Flood Damage and Mortgage Credit Risk: A Case Study of Hurricane Harvey

(Forthcoming, Journal of Housing Research)

Carolyn Kousky
University of Pennsylvania
Wharton Risk Center

Mark Palim
Fannie Mae

Ying Pan
Fannie Mae

July 21, 2020

The authors thank Ben Keys, Howard Kunreuther, Michael Lacour-Little, Philip Mulder, Erin St. Peter and Susan Watcher for their helpful comments and suggestions. We also thank RMS, a catastrophe risk modelling firm, for their generous provision of model results used in this paper. Any opinions expressed are those of the authors and not those of Fannie Mae.

Abstract

Using a unique, loan-level database that combines post-disaster home inspection data, flood zone designations, and loan performance measures in the area impacted by Hurricane Harvey, we examine the link between property damage, flood insurance, and mortgage credit risk. We find that, compared with homes with no damage, loans on moderately to severely damaged homes are more likely to become 90 days delinquent shortly after Harvey. However, longer-term loan performance depends on whether the property is located in areas where borrowers are required to have flood insurance. Where flood insurance is required, loan prepayment rate rises with property damage. In areas where flood insurance is not required, and very few borrowers have flood insurance, we find that as property damage increases, the likelihood of needing a loan modification increases, as does the likelihood of a loan being 180 or more days delinquent or in default during the two years following Hurricane Harvey. Thus, our findings provide direct evidence that flood insurance protects homeowners and mortgage creditors against credit risk arising from flood events.

JEL Codes: Q54, Q58, R20

Key Words: Flood Risk, Credit Risk, Natural Disaster

1. Introduction

Flooding is the costliest natural disaster in the United States and coastal flooding, often triggered by tropical storms or hurricanes, is particularly damaging. Costs from floods have been increasing over the past several decades and are projected to continue to do so from the combined effects of increased development and urbanization (Cutter et al. 2017), as well as climate changes including intensification of rainfall, changing storm patterns, and sea level rise (e.g., Sweet and Park 2014; Mallakpour and Villarini 2015; Garner et al. 2017; Prein et al. 2017). Coastal flooding can arise from a variety of sources, such as tidal flooding, storm surge, or precipitation-induced flooding from tropical storms or hurricanes. Of concern is an observed slowing of tropical cyclones, increasing the likelihood of "stalling" storms that result in greater precipitation and thus flooding (Hall and Kossin 2019). Hurricane Harvey was an extreme example of this phenomena, but climate models project increasing probabilities of similar rainfall levels as the climate warms (Emanuel 2017). As such, understanding the economic impacts of these types of storm events is paramount.

Both academic and popular concern about the possibility of climate change negatively impacting the housing and mortgage markets is growing, but many questions remain (e.g., Dembicki 2019; Olick 2019). Our work makes three contributions to understanding of this topic. First, prior work, discussed further below, has quantified the impacts of flood and storm events on property prices, but investigation of the various impacts on loan performance is more limited and ours is the first to examine this issue from the perspective of a credit risk holder. Second, this paper is the first to quantify the protective benefits of flood insurance to loan outcomes by explicitly comparing homes with and without flood coverage. Third, our paper provides insight on the role of catastrophe modeling for risk management, particularly in the housing and mortgage markets.

We use unique loan-level data from the single-family book of business of the Federal National Mortgage Association ("Fannie Mae") to estimate the impact of flooding from Hurricane Harvey on loan outcomes. Hurricane Harvey set records for rainfall and caused widespread flooding throughout the Houston, Texas area. While much prior work relies on damage measures at a neighborhood or broader geographic level, we are able to use observational inspector data for nearly 30,000 loans in the Harvey-impacted area to quantify the impact of flood damage on a wide range of loan outcomes, including delinquency, forbearance, modification, prepayment, and severe delinquency/default. Using property-level inspector data lets us cleanly identify the impact of property damage on loan outcomes without having to worry about spillover or neighborhood effects contaminating our estimates.

Quantification of the impacts of natural disasters on loan outcomes is sought by real estate finance market stakeholders including investors in mortgage-backed securities and in credit risk transfer securities, since flood-related loan outcomes could lower their returns, with prepayment a concern for the former, and negative loan performance for the latter. Loan modifications and delinquency can drive up costs for servicers. Regulators and Congress are increasingly looking for empirical evidence on this topic to inform risk management policies for lenders and the government sponsored enterprises (GSEs). And finally, there is mounting concern that climate change has the potential to trigger financial shocks across a range of markets; stress tests have been increasingly promoted as a tool to assess resilience to increasing natural disaster risk (Adrian et. al. 2020). Applying a climate stress test to the mortgage industry will necessitate a detailed understanding of how loan outcomes respond to disaster events and how that varies with levels of damage and protective measures, such as insurance, which we examine here.

Flood insurance is a possible mitigating factor that could improve loan outcomes post-disaster. Despite this, many people nationwide at risk of floods are without coverage; for example, three-quarters of buildings flooded by Hurricanes Sandy, Irma, and Harvey were uninsured (Kousky and Lingle 2018). Flood insurance is primarily provided through the federal National Flood Insurance Program (NFIP), housed in the Federal Emergency Management Agency (FEMA). Federally backed loans or loans from federally regulated lenders in FEMA's mapped 100-year floodplain, also referred to as the Special Flood Hazard Area (SFHA), are required by federal law to have flood insurance. In compliance with this, Fannie Mae requires any loan it acquires in the SFHA to have flood insurance.[1] As such, we know with certainty that a property inside the SFHA in our dataset has flood coverage. On the other hand, the take-up rate for flood insurance outside the SFHA among homeowners with mortgages is extremely low—FEMA (2018) estimates it is only approximately 2%—such that the overwhelming majority of our sample outside the SFHA can reasonably be assumed to not have flood insurance.

We are able, therefore, to contrast the loan performance of similarly damaged properties in and outside the SFHA to investigate the role of flood insurance on loan outcomes. We do this using a difference-in-difference approach. Any difference in outcomes between undamaged homes in and out of the SFHA controls for any sorting based on flood risk. Given this, any

[1] Verification of compliance with Fannie Mae's flood insurance requirement is a standard part of pre- and post-acquisition loan level data validation and, separately, the annual audit of loan servicers. Furthermore, as discussed below in Section 2, servicers have a financial interest in ensuring that applicable insurance coverage is present throughout the life of a loan in order to avoid having to repurchase loans from Fannie Mae after a natural disaster. We thus believe any non-compliance to be trivial.

difference in loan performance between damaged and non-damaged homes in and out of the SFHA captures the impact of flood insurance. Using this method, we find that without flood insurance, property damage increases the likelihood of deep delinquency or loan default, but flood insurance protects against these most severe loan outcomes. Flood insurance increases prepayment of loans post-flood, either because insured borrowers use flood insurance proceeds to pay off mortgages or because they are more willing to sell damaged homes to investors since their losses are already covered. We also find that while flood insurance lowers the likelihood of obtaining a loan modification, it does not lower the likelihood of forbearance. Loan forbearance is short-term, temporary relief, and seems to be more universally applied, perhaps before flood insurance payments are available. Loan modifications, on the other hand, are more necessary for those without flood insurance.

We then use a triple-difference method to examine variation across borrower characteristics. We find that, outside the SFHA, the increase in deep delinquency or default rate due to property damage is larger among borrowers with a lower income or higher credit score than their higher income or lower credit score counterparts. (Yet the level of the deep delinquency or default rate is still higher for borrowers with lower credit score.) Therefore, the lower-income or higher credit-score borrowers will benefit the most from having flood insurance. We also examine variations in outcomes by home value. Our findings indicate that NFIP insurance does not fully protect loans on severely damaged, higher-value homes from becoming deeply delinquent or in default, because the coverage limit offered by NFIP (at $250,000) could be insufficient for higher-value homes. All our results are robust to several specification and sample checks.

As past statistics are potentially less reliable indicators of future outcomes in a changing climate, there is an increasing need to use sophisticated, simulation-based catastrophe models to better quantify disaster risk. While widely used in the insurance industry, such a practice has not been as common among lenders or GSEs. We partnered with RMS, a catastrophe modeling firm, to test whether modeled results of property damage can be used to estimate credit risk when actual damage data is not (yet or ever) available.

RMS provided predicted property-level damages from their U.S. flood model for all 72,000 properties in our dataset. The rates of damage from the model matches well with inspection results at a portfolio level, but the predictions do not necessarily match as well at the property level. We examine the association between predicted property damage and loan performance outcomes. Our findings using the catastrophe model are generally consistent with what we find when using data on actual property damage for relatively larger-chance events, including short-term delinquency, forbearance, loan modification, and prepayment. However, for the smaller-chance events such as a loan being deeply delinquent or in default, the estimated impacts of different levels of predicted damage do not match as well with those using actual damage. This indicates that a risk ranking of property damage predicted by catastrophe models could potentially be used to identify loans at greater risk of becoming delinquent, prepaid, and in higher need of forbearance and modifications. However, better property-level predictions of damage are needed for more accurate forecasting of default events triggered by flood damage. We caution, however, that risk managers should fully evaluate any model against their own book of business and analytic needs.

