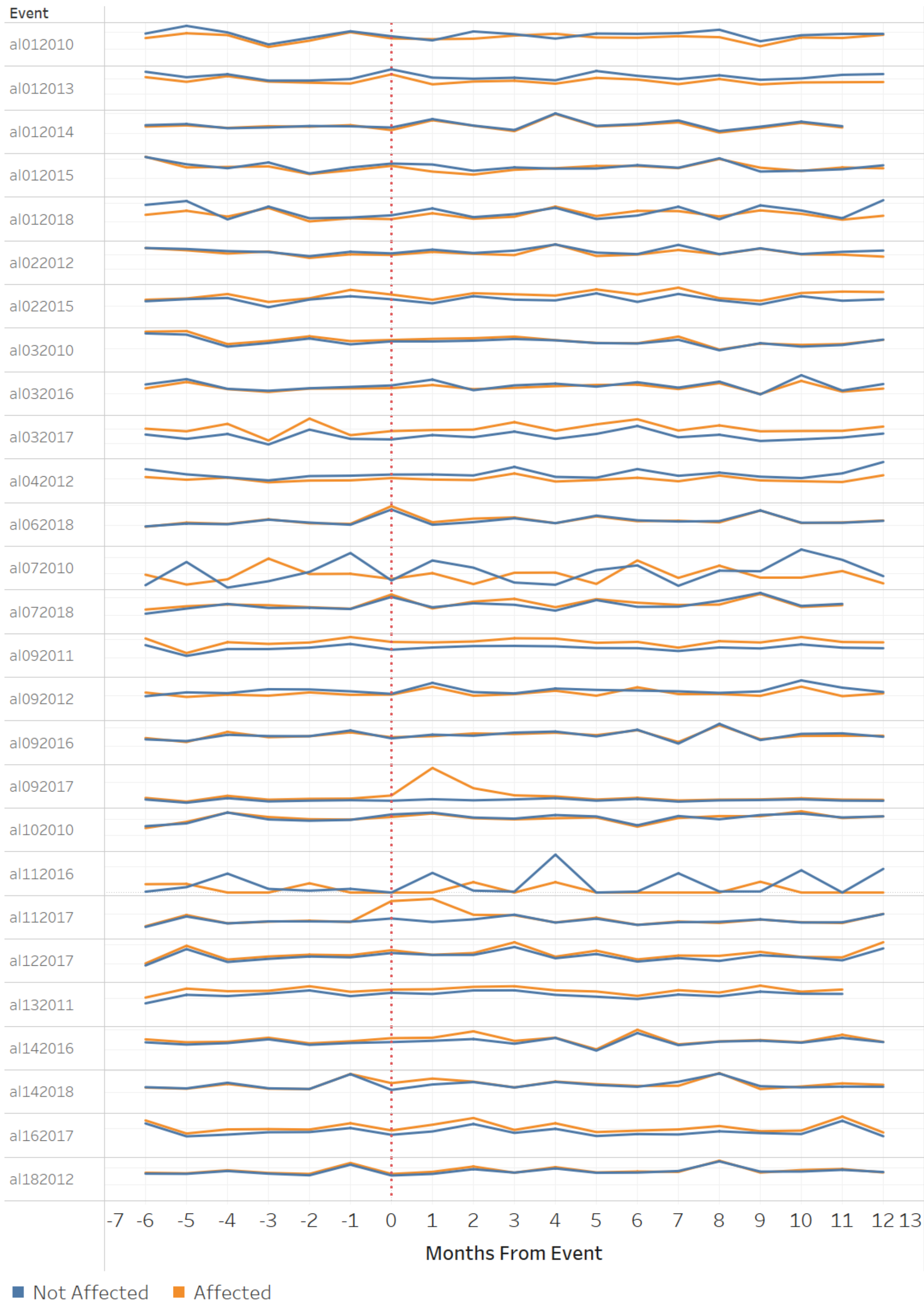


(k) Zip Code Level Minority Population



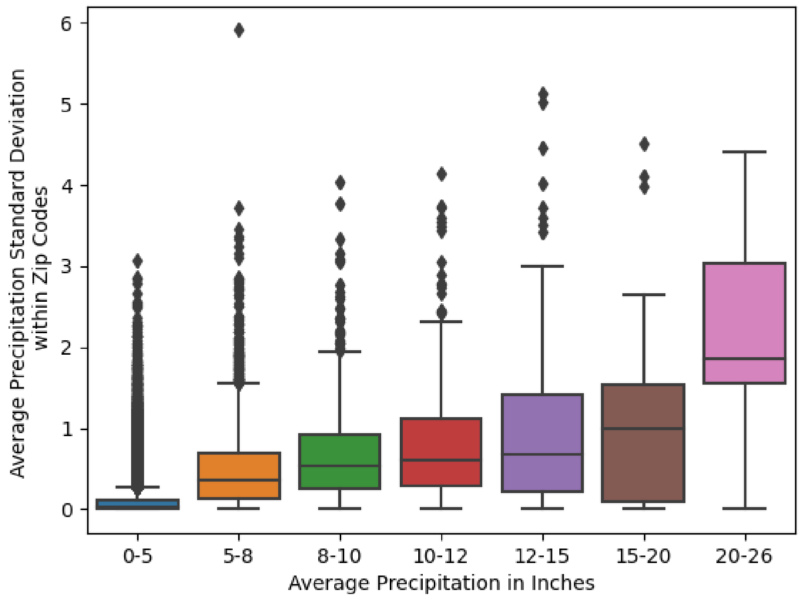
Note: This figure shows the kernel density estimates of several variables separated by control and affected populations.

Figure 9: Rate of 30 Day Delinquencies by Event



Note: This figure shows twenty-eight difference in difference graphs for the rate of 30 day delinquencies. Each row shows one of the the twenty-eight relevant hurricanes included in our analysis.

Figure 10: Standard Deviation of Precipitation within a ZIP Code by Rain Fall Amounts

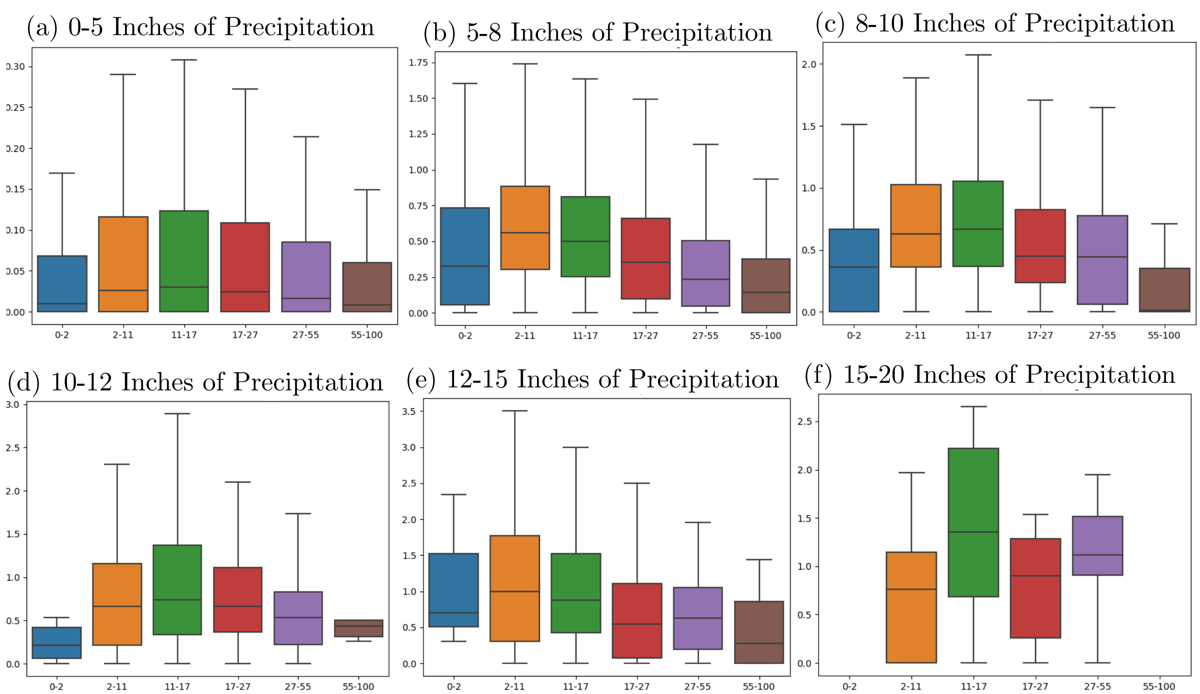


Note: Notes: This figure shows box and whisker plots of the standard deviation of reported precipitation within zip codes grouped by the average calculated precipitation in a zip code.

consider all loans that are affected by an event within a ZIP code even if that ZIP code experiences another event in the prior or post years. Second, in our some overlap sample, we remove a ZIP code from our analysis if the post analysis window of another hurricane event overlaps with the analysis window of the relevant event, and if the overlapping effect causes 5 or more inches of rain in the relevant ZIP code or had a max wind radii of 50 or more in the relevant ZIP code. Third, in our no overlap sample we remove a ZIP code from analysis if the post analysis window of another hurricane event overlaps with the analysis window of the relevant event. Figure 13 presents a demonstration of how the some overlap and no overlap samples are created and Figure 14 shows the change in included populations across the different samples.[5] Our preferred sample is the some overlap sample, which minimizes the effect of overlapping events while preserving as much data as possible by only removing overlapped events if the confounding hurricane event is relatively large. We use this sample for our results discussion.

[5]To demonstrate that parallel trends holds for these samples as well, we include Figures A13 and A12 in the appendix.

Figure 11: Standard Deviation of Precipitation within a ZIP Code by Bachelor Attainment Percentages- grouped by average reported precipitation



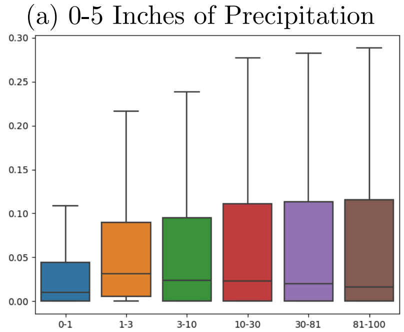
(a) 0-5 Inches of Precipitation (b) 5-8 Inches of Precipitation (c) 8-10 Inches of Precipitation

(d) 10-12 Inches of Precipitation (e) 12-15 Inches of Precipitation (f) 15-20 Inches of Precipitation

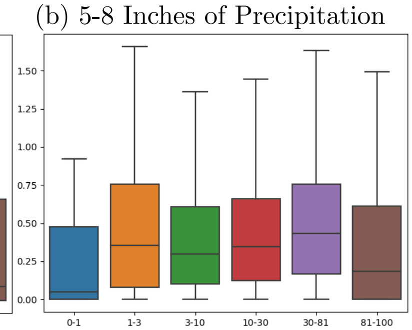
Note: This figure has six sub-figures each for a different grouping of average reported precipitation. Each sub-figure shows box and whisker plots of the standard deviation of reported precipitation within zip codes grouped by percents of bachelor degree attainment rates.