The next section of the paper provides background on flood insurance, the housing market, disaster rebuilding in the United States, and details on the case of Hurricane Harvey. Section 3 discusses the prior literature and Section 4 provides an overview of our data. We introduce our methods in Section 5 and present results in Section 6. Section 7 concludes.

2. Background

Flood Insurance and the Mortgage Market

Flood insurance for residential structures is almost exclusively provided through the federal NFIP. This program, created over fifty years ago and currently housed in FEMA, is designed as a partnership with local governments. When communities join the program, they must adopt minimum land use regulations in the SFHA, or area subject to a 1% annual chance of flooding. Flood insurance is then made available to all residents of the community. Pricing is set by FEMA and the federal government holds the risk, but policies are written and claims managed by private companies for a fee. The NFIP offers building coverage up to $250,000 and contents coverage up to $100,000. For more on the program, see Kousky (2018).

To implement the NFIP, FEMA produces Flood Insurance Rate Maps (FIRMs) that depict SFHAs, as well as flood zones that have historically been used in setting flood insurance premiums. These FEMA flood maps have become the *de facto* flood risk information product in the United States. There is concern, however, that the SFHA designation can be based on outdated data or methods, fail to reflect current conditions, and has only limited inclusion of pluvial, or rainfall-related flood risk (Office of Inspector General 2017). Another concern is that discussing flood hazards in terms of being "in" or "out" of the SFHA creates a false perception that outside the boundary people are "safe" and that inside the SFHA the risk is uniform (ASFPM Foundation 2004). In reality, of course, flood risk varies continuously across the landscape, including beyond the SFHA. Many recent storms, including Hurricanes Katrina, Ike, Sandy, and Harvey, all led to flooding that extended beyond the SFHA and generated flood depths that exceeded the base flood elevation (BFE), the expected elevation of water at a particular location in 100-year event, by several feet (e.g., FEMA 2015).

Borrowers with a federally backed mortgage or borrowing from a federally regulated lender looking to secure their loan with property located in an SFHA must be notified that the property is in an SFHA and must purchase flood insurance.[2] By law, property owners must purchase the lesser of (1) the NFIP maximum coverage amount, (2) the outstanding principal balance of the loan, or (3) the insurable value of the structure. If a property owner does not buy a flood insurance policy, the lender will notify the borrower that they are not in compliance. After a 45-day notice period, if still uninsured, the lender may force place insurance back-dated to cover the period of non-compliance. As of January 1, 2016, banks with more than $1 billion in assets must escrow flood insurance premiums for applicable loans.

After loan origination, lenders may retain the loan in their portfolio, sell, or securitize it in the secondary market. There are several avenues available for this purpose. Government loans can be securitized in mortgage backed securities guaranteed by the Government National

[2] In Texas, a seller of residential property must inform potential buyers in writing whether or not the seller is aware of previous flooding at the property; if it is located in a 100-year floodplain, 500-year floodplain, floodway, flood pool or reservoir; if the property currently has a flood insurance policy; and if the seller ever filed a flood claim on the property. (See Texas Prop. Code § 5.008.)

Mortgage Association (GNMA) ("Ginnie Mae"), a U.S. government corporation. For conventional conforming loans,[3] eligible lenders may sell loans to Fannie Mae or the Federal Home Loan Mortgage Corporation (FHLMC) ("Freddie Mac"), both GSEs who then issue mortgage backed securities with their attached guarantee of timely payment of principal and interest. Non-conforming loans may also be sold or securitized in the secondary market; however, they do not benefit from any governmental or GSE guaranty of timely payment. In the years since the 2008 financial crisis, on average 75 percent of residential mortgage loans originated each year have been securitized through Ginnie Mae or the GSEs.

The loan performance data in our analysis come from Fannie Mae. As outlined in Fannie Mae's Selling and Servicing Guides, when a single-family property securing a mortgage sold to Fannie Mae is in an SFHA, the borrower must have flood insurance and the servicer is responsible for monitoring compliance with this requirement. Fannie Mae conducts annual reviews of sellers and servicers to assess their compliance with its policies, including flood insurance requirements, and has consistently found lenders and servicers in compliance with this provision. Furthermore, servicers have an incentive to ensure that flood insurance remains current on loans where it is required, since in the event of a flood, the servicers may be forced to repurchase a delinquent loan if they have allowed the insurance coverage to lapse.

Post-Flood Rebuilding and Mortgage Relief

[3] Conventional conforming loans are loans that meet eligibility standards of the two major GSEs, Fannie Mae and Freddie Mac, developed in consultation with their regulator and conservator, the Federal Housing Finance Agency (FHFA). Generally speaking, the unpaid principal balance at origination on such loans may not exceed the conforming loan limit for the location and units in the property securing the mortgage as set annually by FHFA and carry some form of credit enhancement if the loan-to-value ratio exceeds 80 percent.

When a disaster event is substantial enough to trigger a disaster declaration by the President, several federal disaster aid programs are activated. In addition, after the most severe events, Congress often passes supplemental legislation to appropriate funds to various recovery programs in different agencies. Even when these programs are activated and funded, however, it is often insurance that has the most immediate impacts on the financial recovery of households.

The primary federal source of recovery for uninsured homeowners is a loan from the Small Business Administration (SBA). Federal grants to household from FEMA—the Individual and Households Program (IHP)—are, contrary to some popular opinion, quite limited. They are capped at just over $30,000 and usually average only a few thousand dollars. According to the FEMA, “IHP is not a substitute for insurance and cannot compensate for all losses caused by a disaster; it is intended to meet basic needs and supplement disaster recovery efforts” (FEMA 2016). After Hurricane Harvey, the average individual assistance payment to homeowners was just over $8,900 (Walls and Cortes, 2018). For comparison, the average NFIP claim after Harvey was close to $117,000.[4]

Residential real estate can be affected in many ways following a disaster event. In areas of strong housing markets, there may be an increase in quick sales to disaster investors at depressed prices.[5] Increased demand for contractors can work in the opposite direction, elevating prices for construction and home improvements. If reconstruction costs are high in relation to home value, individuals receiving flood insurance payouts or disaster aid may use such

[4] Source: https://www.fema.gov/significant-flood-events
[5] https://www.wsj.com/articles/the-new-storm-chasers-real-estate-disaster-investors-11564498767

funds to pay off a mortgage rather than attempt to rebuild. When insurance is used to pay off a mortgage, however, this reduces the amount that homeowners can borrow from the SBA, unless there is written documentation that the lender required the insurance to be used for loan repayment.[6]

Fannie Mae's Servicing Guide[7] outlines servicer requirements in the event of disaster, including providing assistance to borrowers in the form of temporary forbearance, repayment plans, and/or loan modifications. Fannie Mae authorizes servicers to grant an initial forbearance plan that lasts up to six months, which may be extended up to a total of 12 months. When a borrower was on an active forbearance plan, the servicer was required to suspend the reporting of mortgage loan delinquencies to credit bureaus.[8] However, delinquencies are still recorded in Fannie Mae's loan performance data. No later than 30 days prior to the expiration of any forbearance plan term, the servicer must begin attempts to contact the borrower to determine if the hardship has been resolved, the borrower's intention with respect to the property, and advise the borrower of other options, including repayment plans and modifications, to make the loan current again. A repayment plan typically spreads out the past-due amount over a set time frame (e.g., 3, 6, or 9 months) and adds on to the existing mortgage payment. Modifications come in three options depending on whether the borrower has the ability to resume making full pre-disaster monthly payments and making additional monthly payments to cover escrow amounts

---

[6] See: https://www.fema.gov/news-release/2008/06/16/paying-your-mortgage-disaster-funds

[7] The Servicing Guide is available online at: https://www.fanniemae.com/content/guide/servicing/index.html

[8] Effective July 15, 2020, Fannie Mae amended the Servicing Guide to allow credit reporting on delinquent loans during natural disasters consistent with industry-recognized practices.

disbursed during forbearance.[9] When a modification is approved, there is a trial period of three months that requires borrowers to make trial payments on time. At the end of the successful trial period, the modification becomes permanent.

In addition to forbearance and modifications, Fannie Mae also provides flexibility in the standards for limited cash-out refinance for borrowers whose primary residence is damaged. A borrower may obtain a limited cash-out refinance to consolidate an existing home equity line of credit used for repair or cash-out for reimbursement of documented out-of-pocket expenses for the completed repair (not to exceed the lesser of 10% of the balance of the new refinance loan or $15,000).[10]

The Case of Hurricane Harvey

Hurricane Harvey was a hurricane that rapidly intensified to a Category 4 storm before hitting the Texas coast in August 2017. The storm then stalled and dropped a record-breaking amount of rain—over 60 inches (Blake and Zelinsky 2018). The flooding from this event was catastrophic, impacting buildings and the transportation infrastructure. NOAA estimates damages from Hurricane Harvey at $125 billion, making it the second costliest weather disaster

[9] Detailed description of the three types of modification and repayment plans are available at https://www.knowyouroptions.com/options-to-stay-in-your-home/overview/modify-overview/disaster-relief-modifications. In July 2020, Fannie Mae introduced a disaster payment deferral loss mitigation retention solution to assist borrowers with a disaster-related financial hardship return their mortgage to a current status after up to 12 months of missed payments. Unpaid amounts are deferred as a non-interest-bearing balance due at maturity or earlier payoff of the mortgage, and no other changes to the mortgage loan terms; allowing the loan to remain in the pool. A borrower trial period plan is not required, and the solution is available without regard to whether the borrower has received a disaster-related forbearance. As of the October 1, 2020 mandatory effective date, the disaster payment deferral will replace two of the three existing disaster-related modifications (i.e., Extend Modification and Cap and Extend Modification for disaster relief).

[10] Detailed description of disaster-related limited cash-out flexibilities can be found in Fannie Mae's Selling Guide. https://www.fanniemae.com/content/guide/selling/b5/4/02.html

on record in the United States, after Hurricane Katrina.[11] The NFIP paid over 76,200 flood claims for the storm totaling almost $9 billion.[12] While this is substantial, it is important to note that most homes in the impacted area were not insured against flood. Figure 1 shows the Harvey-affected area, measured by the number of claimants for FEMA's IHP (detailed description in section 4) as well as the SFHA (in yellow). Hurricane Harvey flooded a much broader area than just the SFHA.

[Figure 1 Here]

Three quarters of our study sample are households in three counties of Texas: Harris, Fort Bend, and Montgomery. Over six million people lived in 2.3 million housing units in these three counties as of July 2019 according to the Census. As of August 1, 2017, a few weeks before Hurricane Harvey made landfall, there were over 289,600 residential NFIP policies across these three counties. After Harvey, over 51,000 residential claims were filed in these three counties. The spike in claims payments from Harvey in these counties can be seen in Figure 2.[13] This figure also shows that after Harvey, there was an increase in the number of NFIP policies in these three counties, likely due to a combination of federal insurance requirements tied to receipt of disaster aid as well as increased attention to flood risk (Kousky 2017).

[Figure 2 Here]

[11] Source: https://coast.noaa.gov/states/fast-facts/hurricane-costs.html
[12] Source: https://www.fema.gov/significant-flood-events
[13] Thanks to Jacob Bradt for research assistance.

After Harvey, there was a reported surge in investors flipping storm damaged properties for profit or shifting neighborhoods that had previously been predominantly homeowners to having a larger share of rental properties. Several news outlets reported investors offering cash for storm damaged properties (Olick 2019). Many of these investors repaired homes and then sold them to new residents, potentially putting occupants at risk of future floods, and preventing the local government from enacting plans to move some people out of harm's way (Hunn and Dempsey 2018).

3. Prior Literature

There has been very little empirical work on the impact of flooding on mortgage markets. Prior work on housing markets and floods has largely focused on property value impacts. Research has found that property values are lower in the SFHA, likely due to the combined effects of the higher flood risk, flood disclosure requirements, and the mandatory purchase requirement for flood insurance (Bin et al. 2008; Daniel et al. 2009; Beltran et al. 2018). The timing in providing information on the flood hazard, however, can affect home prices. One study found that disclosure laws, which require information to be made available earlier, do lower housing values in flood-prone areas (Pope 2008).

There are also several papers that look at price dynamics following a flood. Several studies have found that after a flood, there is a decline in property values or a decrease in the rate of price growth (Bin and Polasky 2004; Carbone et al. 2006). This drop, however, is often not permanent, with prices rebounding within a decade, sometimes much sooner (Atreya et al. 2013;

Bin and Landry 2013). Declines in property values have also been found outside the SFHA after severe floods occur that cause negative economic impacts, even if specific homes were not themselves damaged (Kousky 2010). Ellen et al. (2020) study Superstorm Sandy and find that house price recovers quickly inside the SFHA but remains depressed outside the SFHA. They also find that the long-term effect is more concentrated in low-income neighborhoods.

There have also been a few studies looking at personal financial outcomes of households after disasters. Deryugina et al. (2018) use tax return data and examine mobility and long-term labor market outcomes after Hurricane Katrina. They find that employment and income rebounded in a few years after only a transitory shock from the storm, but they do not examine impacts of the storm on mortgage debt. Gallagher and Hartley (2017) also look at the case of household finance after Hurricane Katrina. Related to our work, they find a reduction in mortgage debt within six months of the storm in the most flooded area, which they believe could be due to homeowners using flood insurance to repay their mortgages. They find only a short-time and statistically insignificant increase in delinquency.

Our study builds on the work of these previous papers but takes the perspective of a large credit risk holder to examine impacts on loan outcomes specifically, as opposed to a broad look at household finance. We are also able to examine a wide range of loan outcomes directly, including prepayment, loan modifications and forbearance, and different levels of delinquency.

Further, the nature of our data also lets us directly examine the role of flood insurance in protecting against longer-term negative impacts. Our study is an important complement to work on Hurricane Katrina since New Orleans had a very different level of pre-storm flood insurance take-up and atypically high levels of post-storm disaster aid. Two-thirds of New Orleans homeowners carried flood insurance (Meitrodt and Mowbray 2006, cited by Gallagher and Hartley 2017). However, the national rate of homeowners having voluntary flood insurance is very low, and in this way, Texas is more representative. Statistics from FEMA show that, in the case of Hurricane Katrina, the total amount of NFIP paid claims was $16 billion, and there was an additional $5 billion approved for Individual Assistance grants. In contrast, the two numbers were $9 billion and $1.7 billion for Hurricane Harvey, (for reference, this is close to the numbers for Hurricane Sandy at $9 billion and $1.4 billion).[14] After Katrina, the Department of Housing and Urban Development funded generous grants to households in New Orleans. Households have not gotten such large grants in other disasters. This highlights the importance of understanding the role of flood insurance during floods beyond Hurricane Katrina.

4. Data

We define our sample area using data from FEMA's IHP program. This data is available for public download on the FEMA website.[15] We define Harvey-impacted zip codes as those having 20 or more valid registrations for the IHP program, including both homeowners and renters. Out of 782 total zip codes with any valid registrations for Hurricane Harvey, 422 meet this criterion. These Harvey-affected zip codes are presented in the map of Figure 1. In this geographic area, as

[14] Sources: https://www.fema.gov/disaster and https://www.fema.gov/significant-flood-events.
[15] Online at: https://www.fema.gov/media-library/assets/documents/34758

of July 2017 (one month before Hurricane Harvey), there were roughly 302,000 current loans[16] on owner-occupied detached one-unit properties[17] in Fannie Mae's single-family book of business. For our analysis, we include all 27,000 loans that have post-disaster home inspection records (discussed next). We also keep all the loans that experienced post-Harvey delinquency. We randomly sample all loans that have no delinquency history at a 1 to 10 ratio (with the exception that loans in zip codes with less than 20 total loans are sampled at a 1 to 2 ratio). This creates a final sample of 72,000 loans in the Harvey-impacted area. Given the sampling weight, they represent the 302,000 loans in total.

Our dataset contains home inspection information that can be used to measure flood damage. Fannie Mae's contracted servicers conducted post-disaster home inspections on all delinquent loans. The inspections were conducted of the exterior of the property either from a car or a walk around the grounds. The inspection outcome is recorded as one of four categories: no damage, minimal damage, moderate damage, or severe damage. According to Fannie Mae's Servicing Guide, damaged properties securing delinquent loans are required to be inspected at least monthly. Some properties thus have multiple inspection records; we use the worst outcome to define the property's damage. Delinquent loans are required to be inspected at least once. Therefore, the inspected sample has a higher delinquency rate than loans in the full sample. Table 1 presents the loan characteristics of the inspection sample and the full sample. Table 1 shows

[16] Roughly 10,000 loans that were delinquent as of July 2017 are excluded from this analysis because prior delinquency makes it complicated to associate the hurricane event with the consequent loan performance outcomes.

[17] We exclude non-primary residence, multi-unit properties and condos. There are about 50,000 such loans. Although all the empirical results presented in section 7 and 8 are robust when these loans are included, we find that the prepayment and default of these loans are less sensitive to flood damage than owner-occupied detached single-unit homes.

that, on average, the inspected loans are older and more likely to have experienced forbearance, modifications, or default.

[Table 1 Here]

The home inspection data is summarized in Table 2. Column 1 in Table 2 presents the distribution of damage for our sample. About 93% of inspected properties have no damage; 4% have minimal damages; and 3% have moderate to severe damages.[18] The source of the inspection data provides no information as to how home inspectors define different damage levels. Only 61 loans have an estimate of the dollar value of damages available and we use this to gain insight on the magnitude of damages associated with homes in each inspection category. Using the 61 loans, we calculate the ratio of damage to the structure value. The properties labeled with minimal damage have loss ratios between 2% and 9%, with a mean of 5%; the properties labeled with moderate damage have loss ratios between 12% and 33%, with a mean of 19%; and the properties labeled with severe damage have loss ratio between 11% and 169%, with a mean of 57%. The range of loss ratios of moderately damaged properties and severely damaged properties overlap to a great extent, suggesting the difference in these categories may be arbitrary. Therefore, we combine these two categories into one higher damage category. We thus conclude that moderate to severe damage likely indicates loss ratios greater than 10% while minimal damage means loss ratios less than 10%.