Figure 12: Standard Deviation of Precipitation within a ZIP Code by Minority Percentages-grouped by average reported precipitation

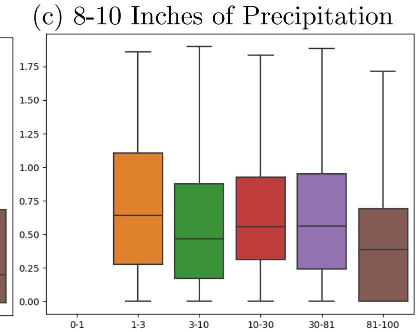
(a) 0-5 Inches of Precipitation



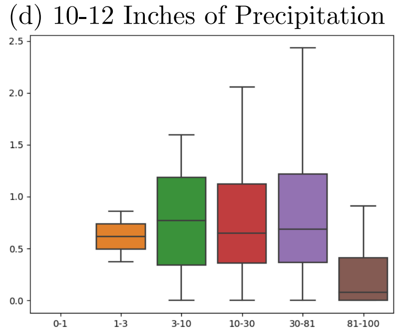
(b) 5-8 Inches of Precipitation



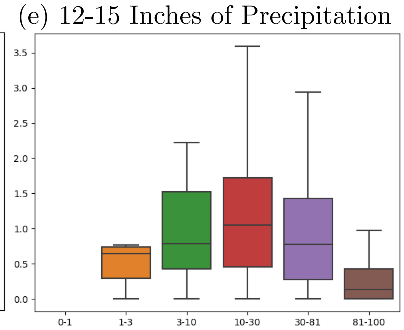
(c) 8-10 Inches of Precipitation



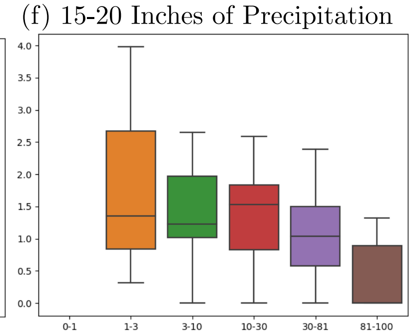
(d) 10-12 Inches of Precipitation



(e) 12-15 Inches of Precipitation



(f) 15-20 Inches of Precipitation



Note: This figure has six sub-figures each for a different grouping of average reported precipitation. Each sub-figure shows box and whisker plots of the standard deviation of reported precipitation within zip codes grouped by percents of minority populations.

Figure 13: Demonstration of Some Overlap and No Overlap Sample Creation

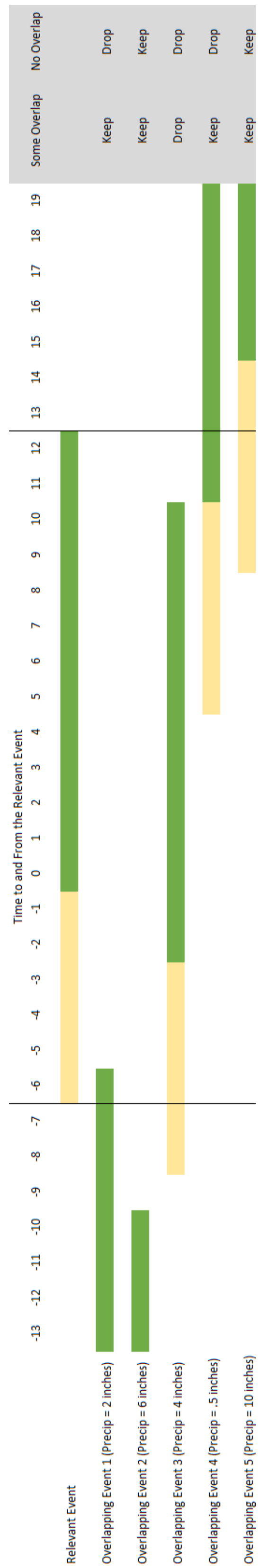
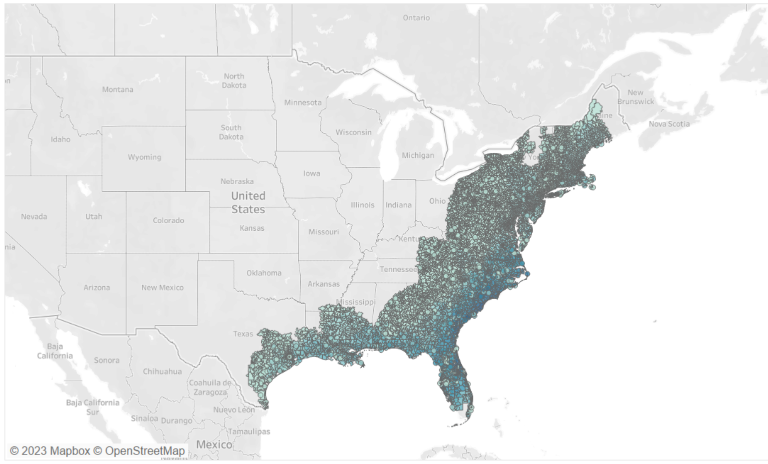
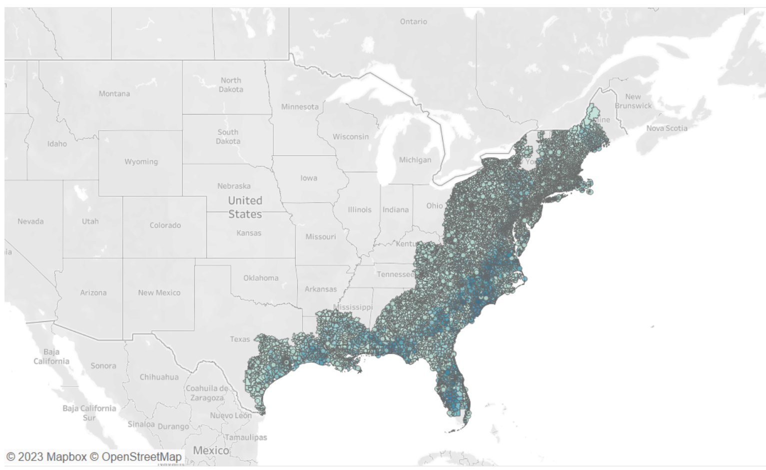


Figure 14: Change in included population across the different samples

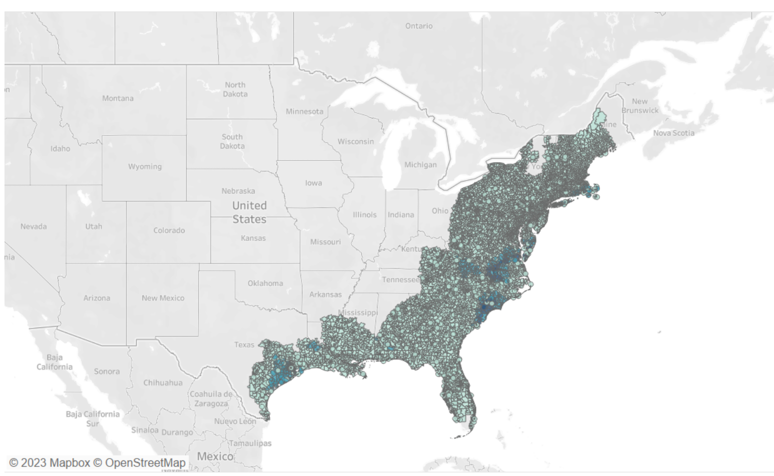
(a) All Sample



(b) Some Overlap Sample



(c) No Overlap Sample



Note: Three maps of the United States depicting the relative presence of affected zip codes in the three defined samples, All Sample, Some Overlap Sample, and No Overlap Sample respectively.

4. Results

4.1 Impact of Hurricanes on Mortgage Performance

First, we estimate the impact of hurricane events on overall mortgage performance using the set of linear probability models shown in Tables 3 and 4. Recall that given the issue of spillovers when the window around an event overlaps with a previous event, we have narrowed our sample to include only those events with overlaps in less severe cases. Across our many specifications, we find a positive and significant impact on the occurrence of 30, 60, 90, 180, and 270-day delinquencies. This is true particularly for mortgages in affected areas after the hurricane with higher amounts of rainfall. We also see that some of increase in delinquencies are associated with location in SFHAs or in counties that receive federal assistance, and that the effects in these areas are increasing with rainfall. For prepays, we see a decrease overall, but assistance and SFHA status is associated with an increase in prepays. Finally, modifications and foreclosures both increase across our various specifications, with less strong evidence on foreclosures.

Narrowing our focus to the first model specification that only includes an interaction of affected counties following hurricanes, we see positive and significant effects on all delinquency periods, modification, and foreclosures. There appears, however, to be a negative change for prepayments when looking at all affected loans. Moving to the second model specification, where we consider affected and levels of rainfall, all delinquency periods seem to have lower incidence of delinquencies in affected areas. However, this is counteracted by the larger-in-magnitude positive effects on delinquency as levels of rainfall increase. There is some evidence of a quite small increase in modifications for loans, increases in foreclosures, and decreases in prepays in these areas, as well. Figure 15 shows the impacts of rain on modifications and delinquencies for affected loans.

The effects on the outcomes of interest in our third specification, which examines loans in counties that received assistance following the hurricane, are similar to those estimated by our second specification with the exceptions of being much larger in magnitude, an apparent decrease in foreclosures for these counties, and a much larger increase in modifications. Intuitively, this could be due to the fact that the homeowners in these counties both received insurance payouts and assistance, allowing them to have higher levels of curtailment, more negotiating power with their lender, and more means to avoid foreclosure outcomes than other affected counties as counties eligible for federal disaster aid are under a disaster declaration, which may lead to automatic forbearance and public notices to servicers and borrowers about modification options by Fannie Mae and Freddie Mac.

Focusing only on the impact on loans in SFHA designated areas, there is an increase in 30, 60, and 90-day delinquencies, but on a much smaller magnitude than loans in assistance counties saw. There appears to be a very small, slightly significant decrease in 180 and 270-day delinquencies, with an increase in prepays and a small increase in foreclosures. The increase in prepays is consistent with other literature that has seen increases in prepays after disasters where insurance is available. Considering all three of the variables: high rainfall, assistance counties, and SFHAs, in the same specification we see relatively consistent estimates with previous specifications.

Next we consider how the interaction of these aid and severity variables may impact the results. Including the amount of rainfall in the ZIP code where the property is located, loans in counties that received assistance, and the interaction between amount of rainfall and being in a county that received assistance shows that the majority of the delinquency counties is being driven by loans in the latter areas. This means that the effect is driven by loans in the most severely affected areas. For these most affected counties, there is evidence of increases in prepays, modifications, and foreclosures. This is reasonable because they most likely experience more damage and may fall behind on payments, then catch up later on. Those who receive assistance in areas with high rainfall might alternatively choose to prepay, rather than immediately pay for repairs or rebuilds. Unsurprisingly, they would likely need more assistance from lenders with modifications to their loans or face foreclosure if they cannot receive a modification.

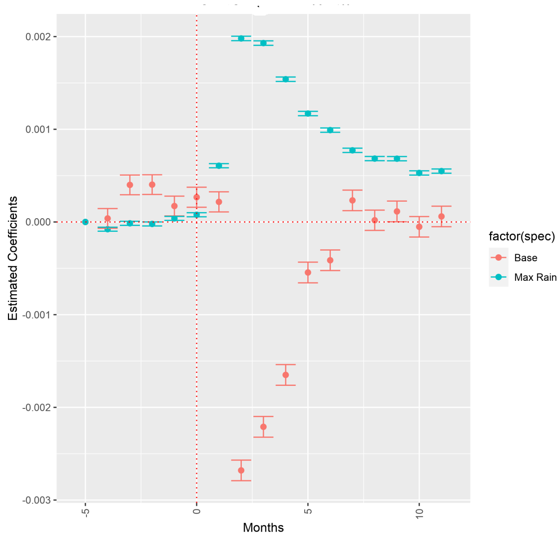
When we look at loans in SFHAs interacted with rainfall, 30-day delinquencies decrease ever so slightly for SFHA loans, but this effect is counteracted as the levels of rainfall increase cause increases in 30-day delinquencies and even one 1-inch of rainfall would lead to overall higher delinquencies. We again see increases in 90, 180, and 270-day delinquencies for SFHA located loans, however these loans do not follow the general trend of the positive effect on delinquencies attenuating over time. There are increases in prepays, and modifications and very small decreases in foreclosure rates in various specifications for these loans, which appear to be counteracted as levels of rainfall increase. One possible mechanism for this is that for the most water-damaged properties, homeowners on average choose to use insurance payouts and/or assistance to prepay their loans, viewing it as "not worth it" to repair or rebuild, given the nature of water damage. Finally, looking at loans in each of the three aforementioned areas together, we see consistent estimates with previous specifications. This is also consistent with what is shown in the prior literature.