[Table 2 Here]

[18] It is estimated that Fannie Mae contacted servicers conducted post-disaster home inspections on 120,000-170,000 properties in TX and found that approximately 6% of properties sustained storm related damage. Therefore, we consider our sample as representative of all home inspections in terms of the share of damaged properties.

We shared our full dataset of 72,000 loans with RMS, a catastrophe modeling firm. RMS is one of several firms that develop and run probabilistic hazard models for many perils; our data draws on their U.S. flood model. Catastrophe modeling grew substantially following Hurricane Andrew in 1992 and the Northridge Earthquake in 1994, driven by insurer demand for more sophisticated risk assessments to inform their pricing and underwriting. For more discussion of catastrophe modeling, see Grossi and Kunreuther (2005). We provide in the appendix a brief introduction from RMS about how they use their catastrophe model for event reconstruction. RMS predicted flood damage associated with Hurricane Harvey at property level. The estimated property damage is measured by the ratio of damage over the structure value. The distribution of estimated damage is presented in columns (2) and (3) in Table 2. Column (2) uses the sample of inspected properties and column (3) uses the full sample. Table 2 shows that the distribution of estimated damage is close to that of inspected damage. The catastrophe model estimates that over 90% of properties have no damage, roughly 5% have a loss ratio less than 10%, and another 4% of properties have a loss ratio over 10%. This is close to the aggregate damage statistics from the inspection data. However, this does not necessarily imply that at the property level, predicted damage matches well to inspected damage. Table 3 shows that predicted damage agrees with the inspection outcome for about 86% of loans and disagrees for about 14% of loans. The agreement, however, almost entirely comes from properties that have no damage. The model predictions capture only about 20% of the actually damaged properties. Even among the captured damaged properties, the level of damage is correctly predicted for 60% of case. It is important to note that U.S. flood models vary, sometimes quite substantially, and that any user of these models needs to undertake appropriate analyses to ensure the model is useful for their portfolio of risks and their particular risk management purposes.[19]

[Table 3 Here]

Our loan-level data comes from Fannie Mae proprietary data on loan characteristics and performance. Table 1 presents all the loan characteristics of the loans used in our analysis. Only about 7% of borrowers in this data are located in an SFHA. Pre-disaster characteristics as of July 2017 include loan age and the mark-to-market combined loan to value ratio (MTMCLTV). Loan characteristics at origination include the debt-to-income ratio, the minimum of borrower's and co-borrower's credit score, number of borrowers, occupancy type (owner or investor), loan product type (30-year, 15-year fixed rate mortgage, or adjustable-rate mortgage), loan purpose (cash-out refinance, rate and term refinance, or purchase money), an indicator for third-party origination and months of reserves. The data also contains loan performance variables, including becoming 90 days delinquent up to five months after Harvey, obtaining forbearance or modification up to 18 months after Harvey, becoming 180 or more days delinquent or defaulting, and prepayment up to 24 months after Harvey. We combine 180 or more days delinquency and default into one outcome because the number of defaulted loans is not large enough for separate empirical analysis. Out of the home-inspection sample of 27,000 loans, there are only 24 defaults as of August 2019. When we include loans that are 180 or more days delinquent, we have a total

[19] We have seen property-level projections from multiple vendors while working on various projects. In our experience, there is a meaningful difference in projected incidence and severity of damage to a specific structure at a given address among catastrophic model results. Such variation is a function in part of differences in modeling approach and the data used to train individual models, among other factors. There appears to be greater consensus regarding the impact of flooding caused by coastal storm surge compared to in-land flooding, for example.

of 89 combined events. In the full sample of 72,000 loans, the count of defaulted loans is also about a quarter of the count of the combined events.

5. Methods

We use the following model to estimate the impact of property damage on loan performance:

$$\Pr(\text{performance outcomes}_i) = f(X_i\beta + \text{property damage}_i\alpha) \quad (1),$$

where i indicates a loan, and X_i refers to the vector of pre-storm loan characteristics of loan i. Property damage_i is a categorical variable with three groups: no, minimal, or moderate to severe damage for every loan i. Performance outcomes include short, medium, and longer-term outcomes, as stated above. For the short-term delinquency outcome and the intermediate-term outcomes, including forbearance and modification, we use a logistic model. For the longer-term outcomes, which includes both loan prepayment and being 180 or more days delinquent or in default, we use a multinomial logit model because prepayment and deep delinquency/default are competing risks. The loan outcome variables of our analysis, and their timing vis-à-vis Harvey, are shown in Figure 3. Note that forbearance can be granted to both current and delinquent borrowers, while modifications are only provided on delinquent loans.

[Figure 3 Here]

Figure 4 presents the rate of loans entering 90 days delinquency by month after Harvey. The chart shows that the first-time 90 days delinquency rate started to rise in October and then soared in November 2017 to 1.6%, which is more than 50 times higher than in a typical month. Until January 2018, the number of first-time 90 days delinquency events was unusually high. This indicates a quick and strong negative impact of Harvey on borrowers' ability to pay their mortgage on time. Our hypothesis is that property damage increases in the probability of a loan becoming 90 days delinquent within a short period after Harvey.

[Figure 4 Here]

Up to 18 months after Hurricane Harvey, 4.3% of loans were granted forbearance and 1.8% of loans were modified. Figure 5 presents the rate of loans entering forbearance, completing forbearance, or starting modification by month beginning in August 2017 when Hurricane Harvey made landfall. About half of forbearances were granted as early as September 2017. About 90% of forbearances were completed by April 2018. Around the same time, the rate of loan modifications was rising. This indicates that temporary forbearance is not enough for some borrowers to recover from the disaster. They needed more permanent payment relief, such as loan modifications, to retain their properties. Our hypothesis is that greater property damage increases the probability of a loan obtaining forbearance or modification.

[Figure 5 Here]

As for longer-term outcomes, our hypothesis is that property damage increases the probability of a loan becoming 180 or more days delinquent or defaulting for two reasons: first, uninsured or underinsured repair costs in addition to mortgage payments and potential relocation costs if the property is uninhabitable can easily surpass a borrower's financial capacity. Second, when the property value of an unrepaired house is lower than loan balance, leaving the borrower with negative equity, the borrower may strategically default even if s/he can afford to remain current on their mortgage.[20] Prepayment is also hypothesized to increase with property damage. There are three mechanisms driving this hypothesis: borrowers could obtain a cash-out refinance to fund property repair; borrowers could sell damaged houses to investors; and borrowers could use flood insurance proceeds to pay off their loan.

We use the difference-in-difference model to test the role of flood insurance in mediating loan outcomes:

$$\Pr(\text{performance outcomes}_i) = f(X_i\beta + \text{property damage}_i * \text{SFHA indicator}_i * \gamma) \quad (2),$$

where $\text{property damage}_i * \text{SFHA indicator}_i$ is a categorical variable with six groups: no, minimal, or moderate to severe damage inside the SFHA, as well as no, minimal, or moderate to severe damage outside the SFHA for every loan i. In this specification, we use whether the property of loan i is located in an SFHA to approximate whether the loan has flood insurance. As discussed above, we are able to do this because Fannie Mae has strict protocols requiring sellers and servicers to enforce flood insurance on all Fannie Mae loans in the SFHA. As such, we are confident that all loans in the SFHA have flood insurance in place. However, it is possible that some loans outside of the SFHA might have flood insurance too. Unfortunately, we do not have data to identify such loans; that said, the take-up rates outside of the SFHA are incredibly low, such that the percentage of our loans outside the SFHA with insurance should be very small.

[20] Among the loans in our sample that become deeply delinquent or default and on the properties that are either actually damaged or predicted to have damage, about 5% have the pre-storm MTMCLTV ratio over 90 percent. These loans are most likely to have a negative equity position (so-called underwater mortgages) after suffering property damage. Although we have no data to determine borrowers' financial capacity after the storm, we cannot rule out cases of strategic default.

Another limitation of the data is that the flood zone information is recorded when loans are delivered to Fannie Mae. SFHAs are examined every five years by FEMA and are sometime updated. Hence, our flood zone data may not perfectly match the actual flood zone when Hurricane Harvey occurred. Given the above data limitations, the estimated effect of being located in the SFHA should be considered as a lower bound of the impact of having flood insurance.

6. Results

6.1. Short-term Outcomes

Table 4 presents the estimated impact of property damage on becoming 90 days delinquent within five months after Hurricane Harvey. Column (1) is the baseline model, which only controls for the pre-storm loan characteristics except the SFHA indicator. Column (2) adds the SFHA indicator and Column (3) adds property damage indicators. Comparing the Gini coefficients of the three models, we see that adding property damage indicators increases model performance more than adding the SFHA indicator. Column (3) indicates that, compared with properties with no damage, moderate to severe damage increases the odds of becoming 90 days delinquent during the five months post-flood by three times.

Columns (4) and (5) both use the model of equation (2) with column (4) using properties having no damage and located outside the SFHA as the reference group and column (5) using properties having no damage and located inside the SFHA as the reference group. By running the same model twice with different reference groups, we can compare the impact of property damage between those inside and outside the SFHA, which is presented in the highlighted cells in the table. Columns (4) and (5) show that moderate to severe damage increases the odds of becoming first-time 90 days delinquent by roughly three times both inside and outside the SFHA. The impact is not statistically different between the two locations. This suggests that, for this short-term outcome variable, flood insurance does not have a mitigating effect on the negative impacts of flood damage to loan performance.

There are a few possible explanations for this finding. First, borrowers with flood insurance might not receive insurance payments immediately post-flood; it could take weeks or months to process the payment and work out a spending plan with their lender. Second, some delinquent borrowers could have accepted forbearance offered by servicers and suspended making mortgage payments to meet other post-disaster financial needs, regardless of whether they expected to receive, or already had obtained, flood insurance proceeds. As we know from Table 2 and Figure 6, the first-time 90 days delinquency rate during the five months after Hurricane Harvey is 3% while the forbearance rate during the same period is 4%.

[Table 4 Here]

6.2. Intermediate Outcomes

Table 5 presents the estimated impact of property damage on the probability of obtaining forbearance. Column (3) shows that, outside of the SFHA, property damage increases the odds of a loan obtaining forbearance by 1.5-1.6 times, regardless the degree of damage. Columns (4) and (5) compare the impact of property damage inside and outside the SFHA. We see that the impact of minor damage is not statistically different between the two locations. However, the impact of moderate to severe damage is stronger outside the SFHA than inside.

[Table 5 Here]

Table 6 presents the estimated impact of property damage on the probability of a loan being modified. The Gini coefficients in columns (1) through (3) again show that adding property damage variables increases model performance more than adding the SFHA indicator. Column (3) shows that, compared with properties having no damage, moderate to severe damage doubles the odds of a loan being modified. Columns (4) and (5) further show that this impact of moderate to severe damage exists only outside the SFHA. This indicates that borrowers whose properties sustain moderate to severe damage but do not have flood insurance are more likely to need a loan modification than those with flood insurance.

[Table 6 Here]

6.3. Longer-term Outcomes

Table 7 presents the impact of property damage on the probability of becoming 180 or more days delinquent or defaulting as of the 24th month after Harvey. We observe that, compared with properties having no damage, moderate to severe damage increases the odds by 2.6 times. Such an impact is statistically significant outside SHFAs but not inside. Recall that loans with moderate to severe damage outside the SFHA are more likely to receive loan modifications, and modifications bring delinquent loans back to being current and thus reduce default probability. Therefore, had Fannie Mae not offered disaster modifications, the loans with moderate to severe damage outside the SFHA would likely have an even higher default probability. In other words, the impact of property damage on the probability of deep delinquency or default would be even greater outside the SFHA.

[Table 7 Here]

Table 8 presents the estimated impact of property damage on prepayment probability as of the 24th months after Harvey. Columns (4) and (5) show that, inside the SFHA, moderate to severe damage increases prepayment odds by 2.1 times, compared with properties having no damage. However, outside the SFHA, property damage seems to have no effect on the prepayment probability.

[Table 8 Here]

In Section 5, we listed three potential reasons why property damage could increase prepayment. Now the empirical results in Table 8 can be used to examine which mechanism best explains the post-storm prepayments. If the dominant driver is borrowers using a cash-out refinance to fund repair costs, we should have seen that the impact of property damage on the prepayment probability is stronger outside the SFHA, where borrowers usually have no flood insurance payments to help cover the cost of repairs. However, this is not what we find, letting us rule out cash-out refinance as the dominant driver of prepayment.

Borrowers have the option of applying flood insurance proceeds to paying off their mortgages. Recall from Section 2 that the average NFIP payment for Harvey claims was close to \$117,000. In our home-inspection sample, the median pre-storm unpaid balance of the loans inside the SFHA and having moderate to severe damage is $122,000. Hence, about half of these loans could be paid off if the borrowers received close to the average NFIP payment. This mechanism can explain why homes inside the SFHA with moderate to severe damage have the highest prepayment rate.

The third potential mechanism through which property damage may increase prepayments is when a borrower sells a damaged house to an investor. Compared to paying off a mortgage with flood insurance proceeds, which could take months, selling a flooded house to an investor for cash can be a faster way for a homeowner to resolve the financial consequences of a flood and move to an undamaged home. News media reports of investors buying flooded houses in Houston appeared as early as September and continued through at least November 2017.[21] For example, the Wall Street Journal, citing Zillow's data of single-family home sales, reported that Houston home sale volume only declined for two months after Harvey and then started to grow in November 2017 as a result of investors purchasing storm-damaged homes.[22]

[Figure 6 Here]

In Figure 6, we plot the monthly prepayment rate by property damage level and by the SFHA indicator. The figure shows that, out of the four groups, loans inside the SFHA with moderate to severe damage, represented by blue bars, have the highest prepayment rate for most of the 24 months after the storm. These borrowers can use flood insurance proceeds to pay off mortgages. However, this is higher during October 2017 and January 2018 than in the other

---

[21] Sources: https://www.reuters.com/article/us-storm-harvey-housing-investors-idUSKCN1BX0DA https://www.npr.org/2017/11/08/562903267/some-real-estate-investors-eager-to-buy-houston-homes-damaged-by-flooding

[22] Source: https://www.wsj.com/articles/the-new-storm-chasers-real-estate-disaster-investors-11564498767

months. It is unlikely that all the prepayments in those early months are due to insurance proceeds. Additionally, in November 2017 and January 2018, the prepayment rate of loans outside of the SFHA with moderate to severe property damage is also very high. This suggests that some of the early prepayment of damaged homes is due to home sales to investors.

One unanswered question is why this happens inside the SFHA more than outside. One potential reason is that the homeowners having flood insurance eventually would receive insurance proceeds as long as they filed claims before the home sale. Therefore, perhaps they are more likely to accept low offers from investors. Another potential reason is that homeowners inside the SFHA might anticipate higher flood insurance premiums and thus be motivated to sell their homes quickly and relocate. Finally, while the flooding from Hurricane Harvey was record-breaking, this region has suffered repeated flooding and homes in the SFHA are more likely to have been inundated more than once; there is anecdotal suggestions in the news media that many homeowners in these zones were “fed up” with flooding and looking to relocate (e.g., Paulson 2019).

In summary, there are two potential mechanisms explaining why property damage increases the probability of prepayment inside the SFHA. One is that borrowers use flood insurance proceeds to pay off their mortgage. The other is that borrowers who have flood insurance proceeds are more willing to sell their damaged homes to investors, often at a depressed price.

6.4. Catastrophe Model Predictions and Loan Outcomes

To investigate the utility of catastrophe models to risk managers, we replicate the analysis on loan outcomes, but replace the actual property damages from inspections with predicted damages from the catastrophe model to examine whether the findings still hold. This substitution allows us to use the full sample of 72,000 loans, thus including the homes that were not inspected. If we find similar results using the modeled damage, it suggests that catastrophe model predictions could be helpful in identifying at-risk loans post-disaster in order to target relief programs. They could also be used for conducting loan-level and portfolio-level loss forecasts quickly after a disaster.

Our analysis still uses the models described by equations (1) and (2). In order to match the categorical variable of the home inspection outcome, we also use the predicted property damage as a categorical variable that has three categories: (a) the loss ratio is zero, (b) the loss ratio is less than 10%, and (c) the loss ratio is equal or greater than 10%. All the result tables presented in this section use the same structure described as follows. Columns (1) and (2) both use equation (1), except column (1) uses the sample of inspected homes and column (2) uses the full sample. By comparing the two columns, we can see whether the findings from the smaller sample can be generalized to the full sample. Columns (3) and (4) both use equation (2), except column (3) uses properties with no damage and located outside the SFHA as the reference group and column (4) uses properties with no damage and located inside the SFHA as the reference group.

Table 9 presents the correlation between predicted property damage and becoming 90 days delinquent up to five months after Harvey. Column (2) indicates that compared with properties having no damage, property damage predicted to be greater than 10% of the structure value increases the odds of becoming 90 days delinquent during the five months following the storm by 2.3 times while property damage predicted to be smaller than 10% increases the odds by 1.8 times. Comparing columns (1) and (2), we can see the odds ratios are very close. However, the model performance, measured by the Gini coefficient, decreases when using the full sample. Columns (3) and (4) show that the impact of property damage is not different inside and outside of the SFHA, which is consistent with our results when we use actual damages.

[Table 9 Here]

One thing is worth noting when we compare the results in Table 9 with those in Table 4. We find that if we use actual damage data in the estimation, only moderate to severe damage increases delinquency. However, when we use predicted damage, both levels of predicted damage increase the odds of delinquency. This change is not just because we switch to a larger sample. In column (1) of Table 9, where we use predicted damage for the smaller sample of inspected properties, we still see that both levels of predicted damage increase delinquency. This is because the catastrophe model does not precisely predict the level of damage at a property level. In the remaining part of this section, we see similar patterns in the results of modification, prepayment and deep delinquency or default.