Overall, it seems areas experiencing more damage have higher rates of delinquencies and modifications, though this is not necessarily the case for foreclosures. There is a substantial trend of delinquency impacts attenuating, from around 0.03 percent to only 0.002 percent. When we add in our controls, we see that the effect is largely driven by SFHAs and Assistance Counties and increasing with rainfall. It is plausible that the impact on delinquencies fades over time as insurers pay out claims, lenders work with borrowers to adjust the terms of their loans, and some borrowers enter foreclosure. We do not see the incidence of claims payout here, but we can see when a loan was modified. Lenders might prefer modification of a loan over foreclosure so that they can still receive back most or all of the value of the loan over the life of the mortgage. Modification is positively and significantly impacted for loans in affected areas after the hurricane. Our estimations show there are positive impacts on mortgages located in ZIP codes with higher levels of rain and in counties which received federal assistance, as well as those in SFHAs located inside or outside of counties receiving federal assistance. Foreclosures appear to also increase, though the impacts tend to be around 3 or more times smaller than for modifications. This is particularly true for loans in affected areas after a hurricane and for these loans that are also located in a county that received federal assistance following the storm, which regularly experience a decrease in foreclosures. The relative magnitudes and different signs of the impacts on modification and foreclosure indeed indicate that modification is a preferable route for lenders to take over foreclosure.

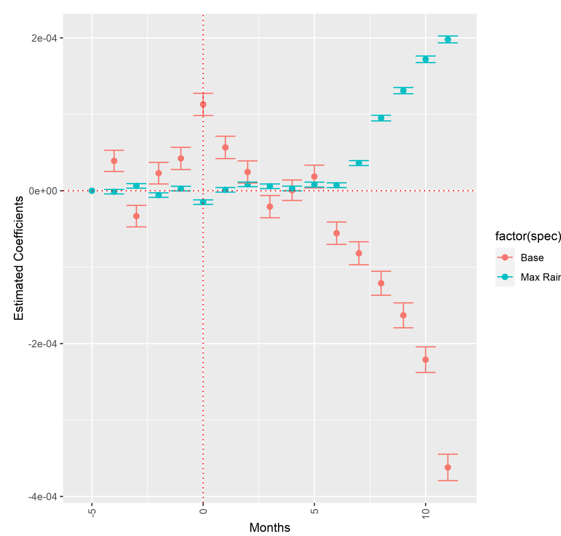
While these results show some clear patterns, it is also important to keep in mind that there is correlation that shows up in the controls we have included in the longer specifications. This can make the exact relationship of the results difficult to determine in some cases. Additionally, as the prepay results are somewhat noisy we examined prepays further. Looking at Figure 16, we do actually see that the severity of an event leads to lower prepayments that is mostly driven by reductions in cashouts and refinances. Additionally, these reductions seem to be present over a year after an event occurs. However, as shown in Figure 17 non-cashout and non-refinance prepays increase in SFHA designated areas. Further the regression results show that this is driven by the hardest hit SFHAs. This finding that non-cashout and non-refinance prepays increase in SFHA designated areas is consistent with what prior literature has found and adds evidence that flood insurance claim payouts may be used in borrowers paying off the unpaid balance on their mortgages.

Figure 15: Event Study Graphs for Delinquency and Modification controlling for storm severity

(a) Delinquency



(b) Modification



4.2 Heterogeneous Impacts by Vulnerable Populations

4.2.1 Heterogeneous Impacts by Race

The next set of model results are summarized in Tables 5 and 6. In these tables, the baseline model is slightly modified to include a term to estimate any differential post-disaster impacts for minority individuals that may exist. In Table 5, there are several specifications that indicate a statistically significant differential impact on minority populations leading to higher rates of 30, 60, and 90-day delinquencies on the magnitude of around 0.04 percent. This indicates that minorities are facing impacts of around twice the size of the overall population on average. There are more prominent and consistent effects for 90-day delinquencies. When we control for amount of rain, we can see that these longer term delinquencies are more prominent for minorities as rainfall increases. However, there is little evidence that these differential impacts remain for 180-day or 270-day delinquencies. This is unsurprising as the effects for the overall dataset wear off by 280-day delinquencies with only small effects remaining by 180-days. Given that it is more pronounced for minorities than non-minorities, we can infer that much of the attenuation is coming from this group. While the results do not explain what drives this disparity, the important takeaway is that minority individuals are

Table 3: Baseline Linear Probability Model Delinquency Results

Equation	**Variable of Interest**	**30 Days Delinquent**	**60 Days Delinquent**	**90 Days Delinquent**	**180 Days Delinquent**	**270 Days Delinquent**
LPM1	AfterXAffected	0.000281*** 27.10	0.000334*** 51.28	0.000246*** 47.65	0.0000932*** 22.23	0.0000224*** 5.93
LPM2	AfterXAffected	-0.000302*** -17.92	-0.000151*** -14.27	-0.000206*** -24.41	-0.000134*** -19.39	-0.0000829*** -13.26
LPM2	AfterXAffectedXMax Rain	0.000168*** 44.59	0.000140*** 59.02	0.000130*** 69.25	0.0000654*** 44.47	0.0000303*** 23.81
LPM3	AfterXAffected	-0.0000344** -2.89	0.0000777*** 10.43	0.0000249*** 4.22	-0.00000675 -1.39	-0.0000214*** -4.85
LPM3	Assistance CountyXAfterXAffected	0.00133*** 54.55	0.00108*** 70.19	0.000930*** 76.45	0.000421*** 43.89	0.000184*** 21.78
LPM4	AfterXAffected	0.000293*** 26.85	0.000309*** 45.28	0.000224*** 41.69	0.0000916*** 21.17	0.0000285*** 7.35
LPM4	SFHAXAfterXAffected	-0.000111** -3.18	0.000236*** 10.49	0.000206*** 11.15	0.0000154 0.98	-0.0000575*** -3.93
LPM5	AfterXAffected	-0.000192*** -10.94	-0.000102*** -9.25	-0.000170*** -19.44	-0.000113*** -15.91	-0.0000675*** -10.56
LPM5	AfterXAffectedXMax Rain	0.0000686*** 14.19	0.0000628*** 20.61	0.0000699*** 28.87	0.0000418*** 21.97	0.0000208*** 12.50
LPM5	SFHAXAfterXAffected	-0.000127*** -3.64	0.000224*** 9.96	0.000201*** 10.85	0.0000162 1.02	-0.0000563*** -3.84
LPM5	Assistance CountyXAfterXAffected	0.00104*** 33.38	0.000816*** 41.18	0.000640*** 40.76	0.000249*** 19.98	0.0000994*** 8.97
LPM6	AfterXAffected	0.0000281 1.37	0.000104*** 7.95	-0.00000329 -0.31	-0.0000384*** -4.35	-0.0000667*** -8.20
LPM6	AfterXAffectedXMax Rain	-0.0000243*** -3.69	-0.00000995* -2.38	0.0000115*** 3.44	0.0000127*** 4.61	0.0000182*** 7.22
LPM6	Assistance CountyXAfterXAffected	0.0000838 1.51	0.0000994** 2.84	0.0000691* 2.49	-0.0000449* -2.10	0.0000653*** 3.53
LPM6	Assistance CountyXAfterXAffectedXMax Rain	0.000203*** 20.96	0.000154*** 25.29	0.000123*** 25.46	0.0000626*** 16.56	0.00000664* 2.03
LPM7	AfterXAffected	-0.000286*** -16.16	-0.000169*** -15.24	-0.000223*** -25.46	-0.000134*** -18.94	-0.0000702*** -11.04
LPM7	AfterXAffectedXMax Rain	0.000166*** 42.12	0.000137*** 55.47	0.000128*** 65.70	0.0000646*** 42.80	0.0000282*** 21.78
LPM7	SFHAXAfterXAffected	-0.000144* -2.52	0.000138*** 3.71	0.000136*** 4.37	-0.00000448 -0.16	-0.000121*** -4.75
LPM7	SFHAXAfterXAffectedXMax Rain	0.0000198 1.48	0.0000375*** 4.35	0.0000287*** 4.05	0.00000980 1.66	0.0000209*** 3.94
LPM8	AfterXAffected	0.0000521* 2.44	0.0000936*** 6.94	-0.0000142 -1.32	-0.0000359*** -4.03	-0.0000527*** -6.45
LPM8	AfterXAffectedXMax Rain	-0.0000278*** -4.15	-0.0000136** -3.21	0.00000878** 2.59	0.0000115*** 4.12	0.0000157*** 6.24
LPM8	SFHAXAfterXAffected	-0.000210*** -3.68	0.0000865* 2.32	0.0000946** 3.05	-0.0000231 -0.85	-0.000126*** -4.93
LPM8	SFHAXAfterXAffectedXMax Rain	0.0000277* 2.07	0.0000436*** 5.06	0.0000337*** 4.75	0.0000127* 2.15	0.0000209*** 3.94
LPM8	Assistance CountyXAfterXAffected	0.0000842 1.51	0.0000772* 2.20	0.0000504 1.82	-0.0000484* -2.25	0.0000647*** 3.49
LPM8	Assistance CountyXAfterXAffectedXMax Rain	0.000204*** 21.00	0.000157*** 25.67	0.000125*** 25.86	0.0000631*** 16.71	0.00000715* 2.19

Note: * p<0.1 ** p<0.05 ** p<0.01.

Table 4: Baseline Linear Probability Model Loan Outcomes Results

Equation	Variable of Interest	Prepay	Modification	Foreclosed
LPM1	AfterXAffected	-0.000619*** -49.12	0.000125*** 37.98	0.0000593*** 18.66
LPM2	AfterXAffected	-0.000225*** -11.32	-0.000140*** -25.83	0.0000996*** 18.45
LPM2	AfterXAffectedXMax Rain	-0.000113*** -25.92	0.0000764*** 63.26	-0.0000115*** -11.09
LPM3	AfterXAffected	-0.000276*** -18.92	-0.0000161*** -4.26	0.0000876*** 22.70
LPM3	Assistance CountyXAfterXAffected	-0.00144*** -50.32	0.000595*** 76.13	-0.000118*** -18.67
LPM4	AfterXAffected	-0.000651*** -48.95	0.000116*** 34.02	0.0000542*** 16.66
LPM4	SFHAXAfterXAffected	0.000312*** 7.59	0.0000923*** 7.36	0.0000497*** 3.98
LPM5	AfterXAffected	-0.000415*** -19.99	-0.000108*** -19.31	0.0000830*** 15.13
LPM5	AfterXAffectedXMax Rain	0.0000398*** 6.97	0.0000332*** 21.38	-0.000000229 -0.17
LPM5	SFHAXAfterXAffected	0.000369*** 8.96	0.0000855*** 6.81	0.0000526*** 4.20
LPM5	Assistance CountyXAfterXAffected	-0.00161*** -42.90	0.000458*** 45.41	-0.000119*** -14.71
LPM6	AfterXAffected	0.000136*** 5.50	-0.0000532*** -7.91	0.000118*** 16.72
LPM6	AfterXAffectedXMax Rain	-0.000165*** -20.17	0.0000149*** 6.99	-0.0000122*** -5.76
LPM6	Assistance CountyXAfterXAffected	-0.00362*** -57.37	0.000281*** 15.63	-0.000232*** -17.96
LPM6	Assistance CountyXAfterXAffectedXMax Rain	0.000432*** 38.01	0.0000384*** 12.34	0.0000248*** 9.68
LPM6	AfterXAffected	-0.000213*** -10.12	-0.000147*** -26.34	0.0000967*** 17.47
LPM7	AfterXAffectedXMax Rain	-0.000126*** -27.40	0.0000751*** 60.13	-0.0000121*** -11.44
LPM7	SFHAXAfterXAffected	-0.000171** -2.64	0.0000519* 2.47	0.0000236 1.12
LPM7	SFHAXAfterXAffectedXMax Rain	0.000139*** 9.06	0.0000167*** 3.61	0.00000711 1.62
LPM7	AfterXAffected	0.000156*** 6.02	-0.0000566*** -8.31	0.000116*** 16.14
LPM7	AfterXAffectedXMax Rain	-0.000182*** -21.76	0.0000134*** 6.26	-0.0000130*** -6.13
LPM8	SFHAXAfterXAffected	-0.000186** -2.85	0.0000306 1.46	0.0000226 1.07
LPM8	SFHAXAfterXAffectedXMax Rain	0.000174*** 11.30	0.0000171*** 3.70	0.00000939* 2.14
LPM8	Assistance CountyXAfterXAffected	-0.00367*** -58.12	0.000273*** 15.16	-0.000237*** -18.26
LPM8	Assistance CountyXAfterXAffectedXMax Rain	0.000439*** 38.60	0.0000393*** 12.66	0.0000253*** 9.91

Note: * p<0.1 ** p<0.05 ** p<0.01.

unable to catch up on mortgage payments as quickly as non-minority individuals following disaster events.

There are also significant differential impacts for minority populations when looking at modifications and foreclosures. In most cases, there are slightly higher rates of modifications for minorities. In some cases, we see the significance decrease or even a sign change. In these specifications, it appears that the interaction of the minority term with other covariates, such as *max rain* and *assistance county* is offsetting this effect and shows that these other controls have a stronger impact when we consider minority groups. We also see here that increases in rain increases the likelihood for minorities to experience modifications, indicating that minorities are more likely to modify their loans if they are in an area that was more severely impacted by a storm. One factor that is likely to make it difficult for minorities to avoid falling behind and needing to make modifications to their loan is the more significant impact to their financial stability from disasters. A study by Farrell et al. (2020) found that the median Black and Hispanic families earn roughly 70 cents in take-home income for every dollar earned by White families. Furthermore, the median White family has \$3,247 in liquid assets compared to just \$1,029 for Black families and \$1,527 for Hispanic families. This means minority households will be less suited to sustain mortgage payments in the case of an income shock and are less likely to be able to catch up on payments after the shock. Evidence of this effect is provided by Chun et al. (2023) who find that Black and Hispanic respondents are more vulnerable to housing-related hardships than White respondents, particularly those households with limited liquid assets because liquid assets act as a strong mediator of the housing hardship disparities between White and Black/Hispanic households.

We see similar impacts for foreclosures, as well. However, the interaction of the minority term with *max rain* and *assistance county* are significant and negative. Therefore, we are seeing that modifications are being driven by more severely impacted counties, while minority foreclosures are being driven by those living outside more severely affected counties. A possible explanation for this could be that these loans are located in areas that are not receiving assistance which can help individuals continue making some payments and get approval for a modification. Additionally, lenders are more likely to provide modifications in more severely impacted counties if they become a federally declared disaster area or if a larger number of borrowers are affected because Freddie Mac and Fannie Mae may make additional announcements or press releases that outline modification opportunities for wide scale disasters.[6] Outside of these areas, negotiating a modification may be more difficult for borrowers that experience damage.

Also in Table 6, we see that prepayments are often lower for minority borrowers. There is an increase when we consider minority borrowers in assistance counties and the effect is increasingly positive with amount of rainfall. A similar story of easier access to assistance would explain an increase in the likelihood of being able to prepay. Though, overall, this route appears to be less likely for minorities compared to non-minorities. There is further discussion about these results with regards to welfare implications later in this section.

Table 5: Minority Linear Probability Model Delinquency Results

Equation	**Variable of Interest**	**30 Days Delinquent**	**60 Days Delinquent**	**90 Days Delinquent**	**180 Days Delinquent**	**270 Days Delinquent**
LPM1	AfterXAffectedXMinority	0.000376*** 12.26	0.000443*** 22.13	0.000378*** 23.36	0.000108*** 8.07	-0.0000227 -1.87
LPM2	AfterXAffectedXMinority	0.000298*** 9.71	0.000379*** 18.88	0.000318*** 19.58	0.0000773*** 5.75	-0.0000371** -3.04
LPM3	AfterXAffectedXMinority	0.000310*** 10.12	0.000390*** 19.46	0.000332*** 20.50	0.0000871*** 6.49	-0.0000319** -2.62
LPM4	AfterXAffectedXMinority	0.000378*** 12.33	0.000440*** 21.98	0.000375*** 23.20	0.000108*** 8.07	-0.0000217 -1.79
LPM5	AfterXAffectedXMinority	0.000295*** 9.63	0.000371*** 18.52	0.000312*** 19.22	0.0000760*** 5.66	-0.0000366** -3.00
LPM6	AfterXAffectedXMinority	-0.000175*** -3.51	-0.0000489 -1.50	-0.0000527* -1.99	-0.0000998*** -4.47	-0.000149*** -7.30
LPM6	AfterXAffectedXMinorityXMax Rain	0.000125*** 12.36	0.000113*** 17.32	0.0000983*** 18.71	0.0000470*** 11.44	0.0000297*** 8.37
LPM7	AfterXAffectedXMinority	-0.000104** -2.88	0.0000609* 2.57	0.0000454* 2.36	-0.0000325* -1.99	-0.0000832*** -5.53
LPM7	Assistance CountyXAfterXAffectedXMinority	0.00154*** 22.69	0.00123*** 27.63	0.00107*** 30.03	0.000445*** 15.88	0.000191*** 7.73
LPM8	AfterXAffectedXMinority	0.000405*** 12.54	0.000370*** 17.67	0.000322*** 19.15	0.000104*** 7.61	-0.0000180 -1.46
LPM8	SFHAXAfterXAffectedXMinority	-0.000222* -2.18	0.000611*** 8.89	0.000467*** 8.10	0.0000332 0.65	-0.0000315 -0.66
LPM9	AfterXAffectedXMinority	-0.0000210 -0.40	-0.0000631 -1.87	-0.0000561* -2.05	-0.0000811*** -3.60	-0.000139*** -6.83
LPM9	SFHAXAfterXAffectedXMinority	-0.000231* -2.26	0.000628*** 9.11	0.000488*** 8.44	0.0000530 1.04	-0.0000123 -0.26
LPM9	Assistance CountyXAfterXAffectedXMinority	0.00164*** 18.37	0.00114*** 19.47	0.000993*** 21.04	0.000376*** 10.03	0.0000952** 2.86
LPM9	AfterXAffectedXMinorityXMax Rain	-0.0000250 -1.88	0.0000151 1.75	0.0000121 1.74	0.0000134* 2.46	0.0000210*** 4.43

Note: * p<0.1 ** p<0.05 ** p<0.01.

[6] The Enterprises' loss mitigation programs, which enable modifications and forbearance, have changed overtime and our analyses does not directly account for these changes. Significant changes occurred in response to COVID-19, which is outside of our analysis window.

Table 6: Minority Linear Probability Model Loan Outcomes Results

Equation	**Variable of Interest**	**Prepay**	**Modification**	**Foreclosed**
LPM1	AfterXAffectedXMinority	-0.000232*** -7.81	0.000222*** 19.14	0.000105*** 10.42
LPM2	AfterXAffectedXMinority	-0.000180*** -6.04	0.000187*** 16.03	0.000111*** 10.93
LPM3	AfterXAffectedXMinority	-0.000161*** -5.39	0.000193*** 16.58	0.000111*** 10.95
LPM4	AfterXAffectedXMinority	-0.000237*** -7.95	0.000221*** 19.06	0.000104*** 10.37
LPM5	AfterXAffectedXMinority	-0.000178*** -5.95	0.000184*** 15.75	0.000111*** 10.94
LPM6	AfterXAffectedXMinority	-0.000371*** -7.89	-0.0000427* -2.22	0.000189*** 10.92
LPM6	AfterXAffectedXMinorityXMax Rain	0.0000508*** 5.22	0.0000609*** 16.61	-0.0000208*** -7.22
LPM7	AfterXAffectedXMinority	-0.000351*** -9.93	-0.00000244 -0.17	0.000161*** 12.39
LPM7	Assistance CountyXAfterXAffectedXMinority	0.000709*** 10.83	0.000728*** 28.95	-0.000184*** -9.97
LPM8	AfterXAffectedXMinority	-0.000218*** -6.89	0.000189*** 15.93	0.0000695*** 6.83
LPM8	SFHAXAfterXAffectedXMinority	-0.000161 -1.74	0.000284*** 6.39	0.000306*** 7.64
LPM9	AfterXAffectedXMinority	-0.000263*** -5.31	-0.0000322 -1.65	0.000135*** 7.76
LPM9	SFHAXAfterXAffectedXMinority	-0.000192* -2.06	0.000285*** 6.40	0.000306*** 7.57
LPM9	Assistance CountyXAfterXAffectedXMinority	0.000831*** 9.62	0.000731*** 21.77	-0.000172*** -7.08
LPM9	AfterXAffectedXMinorityXMax Rain	-0.0000307* -2.39	-0.00000336 -0.69	-0.00000339 -0.91

Note: * p<0.1 ** p<0.05 ** p<0.01.

4.2.2 Heterogeneous Impacts by Income

We now consider possible heterogeneity of impacts for low-income borrowers in Tables 7 and 8. Here, we see that low-income itself leads to higher rates of delinquencies. The other controls of rainfall, assistance, and SFHA do not appear to mean much for delinquencies, though. There is also little evidence of heterogeneous outcomes when investigating prepayments, modifications, or foreclosures for low-income borrowers.

Table 7: Low Income Linear Probability Model Delinquency Results

Equation	Variable of Interest	30 Days Delinquent	60 Days Delinquent	90 Days Delinquent	180 Days Delinquent	270 Days Delinquent
LPM1	AfterXAffectedXLow Income	0.000105*** 3.87	0.000111*** 6.40	0.0000337* 2.51	-0.00000548 -0.51	0.0000360*** 3.75
LPM2	AfterXAffectedXLow Income	0.000111*** 4.12	0.000116*** 6.72	0.0000389** 2.89	-0.00000289 -0.27	0.0000372*** 3.88
LPM3	AfterXAffectedXLow Income	0.000143*** 5.30	0.000142*** 8.20	0.0000605*** 4.49	0.00000660 0.62	0.0000413*** 4.31
LPM4	AfterXAffectedXLow Income	0.000101*** 3.74	0.000120*** 6.94	0.0000417** 3.09	-0.00000483 -0.45	0.0000340*** 3.54
LPM5	AfterXAffectedXLow Income	0.000134*** 4.95	0.000146*** 8.43	0.0000629*** 4.67	0.00000411 0.38	0.0000378*** 3.95
LPM6	AfterXAffectedXLow Income	0.000199*** 4.48	0.000130*** 4.56	0.0000730** 3.29	-0.0000603*** -3.39	0.0000435** 2.74
LPM6	AfterXAffectedXLow IncomeXc.max_rain	-0.0000253* -2.49	-0.00000389 -0.60	-0.00000986 -1.94	0.0000166*** 4.25	-0.00000183 -0.54
LPM7	AfterXAffectedXLow Income	0.000197*** 6.42	0.000142*** 7.24	0.0000794*** 5.19	0.000000558 0.05	0.0000476*** 4.31
LPM7	Assistance CountyXAfterXAffectedXLow Income	-0.000238*** -3.68	0.00000149 0.04	-0.0000837** -2.59	0.0000280 1.12	-0.0000281 -1.27
LPM8	AfterXAffectedXLow Income	0.0000952*** 3.38	0.000120*** 6.67	0.0000380** 2.73	0.00000533 0.48	0.0000318** 3.24
LPM8	SFHAXAfterXAffectedXLow Income	0.0000759 0.74	0.00000682 0.10	0.0000453 0.84	-0.000121** -2.68	0.0000265 0.65

Note: * p<0.1 ** p<0.05 ** p<0.01.