Table 10 presents the correlation between predicted property damage and obtaining forbearance after Hurricane Harvey. Columns (2) and (3) indicate that compared with properties with no damage, predicted property damage roughly doubles the odds of obtaining forbearance. The impact of property damage is about the same both inside and outside the SFHA. Recall that our results using actual damages also indicated that property damage increases the probability of forbearance both inside and outside the SFHA.

[Table 10 Here]

Table 11 presents the correlation between predicted property damage and a loan being modified after Harvey. Column (3) indicates that compared with properties with no damage, predicted property damage increases the odds of being modified by 1.6-1.9 times outside the SFHA. Column (4) shows that property damage predicted to be greater than 10% also increases the odds of loan modification inside the SFHA. However, when we use the inspection sample, property damage does not increase the odds of modification inside the SFHA. It thus seems in this case that the estimation result using actual damages is more reliable. [23]

[Table 11 Here]

Table 12 presents the correlation between predicted property damage and the odds of becoming 180 or more days delinquent or defaulting. The contrast of column 3 and column 4 shows that predicted damage increases the odds of deep delinquency or default outside the SFHA, but not inside. This pattern is consistent with the finding using actual damage. However, column 3 shows that less than 10%, not greater than 10% predicted damage, increases the odds of deep delinquency or default. This counter-intuitive risk ranking, which we have not seen in

[23] We conducted a robustness test of adding servicer fixed effects to the models on forbearance and modification to address the concern that some servicers may be more aggressive in offering forbearance and modifications than other servicers. Because there are many servicers, we added the indicators for each of the top five servicers, who combined account for half of the loans in the sample. The servicer fixed effects do not change the estimated impact of property damage either inside or outside the SFHA. The same robustness test is also conducted for the inspection sample, in which the top five servicers account for 80% of the inspected loans. The servicer fixed effects do not change these results either.

other loan performance outcomes, suggests that the inaccurate property-level damage prediction by the catastrophe model can be problematic for a rare outcome, such as deep delinquency or default.

We also notice the different results in columns (1) and (2) when we switch from the inspection sample to the full sample. Column (1) indicates that property damage predicted to be greater than 10% increases the odds of deep delinquency or default by 3.2 times, however, column (2) shows that this impact is small and statistically insignificant. We haven't seen such a contrast between the two samples from other outcomes. Recall that the inspection sample has a larger share of loans entering deep delinquency or defaulting due to Fannie Mae inspection priorities. This again suggests that, for a rare event, predicted damage needs to match better with actual damage at a property level in order to deliver a robust estimated impact of property damage.

[Table 12 Here]

Lastly, Table 13 presents the correlation between predicted property damage and the prepayment probability. Column (3) shows that compared with properties with no damage, property damage predicted to be greater than 10% of the structure value increases the odds of prepayment by 1.8 times and property damage predicted to be less than 10% increases the odds of prepayment by 1.2 times. And columns (4) shows that this effect does not exist outside. This pattern is consistent with the finding using actual damages.

[Table 13 Here]

6.5 Heterogeneous Impacts

In this section, we examine the impact of property damage and flood insurance on loan performance for heterogeneous borrowers based on the value of their home, their income, and their credit score. In order to have a large enough sample size in subgroups by property or borrower characteristics, we use the full sample with predicted property damage.

As noted above, the building coverage limit offered by NFIP is up to $250,000. This cap, while providing sufficient coverage for to low-to-medium valued houses, could be insufficient for a high-valued home. Therefore, we would expect that the protective role of NFIP policies is stronger for low-to-medium valued houses. We test this hypothesis using two subgroups: the homes with the mark-to-market value prior to Hurricane Harvey at or below $350,000 (insurance applies only to structure value; this cutoff is higher than the NFIP cap to account for land value)[24] and the homes valued above $350,000. Table 14 contrasts the two types of homes in terms the odds ratio of becoming deeply delinquent or defaulting. All the following tables use the same framework. Columns (1) and (2) are the results for lower-valued homes and columns (3) and (4) are the results for higher-valued homes. All four columns use the difference-in-difference model specified by the equation (2), with columns (1) and (3) using the predicted undamaged homes outside the SFHA as the reference group and the columns (2) and (4) using predicted undamaged homes inside the SFHA as the reference group. Columns (1) and (2) of Table 14 show that predicted property damage increases the odds of deep delinquency or default for lower-valued

[24] The cut-off of $350,000 is chosen for the following reason. A Homeowner buys flood insurance only for the structure and contents, not for the land of the house. Given that the average land share of property value in Harris county, TX in 2017 is 28% (Larson et.al. 2019), a home with the structure value at $250,000 is worth about $350,000 in total. In the full sample, $350,000 is at about 70th percentile of the home value distribution.

homes outside the SFHA but not for those inside. Evidently, flood insurance protects borrowers with lower-value homes from defaulting following property damage. However, column (4) shows that, for higher-value homes, property damage increases the odds of deep delinquency or default even inside the SFHA. This shows that the protective role of NFIP coverage is lessened for higher-valued homes.

[Table 14 Here]

Considering the positive correlation between home value and borrowers' incomes, we also expect that the NFIP would be more protective for lower-income borrowers. In addition, it is reasonable to assume that higher-income borrowers are more likely to have greater financial resources to handle emergency financial needs. To test this hypothesis, we divide the full sample into two groups by the borrower's income as of loan origination: above or below the sample median. Unfortunately, we do not have borrowers' incomes from the time Hurricane Harvey hit. There are two shortcomings of using borrower income as of loan origination: first, the incomes are recorded in different years. Hence, we adjust all incomes to 2017-dollars. Second, more than half of the loans have single borrowers. A single borrower's income may not represent the total household income. Therefore, the median income is determined separately for single-borrower loans at $80,000 and multiple-borrower loans at $120,000.

Table 15 contrasts lower-income borrowers and higher-income borrowers in terms of the odds of becoming deeply delinquent or defaulting. Columns (1) and (3) show that, outside of the SFHA, property damage increases the odds of becoming deep delinquent or defaulting for lower-income borrowers but not for higher-income borrowers. This suggests that higher-income borrowers are more resilient to hazard events. Columns (2) shows that property damage does not increase deep delinquency or default odds for lower-income borrowers inside the SFHA, which indicates the protective role of flood insurance.

[Table 15 Here]

Lastly, we examine whether property damage impacts vary according to the credit score of borrowers. We again split the full sample into two subgroups by borrowers' origination credit scores. We use 720 as the cut-off score between the two groups because a credit score above 720 is generally considered "good" by lenders. In the full sample, the credit score of 720 is about the median of all borrowers. Table 16 presents the contrast between borrowers with lower credit score and those with higher credit score. Comparing column (3) with column (1), we can see that borrowers with higher credit score are more sensitive to property damage than those with lower credit score. This does not mean that borrowers with higher credit score default more than their counterparts with lower credit score. Instead, the difference arises from the two reference groups: the no-damage and lower-credit-score borrowers have much higher deep delinquency or default rate than the no-damage and higher-credit-score borrowers. Specifically, the deep delinquency or default rate is 36 bps among no-damage and lower-credit-score borrowers, but only 8 bps among no-damage and higher-credit-score borrowers. In contrast, out of the properties that are predicted to have 10% or more loss, the deep delinquency or default rate is 43 bps among borrowers with lower credit score and 19 bps among borrowers with higher credit score. The above statistics indicate that borrowers with lower credit score can become deeply delinquent or default for many reasons other than flood damage. In contrast, borrowers with higher credit score rarely default unless unavoidable things, such as natural disasters, happen.

And there could be strategic default among the borrowers who usually have high credit score. Therefore, flood insurance may be more useful to borrowers with higher credit score than those with lower credit score in reducing deep delinquency and default on a relative basis given the different baseline rate of performance on these outcome metrics. However, column (4) shows that the borrowers with higher credit score inside the SFHA having predicted damage greater than 10% of structure value still have high odds of becoming deeply delinquent or defaulting relative to their no-damage counterparts. This might be because the coverage cap of NFIP limits its protective role. This could also be because projected damage introduces measurement error bias.

[Table 16 Here]

We present in the appendix (Tables A1 – A3) the prepayment regression results by home value, borrowers' income and borrower s' credit score. All the tables show that, inside the SFHA, prepayment odds increase as property damage becomes more severe. Such a pattern does not vary by any of the three characteristics mentioned above. Outside of the SFHA, there is no clear pattern of the association between property damage and prepayment odds. Therefore, this indicates that access to flood insurance increases the chances of all borrowers inside the SFHA to pay off mortgage, and thus reduce their chances of defaulting sometime in the future.

7. Conclusion

This paper uses Hurricane Harvey as a case study to examine the link between property damages, flood insurance, and credit risk. The unique dataset of Fannie Mae post-disaster home inspections provides property-level actual damage information from Hurricane Harvey. Further, Fannie Mae's requirement that all properties in the SFHA (100-year floodplains) have flood insurance allows us to identify the impact of insurance on loan outcomes by comparing the loan performance gap between damaged homes and non-damaged homes inside and outside the SFHA. We use this difference-in-difference method to examine short, intermediate, and longer-term loan performance measures.