We also consider heterogeneity in outcomes specifically for minority low-income borrows. There are no clear patterns arising other than a potentially slightly stronger effect on delinquencies of being low-income for non-minority borrowers.

4.3 Welfare Discussion

The results in Section 4.1 imply that there are negative welfare impacts on households experiencing a hurricane event. There are clear shocks to the mortgage performance leading to higher rates of delinquency, especially within 60-90 days following a hurricane. This leads to a significant financial burden on households attempting to catch up on their mortgages. It also causes financial strain on lenders who are not receiving payments from those borrowers for several months. In many cases, borrowers cannot necessarily catch up, so a modification to the loan might be made. While a modification is lower cost than foreclosure and a better outcome for both borrower and lender, it is not cost-less and in these cases, the lender is taking on extra financial strain. Modifications do not always lead to borrowers becoming current as well. If a foreclosure occurs, the lender faces even higher costs and borrowers are displaced from their homes and face negative impacts on their access to credit. This creates a

Table 8: Low Income Linear Probability Model Loan Outcomes Results

Equation	Variable of Interest	Prepay	Modification	Foreclosed
LPM1	AfterXAffectedXLow Income	0.000144*** 5.25	-0.0000344*** -4.04	0.0000308*** 4.02
LPM2	AfterXAffectedXLow Income	0.000140*** 5.09	-0.0000313*** -3.68	0.0000303*** 3.96
LPM3	AfterXAffectedXLow Income	0.000103*** 3.74	-0.0000173* -2.03	0.0000273*** 3.56
LPM4	AfterXAffectedXLow Income	0.000156*** 5.68	-0.0000309*** -3.63	0.0000329*** 4.29
LPM5	AfterXAffectedXLow Income	0.000113*** 4.12	-0.0000166 -1.95	0.0000296*** 3.85
LPM6	AfterXAffectedXLow Income	-0.000119** -2.72	-0.0000116 -0.82	0.0000634*** 4.86
LPM6	AfterXAffectedXLow IncomeXc.max_rain	0.0000750*** 7.62	-0.00000570 -1.76	-0.00000957*** -3.63
LPM7	AfterXAffectedXLow Income	-0.000134*** -4.25	0.0000130 1.34	0.0000421*** 4.61
LPM7	Assistance CountyXAfterXAffectedXLow Income	0.00107*** 16.65	-0.000135*** -6.70	-0.0000665*** -4.15
LPM8	AfterXAffectedXLow Income	0.000171*** 5.93	-0.0000341*** -3.90	0.0000337*** 4.29
LPM8	SFHAXAfterXAffectedXLow Income	-0.000173 -1.76	0.0000377 1.05	-0.0000106 -0.33

Note: * p<0.1 ** p<0.05 ** p<0.01.

clear problem for the mortgage market in responding to these major natural disaster events.

The results from Section 4.2 additionally imply that delinquencies are more common following natural disaster events for minority individuals. It is important to keep in mind that this effect may not be limited in scope to their mortgages. Longer term delinquencies also have a larger negative effect on credit scores. Therefore, if minority individuals are experiencing these at higher rates, then they are more likely to also have larger negative impacts to their credit. This can have long-lasting effects on financial health and housing stability. Another concern that follows is the inability for these individuals to move to less disaster-risk prone areas. If their credit score is negatively impacted when their property is hit by a hurricane, then they may not be able to secure a mortgage on a new home in a less risky area and will be more likely to face another hurricane event in the future.

As was initially discussed in Section 1., higher sea levels with hotter temperatures is a recipe for increasingly worse hurricane seasons, which in turn will harm the welfare of both mortgage borrowers and lenders. While modifications are preferred to foreclosures and delinquencies are not defaults, they do increase costs on the financial system and more frequent and severe storms will increase these costs. Further, our results show that these changes may occur with differentially high impacts on minority individuals. This will, in turn, exacerbate financial differentials for minority individuals, making it more difficult for them to accumulate wealth in comparison to their White counterparts. One caveat to that is the negative results on foreclosures for minority borrowers.

5. Conclusion

A growing literature demonstrates the severe risks hurricanes and other climate related hazards impose on the housing finance system. In particular, damages from physical events like hurricanes can have lasting impacts on local housing markets, economies, and borrowers' abilities to pay their debts. In this paper we study how hurricanes have impacted mortgage performance from 2010 to 2018 and we make three important contributions to the literature.

First, we use a stacked differences in differences analysis to study multiple hurricanes as opposed to one event which increases the external validity of our results. We find that the impact of hurricanes increases the rate of delinquencies, modifications, foreclosures, and decreases prepays for the average loan. Second, with the richness of our data we are able to consider both disaster aid and severity. We find that event severity increases delinquencies, foreclosures, modifications, and prepays. SFHA and FEMA Assistance county variables, which capture some of what aid is available are highly correlated with the severity of the event making it difficult to separate the full effect of aid and severity. However we do find evidence that availability of aid increases certain types of prepays (non-cash out and non-refinance) consistent with the existing literature. A final notable contribution of our paper is that we are able to consider the underlying heterogeneity in borrowers and study whether hurricanes exacerbate existing inequalities. We find that minority borrowers do experience an increase in modifications and delinquencies relative to the overall population. Whereas, we only find clear evidence for a relative increase in delinquencies for low-income borrowers. Future work should consider the mechanisms that drive the disparities in these outcomes.

These results demonstrate that hurricanes negatively impact the welfare of both borrowers and lenders through decreased loan performance and that the impacts are worse for more vulnerable borrowers. The increased rates of delinquencies and modifications, which are our largest and most consistent results, increase costs to the financial system through increased servicing costs and potential decreases in credit. Modifications in particular are considered a solution in the housing finance market because they are lower costs than the alternative of default and foreclosure. However, in the context of the increasing severity of disaster events the relevant alternative when considering the costs of modification is not the cost of foreclosure, but instead the cost of a loan that never needed a modification.

This paper is limited in that we only study hurricanes and associated rainfall. Water damage is a particularly costly event because it can make places unlivable for long periods of time. Wildfires can have similar lasting destruction, but also impact a different geographic region with different housing markets, local economies, and underlying borrower characteristics. Flooding from significant rain events can be different than hurricanes as well as they may not get the same amount of aid or intervention without being a named storm. Our study is also limited since we focus only on one year outcomes. Events like foreclosure may take longer, however longer timelines also increase the difficulty of identifying the underlying driver of the event. Finally, while our data is rich many of the borrower characteristics used to model loan performance are based on the characteristics at origination and may have changed by the time of an event.

Future work should build on this work by considering other natural hazards and longer time lines. Allowing for a longer post period, would allow researchers to study whether the increasing modifications keep borrowers current in the long term or do foreclosures increase over time. Even though hurricanes are technically exogenous, the highly geographically concentrated nature of hurricanes means that the same regions experiences hurricanes year after year. This correlation makes it difficult to have clean estimates especially as the post event period is extended. Future research should consider how to incorporate these repeat events and also consider the seasonality of hurricanes relative to the seasonality of mortgage markets in different areas. Further analysis could more closely consider the local economic conditions and recovery to consider how hurricanes work as a double trigger event. Finally, better data on actual damages, and aid or insurance could enable researchers to add to the discussion the impact of severity separate from the impact of intervention.

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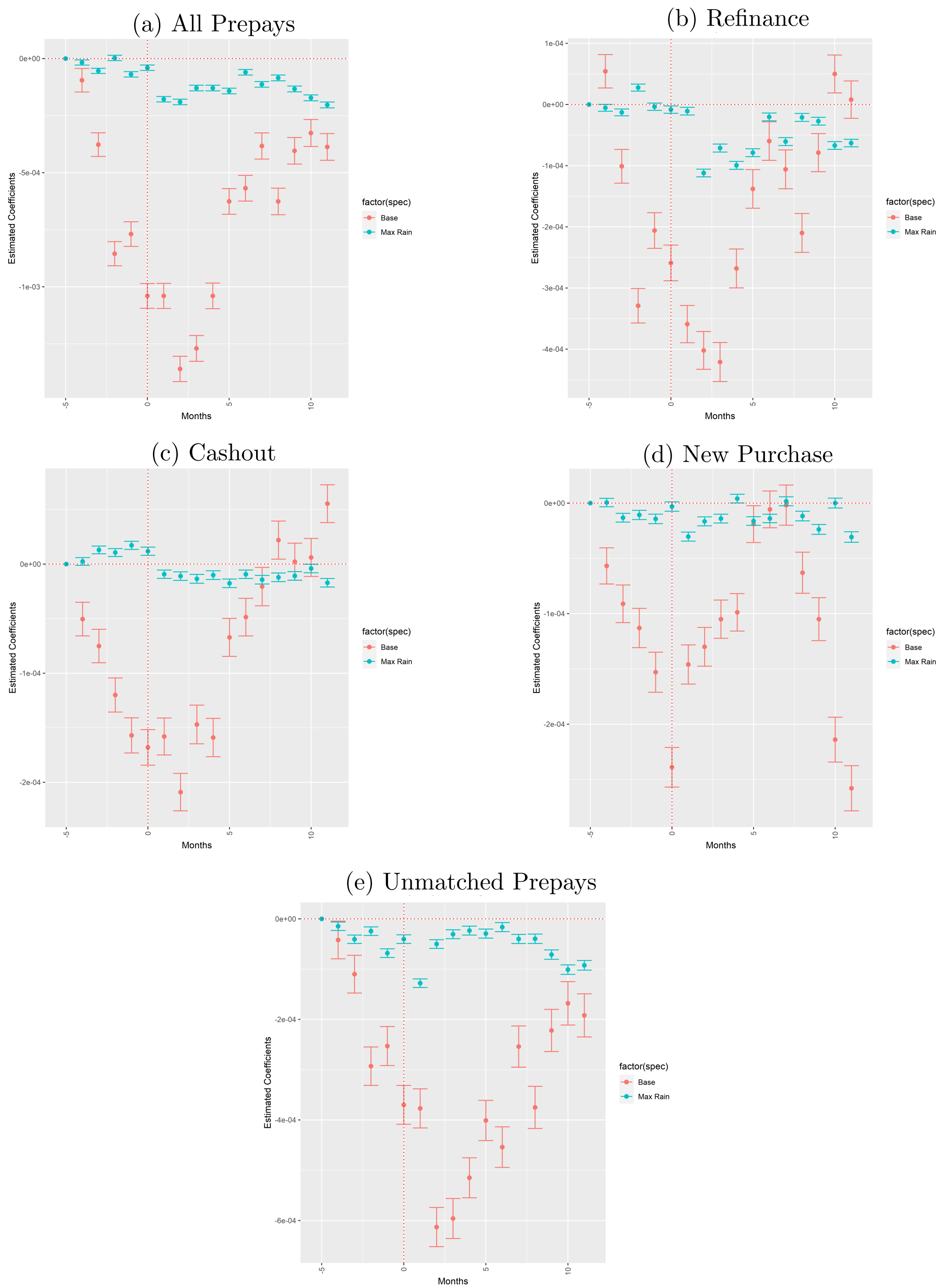
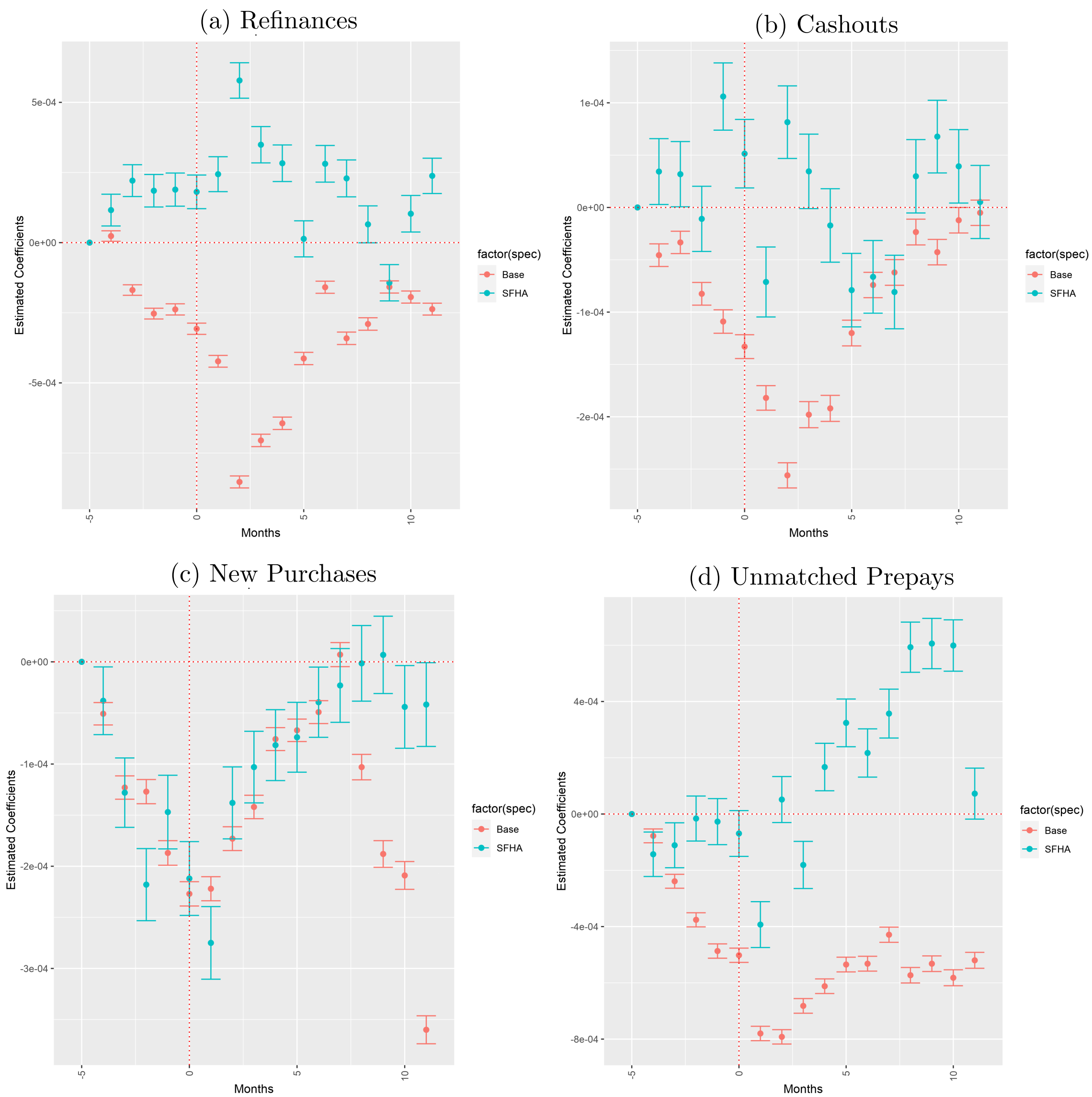
Figure 16: Event Study Graphs for Prepay and Prepay Types



Note: This figure contains five event study graphs, depicting the estimated coefficients for affected, and affected × max rain. Event study's are depicted for All Prepays, Refinance, Cashout, New Purchase, and Unmatched Prepays respectively.

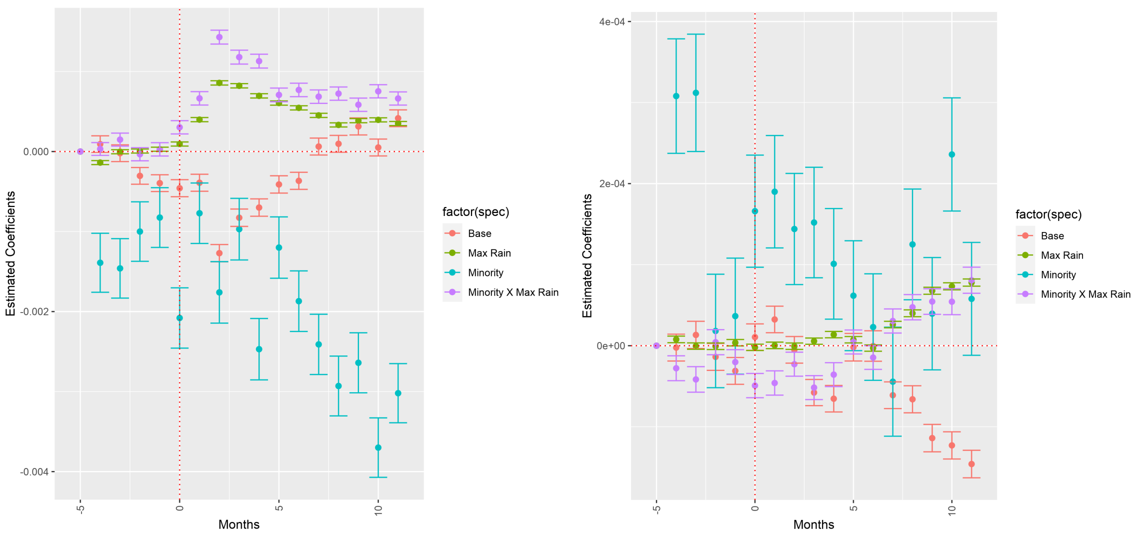
Figure 17: Event Study Graphs For effect of SFHA on prepay



Note: This figure contains four event study graphs, depicting the estimated coefficients for affected, and affected × SFHA. Event study's are depicted for All Refinance, Cashout, New Purchase, and Unmatched Prepays respectively.

Figure 18: Event Study Graphs For Minority effects on Delinquency and Modification

(a) Delinquency (b) Modification



Note: This figure contains two event study graphs, depicting the estimated coefficients for affected, affected × max rain, minority, and minority × max rain. Event study's are depicted for delinquency and modifications respectively.

A Appendix Tables

Table A1: Affected and Unaffected Observations By Event

Event	**Affected**			**Unaffected**		
	Weighted Observations	Percent of Total	Unique Observations	Weighted Observations	Percent of Total	Unique Observations
al012010	34,993	0.1%	12,782	349,930	0.1%	16,784
al012013	1,086,659	3.3%	449,912	10,866,590	3.3%	504,993
al012014	238,480	0.7%	69,209	2,384,800	0.7%	166,398
al012015	127,021	0.4%	38,633	1,270,210	0.4%	90,776
al012018	127,237	0.4%	39,837	1,272,620	0.4%	91,322
al022012	422,799	1.3%	200,328	4,227,990	1.3%	201,705
al022015	453,304	1.4%	144,706	4,533,040	1.4%	234,489
al032010	400,846	1.2%	178,774	4,008,460	1.2%	210,540
al032016	981,923	3.0%	318,234	9,819,490	3.0%	412,379
al032017	323,497	1.0%	107,315	3,235,050	1.0%	229,780
al042012	1,070,122	3.3%	522,523	10,701,220	3.3%	351,170
al062017	153,573	0.5%	49,985	1,535,740	0.5%	68,624
al062018	897,810	2.8%	254,166	8,979,760	2.8%	622,338
al072010	210,641	0.6%	80,757	2,106,410	0.6%	125,504
al072018	249,408	0.8%	79,168	2,495,340	0.8%	171,467
al092011	5,978,469	18.4%	2,462,519	59,784,690	18.4%	2,453,824
al092012	1,291,169	4.0%	619,386	12,911,690	4.0%	651,343
al092016	1,373,371	4.2%	441,934	13,734,170	4.2%	798,132
al092017	757,881	2.3%	248,168	7,578,880	2.3%	435,542
al102010	162,528	0.5%	58,731	1,625,280	0.5%	102,063
al112016	406,621	1.3%	135,244	4,066,250	1.3%	223,844
al112017	3,901,924	12.0%	1,271,450	39,020,000	12.0%	2,019,016
al122017	219,497	0.7%	63,754	2,194,990	0.7%	150,702
al142016	2,168,313	6.7%	728,075	21,683,430	6.7%	1,155,752
al142018	1,063,149	3.3%	306,588	10,635,580	3.3%	721,557
al162017	182,171	0.6%	58,500	1,821,920	0.6%	135,069
al182012	8,211,853	25.3%	3,752,230	82,118,530	25.3%	3,213,966
Total	32,495,259	100.0%		324,962,060	100.0%	