We find that property damage caused by Hurricane Harvey increases short-term mortgage delinquency and the probability of obtaining forbearance. In the longer run, if the borrowers have flood insurance, the loans on damaged properties are no more likely than those on undamaged homes to become deeply delinquent or to default. Borrowers with flood insurance are more likely to prepay their mortgage, either because they can use insurance proceeds to pay off their mortgage, or because they are more willing to sell their damaged homes to investors since their losses are already compensated by insurance. For those who have no flood insurance, however, short-term delinquency is more likely to lead to longer-term problems: the loans are more likely to need modifications or become deeply delinquent or go into default.

We also obtained loan-level predicted property damage from a catastrophe modelling firm for a larger sample of loans in the Harvey-affected area and examined the association between predicted property damage and loan performance. Consistent with the results using actual damage, we find that the predicted damage increases short-term delinquency and forbearance both inside and outside of the SFHA. However, in the longer run, predicted damage increases prepayment only inside the SFHA and increases deep delinquency or default only outside the SFHA. Therefore, the role of flood insurance is clearly seen in the larger sample with the predicted damage measure. Nonetheless, due to the fact that the predicted damage by the catastrophe model is not as accurate at property level, the magnitude of estimated impacts of different levels of damage does not always match with the estimates using actual damage. When it comes to a rare event, such as deep delinquency and default, the estimates further diverge: even the default risk ranking is flipped between minor and severe predicted damage. Therefore, in the case of Hurricane Harvey, the catastrophe model can be useful to forecast the risk of short-term delinquency, forbearance, modification, and prepayment at property level or portfolio level. However, more accurate property-level damage prediction is needed for the catastrophe model to forecast loan defaults triggered by flood damage.

In addition, using the predicted property damage and the full sample, we find that, outside of the SFHA, the probability of becoming deeply delinquent or defaulting is more sensitive to flood damage for borrowers with lower income or higher credit scores, which suggests that such populations would benefit more from flood insurance than their higher-income or lower-credit-score counterparts. Inside the SFHA, we find that flood insurance protects loans on lower-valued properties from defaulting more than loans on higher-value properties, perhaps because NFIP has a coverage limit of $250,000. We also find that flood insurance increases the prepayment probability of all owners of damaged homes, regardless their income, credit score, or home value.

As flood events continue outside of the mapped SFHAs, it is helpful to identify and quantify the protective value of flood insurance. Our paper presents strong empirical evidence that flood insurance not only provides financial protection to households, but also to lenders and other credit risk holders such as the GSEs. Despite these benefits, very few homeowners outside the SFHA have a flood insurance policy. We also find the protective benefits of flood insurance to be stronger for lower-income households, providing support for policy proposals to create a federal means-tested assistance program for flood insurance to help lower-income families afford this coverage. Our finding that not all borrowers with higher-value homes inside the SFHA can avoid deep delinquency or default following a hurricane suggests that flood insurance market product set could expand to meet needs not currently met under the NFIP. Our paper also offers the necessary quantification to aid practitioners in designing regulations, conducting stress tests, and other risk management activities.

References

Adrian, T., J. Morsink and L. Schumacher (2020). “Stress Testing at the IMF.” International Monetary Fund Monetary and Capital Markets Departmental Paper No. 20/04.

ASFPM Foundation (2004). Is the 1% chance flood standard sufficient? Washington, DC, ASFPM Foundation in collaboration with the National Academies Disasters Roundtable.

Atreya, A., S. Ferreira and W. Kriesel (2013). "Forgetting the Flood? An Analysis of the Flood Risk Discount over Time." Land Economics **89**(4): 577-596.

Beltran, A., D. Maddison and R. J. R. Elliott (2018). "Is Flood Risk Capitalised Into Property Values?" Ecological Economics **146**: 668-685.

Bin, O., J. B. Kruse and C. E. Landry (2008). "Flood Hazards, Insurance Rates, and Amenities: Evidence from the Coastal Housing Market." Journal of Risk and Insurance **75**(1): 63-82.

Bin, O. and C. E. Landry (2013). "Changes in implicit flood risk premiums: Empirical evidence from the housing market." Journal of Environmental Economics and Management **65**(3): 361-376.

Bin, O. and S. Polasky (2004). "Effects of Flood Hazards on Property Values: Evidence before and after Hurricane Floyd." Land Economics **80**(4): 490-500.

Blake, E. S. and D. A. Zelinsky (2018). National Hurricane Center Tropical Cyclone Report: Hurricane Harvey, National Oceanic and Atmospheric Administration, National Weather Service

Carbone, J. C., D. G. Hallstrom and V. K. Smith (2006). "Can Natural Experiments Meausre Behavioral Responses to Environmental Risks?" Environmental and Resource Economics **33**: 273-297.

Cutter, S. L., C. T. Emrich, M. Gall and R. Reeves (2017). "Flash flood risk and the paradox of urban development." Natural Hazards Review **19**(1): 05017005.

Daniel, V. E., R. J. G. M. Florax and P. Rietveld (2009). "Flooding risk and housing values: An economic assessment of environmental hazard." Ecological Economics **69**(2): 355-365.

Dembicki, G. (2019). A ‘Big Short’ Investor’s New Bet: Climate Change Will Bust the Housing Market. Vice.

Deryugina, T., L. Kawano and S. Levitt (2018). "The Economic Impact of Hurricane Katrina on Its Victims: Evidence from Individual Tax Returns." American Economic Journal: Applied Economics **10**(2): 202-233.

Douglas, P. (2018). “Flooding Frequency and Intensity are Increasing – Are You Factoring the Latest Trends?”
https://www.aerisweather.com/blog/2018/07/24/flooding-frequency-increasing/

Ellen, I., R. Meltzer and X. Li (2020). "Heterogeneity in the Recovery of Local Real Estate Markets After Extreme Events: The Case of Hurricane Sandy." American Real Estate and Urban Economic Association Conference January, 2020

Emanuel, K. (2017). "Assessing the present and future probability of Hurricane Harvey's rainfall." Proceedings of the National Academy of Sciences **114**(48): 12681-12684.

FEMA (2015). Designing for Flood Levels above the BFE after Hurricane Sandy. Washington, DC, Federal Emergency Management Agency

FEMA (2016). Individuals and Households Progam Unified Guidance. Washington, DC, Federal Emergency Management Agency. September.

FEMA (2018). An Affordability Framework for the National Flood Insurance Program. Washington, DC, Department of Homeland Security, Federal Emergency Management Agency. April 17.

Gallagher, J. and D. Hartley (2017). "Household Finance after a Natural Disaster: The Case of Hurricane Katrina." American Economic Journal: Economic Policy **9**(3): 199-228.

Garner, A. J., M. E. Mann, K. A. Emanuel, R. E. Kopp, N. Lin, R. B. Alley, B. P. Horton, R. M. DeConto, J. P. Donnelly and D. Pollard (2017). "Impact of climate change on New York City's coastal flood hazard: Increasing flood heights from the preindustrial to 2300 CE." Proceedings of the National Academy of Sciences **114**(45): 11861-11866.

Grossi, P. and H. Kunreuther, Eds. (2005). Catastrophe Modeling: A New Approach to Managing Risk. Huebner International Series on Risk, Insurance and Economic Security, Springer.

Hall, T. M. and J. P. Kossin (2019). "Hurricane stalling along the North American coast and implications for rainfall." npj Climate and Atmospheric Science **2**(17): article 17.

Hunn, D. and M. Dempsey (2018) "In Houston's Flooded Neighborhoods, Real Estate Investors See an Opportunity." Houston Chronicle.

Larson, W., J. Shui, M. Davis, S. Oliner (2019). "The Price of Residential Land for Counties, ZIP codes, and Census Tracts in the United States." FHFA Working Paper 19-01.

Kousky, C. (2010). "Learning from Extreme Events: Risk Perceptions after the Flood." Land Economics **86**(3): 395-422.

Kousky, C. (2017). "Disasters as Learning Experiences or Disasters as Policy Opportunities? Examining Flood Insurance Purchases after Hurricanes." Risk Analysis **37**(3): 517-530.

Kousky, C. (2018). "Financing Flood Losses: A Discucssion of the National Flood Insurance Program." Risk Management and Insurance Review **21**(1): 11-32.

Kousky C. and B. Lingle (2018). “The 3 Maps That Explain Residential Flood Insurance Purchases.” BRINK.
https://www.brinknews.com/the-3-maps-that-explain-residential-flood-insurance-purchases/

Mallakpour, I. and G. Villarini (2015). "The changing nature of flooding across the central United States." Nature Climate Change **5**(March): 250-254.