B Appendix Figures

Figure A1: Rate of 180 Day Delinquencies by Time From A Hurricane Event

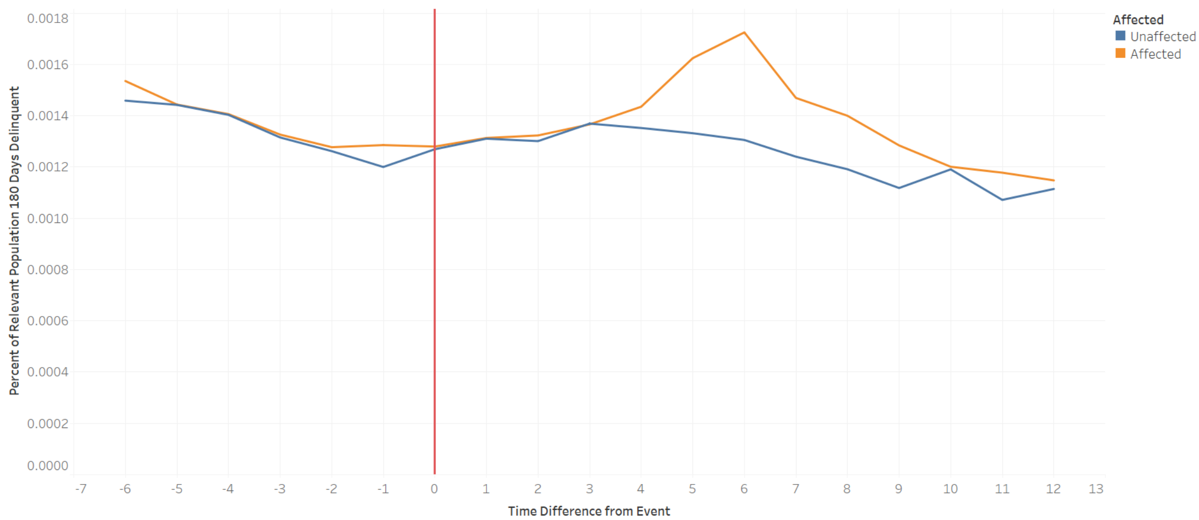


Figure A2: Rate of Prepay by Time From A Hurricane Event

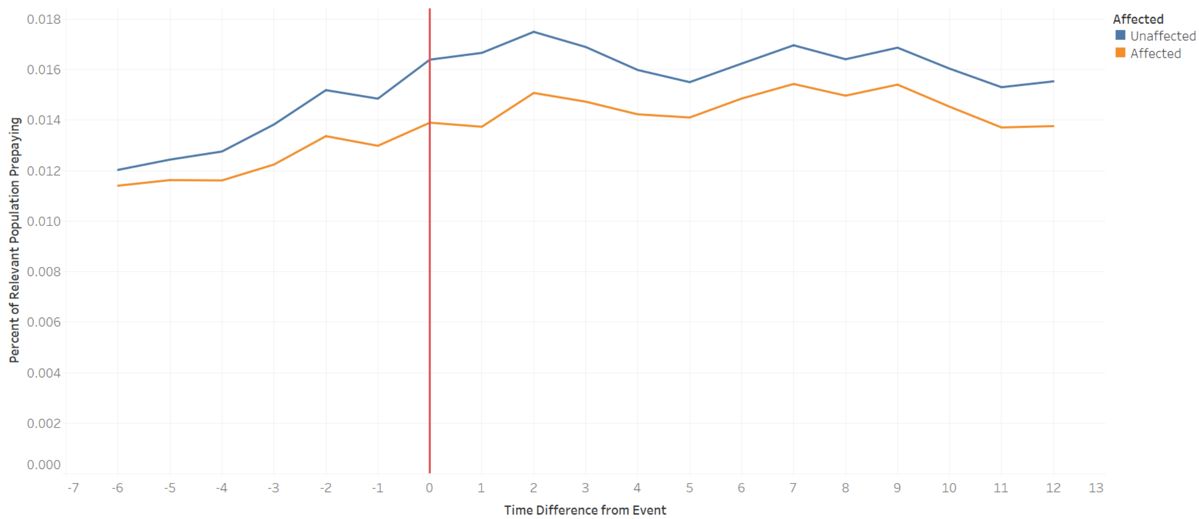


Figure A3: Rate of Modification by Time From A Hurricane Event

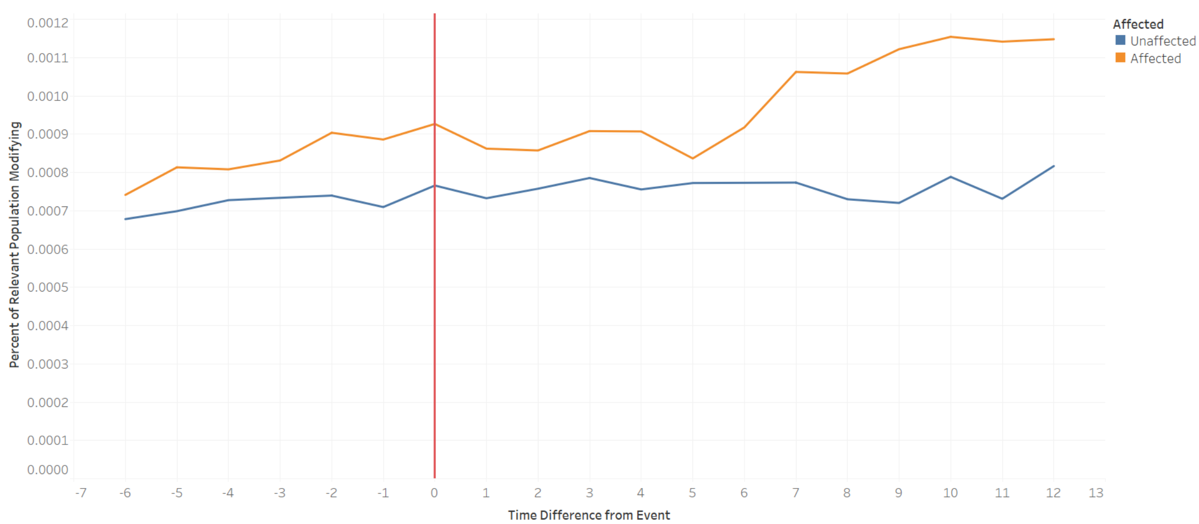


Figure A4: Rate of Foreclosures by Time From A Hurricane Event

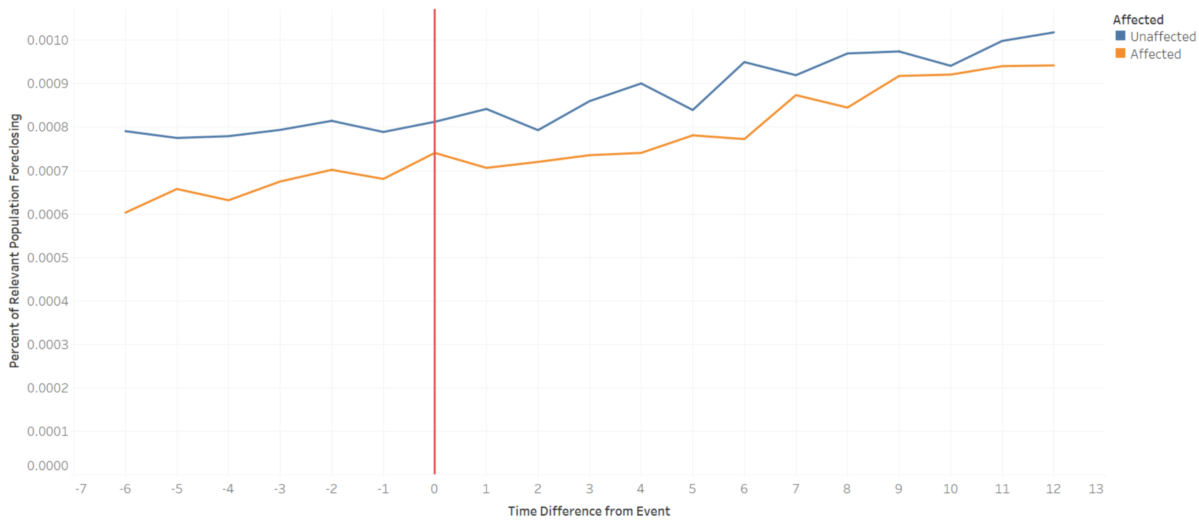


Figure A5: Rate of 180 Day Delinquencies by Time From A Hurricane Event and by Minority Status

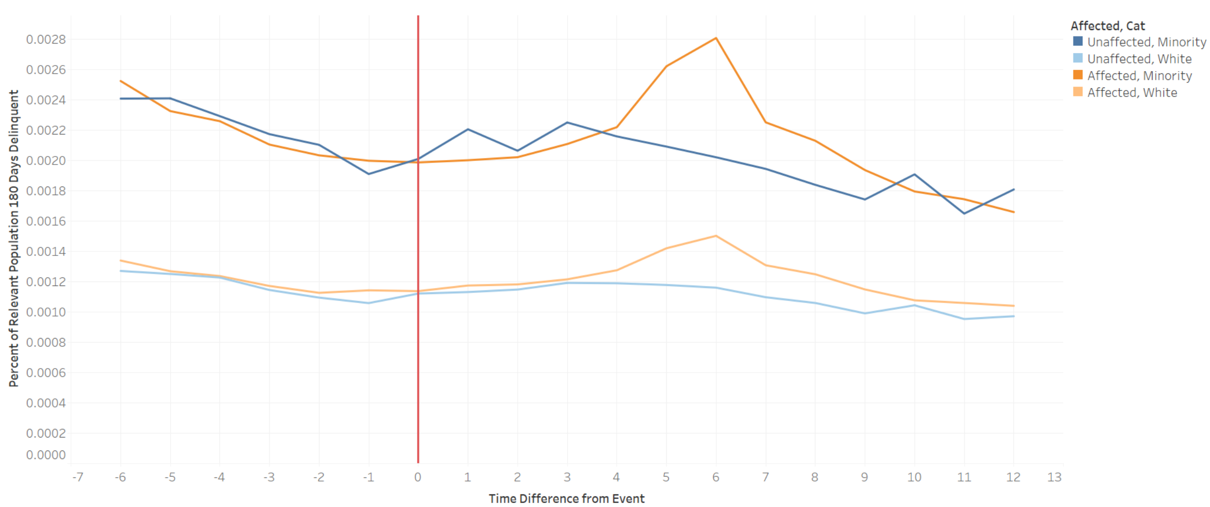


Figure A6: Rate of Prepay by Time From A Hurricane Event and by Minority Status

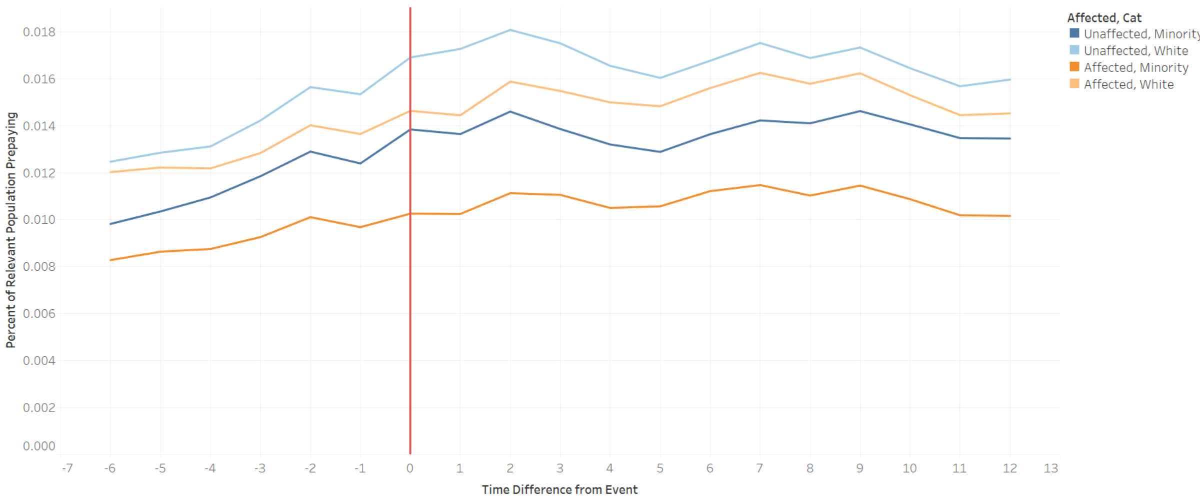


Figure A7: Rate of Modificatoin by Time From A Hurricane Event and by Minority Status

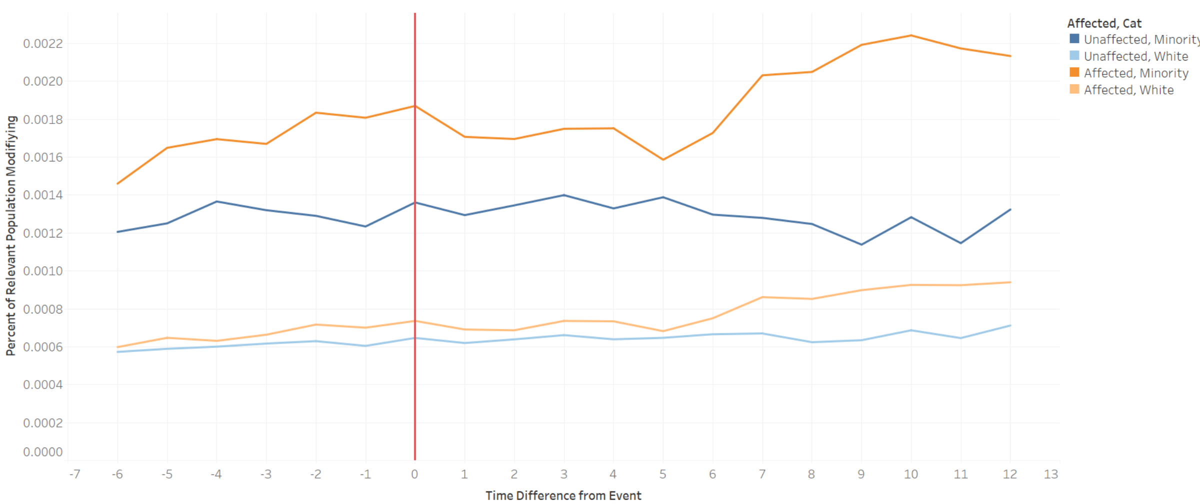


Figure A8: Rate of 180 Day Delinquencies by Time From A Hurricane Event and by Low Income Status

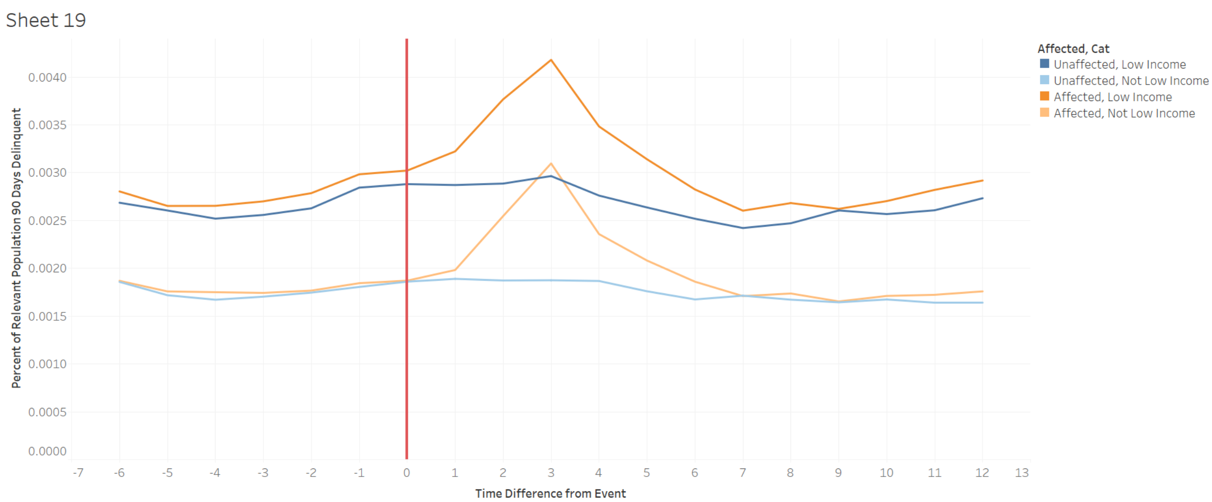


Figure A9: Rate of Prepay by Time From A Hurricane Event and by Low Income Status

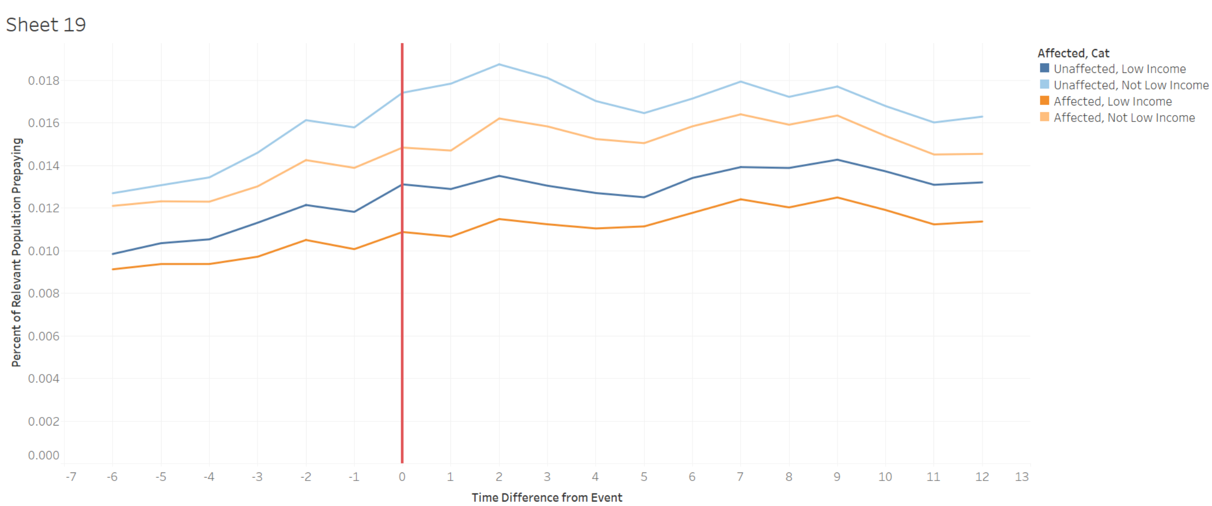


Figure A10: Rate of Modification by Time From A Hurricane Event and by Low Income Status

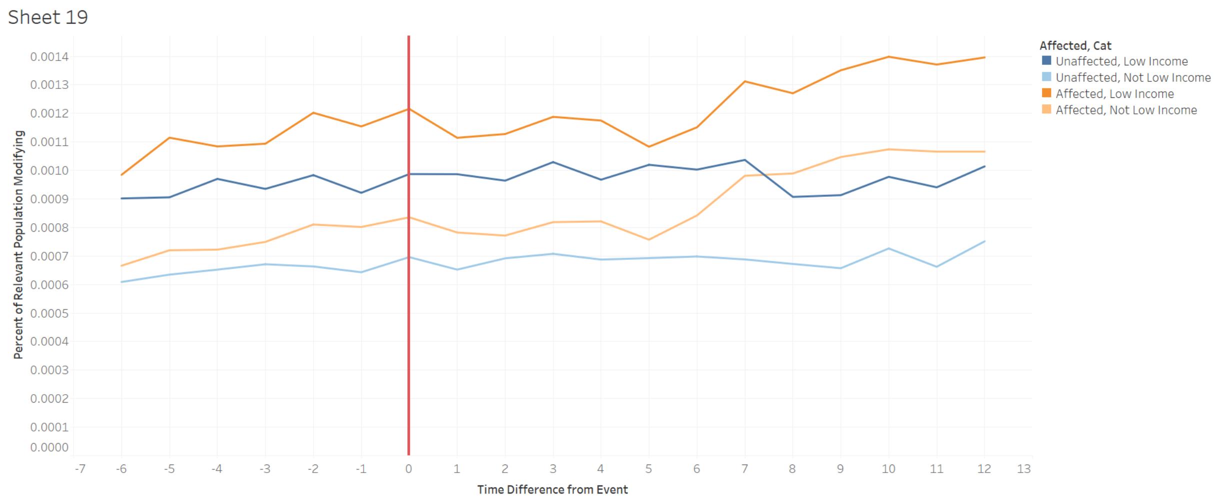


Figure A11: Rate of Foreclosure by Time From A Hurricane Event and by Low Income Status

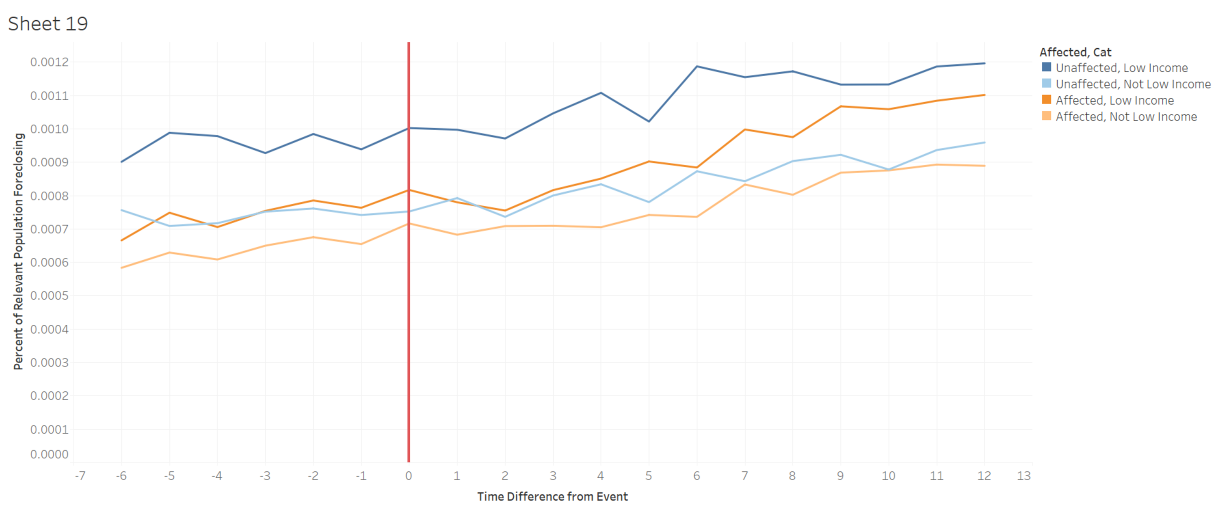


Figure A12: Rate of 30 Day Delinquencies by Event: Some Overlap Sample

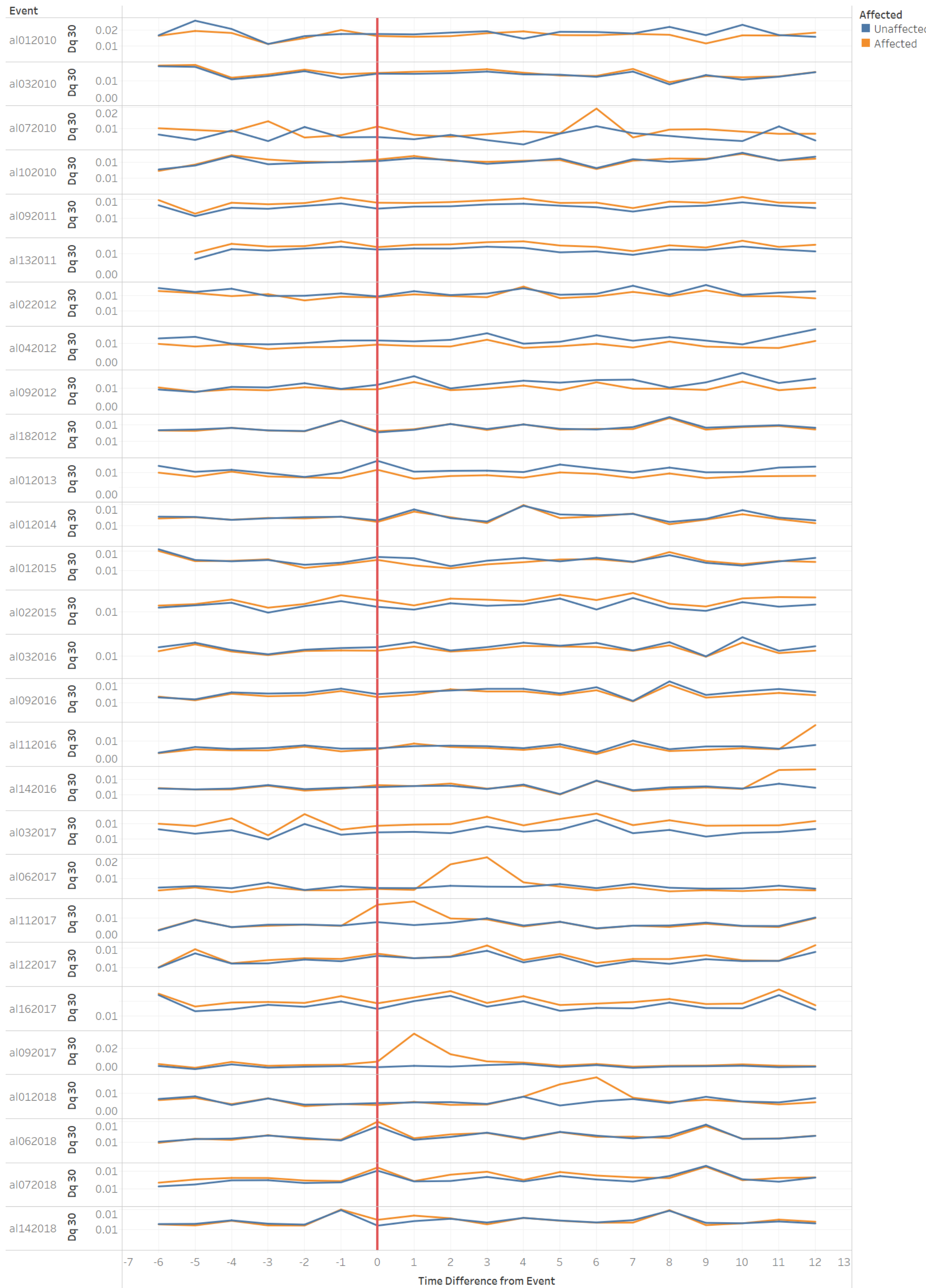


Figure A13: Rate of 30 Day Delinquencies by Event: No Overlap Sample