Meitrodt, Jeffrey, and Rebecca Mowbray. 2006. “After Katrina, pundits criticized New Orleans, claiming too many residents had no flood insurance. In fact, few communities were better covered.” Times-Picayune, March 19.
https://levees.org/wp-content/uploads/2011/04/After-Katrina-Pundits-Criticized-New-Orleans.pdf

Office of Inspector General (2017). FEMA Needs to Improve Management of Its Flood Mapping Programs Washington, DC, US Department of Homeland Security.September

Olick, D. (2019) “The Mortgage Industry Isn’t Ready for a Foreclosure Crisis Created by Climate Change.” CNBC.com. January 17

Ouazad, A. and M. Kahn, E. (2019). "Mortgage Finance in the Face of Rising Climate Risk." NBER Working Paper 26322.

Paulson, S. (2019) “Flood the Market.” The Daily. August 27

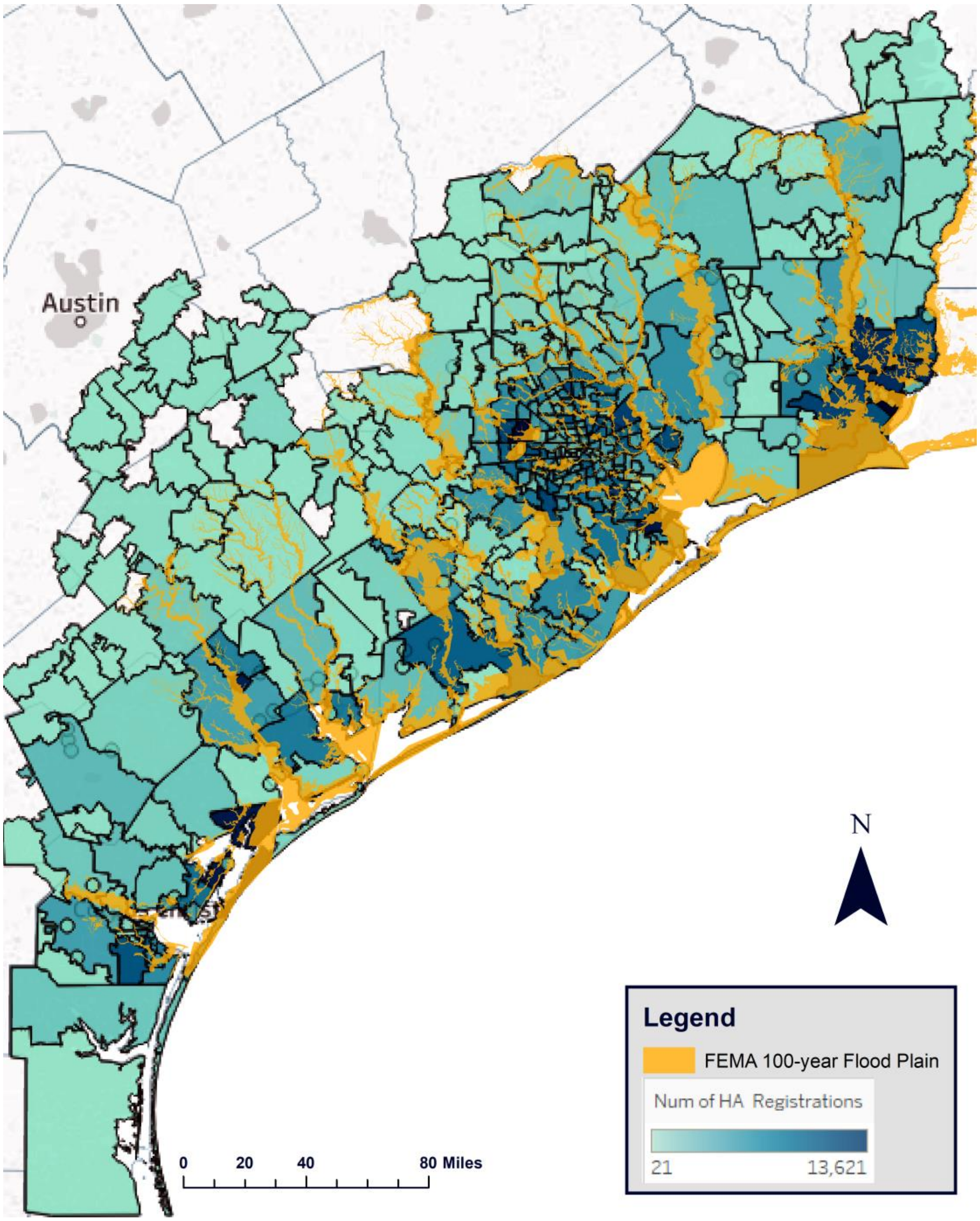
Pope, J. C. (2008). "Do Seller Disclosures Affect Property Values? Buyer Information and the Hedonic Model." Land Economics **84**(4): 551-572.

Prein, A. F., C. Liu, K. Ikeda, S. B. Trier, R. M. Rasmussen, G. J. Holland and M. P. Clark (2017). "Increased rainfall volume from future convective storms in the US." Nature Climate Change **7**(12): 880-884.

Sweet, W. V. and J. Park (2014). "From the extreme to the mean: Acceleration and tipping points of coastal inundation from sea level rise." Earth's Future **2**(12): 579-600.

Walls, M. and D. H. Cortes (2018). “Recovering from Disasters: Evaluating FEMA’s Housing Assistance program in the 2017 Hurricane Season.” Resources for the Future Common Resources 09.19.18.
https://www.resourcesmag.org/common-resources/recovering-from-disasters-evaluating-femas-housing-assistance-program-in-the-2017-hurricane-season/

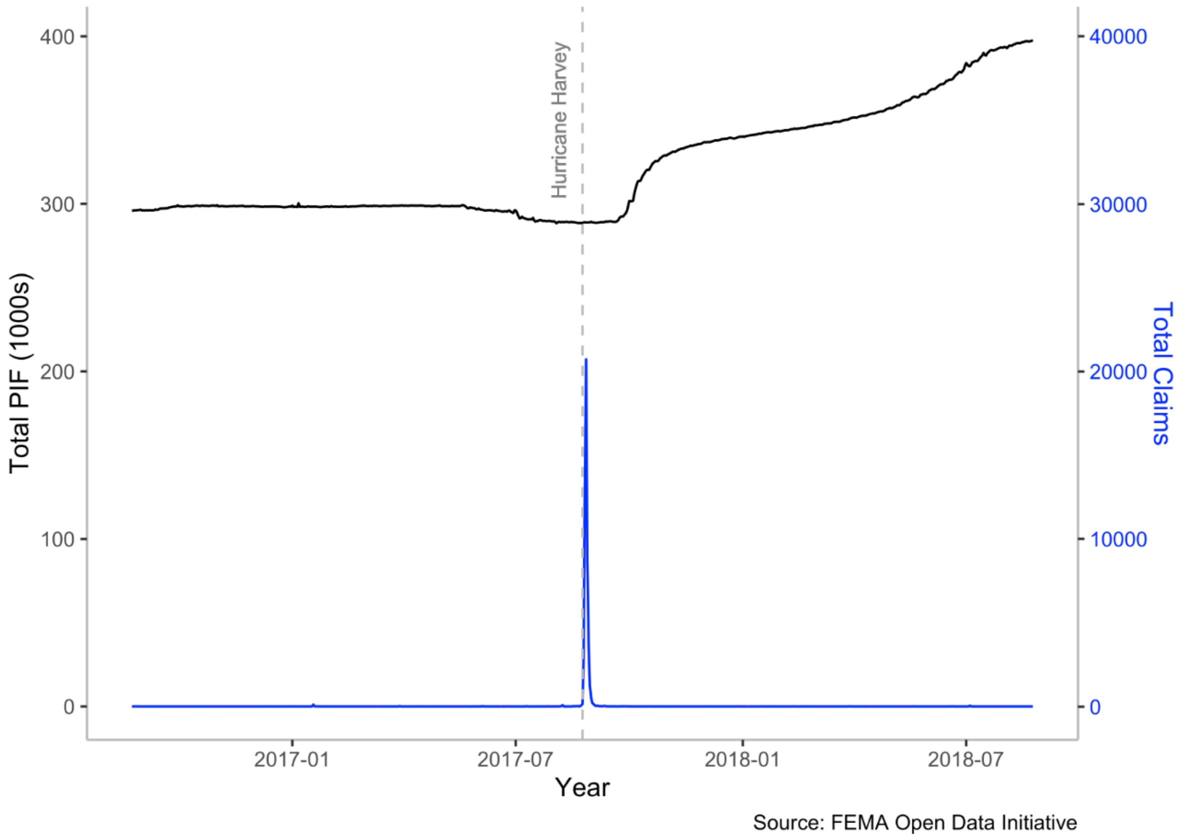
Figure 1. The Map of Harvey-Affected Zip Codes[25]



Note: Harvey-affected area is defined by the zip codes where there are 20 or more registrations (including both owners and renters) to FEMA's Housing Assistance (HA) Program after Hurricane Harvey.

[25] Thank Logan Regier for research assistance in mapping.

Figure 2. Daily Residential NFIP Policies-in-Force (PIF) and Daily Residential Claims in Harvey-Impacted Region



Note:

1. The figure includes Fort Bend, Harris, and Montgomery Counties in Texas.
2. The date of daily claims uses the date when water damage happened.

Figure 3. Timeline of Loan Performance

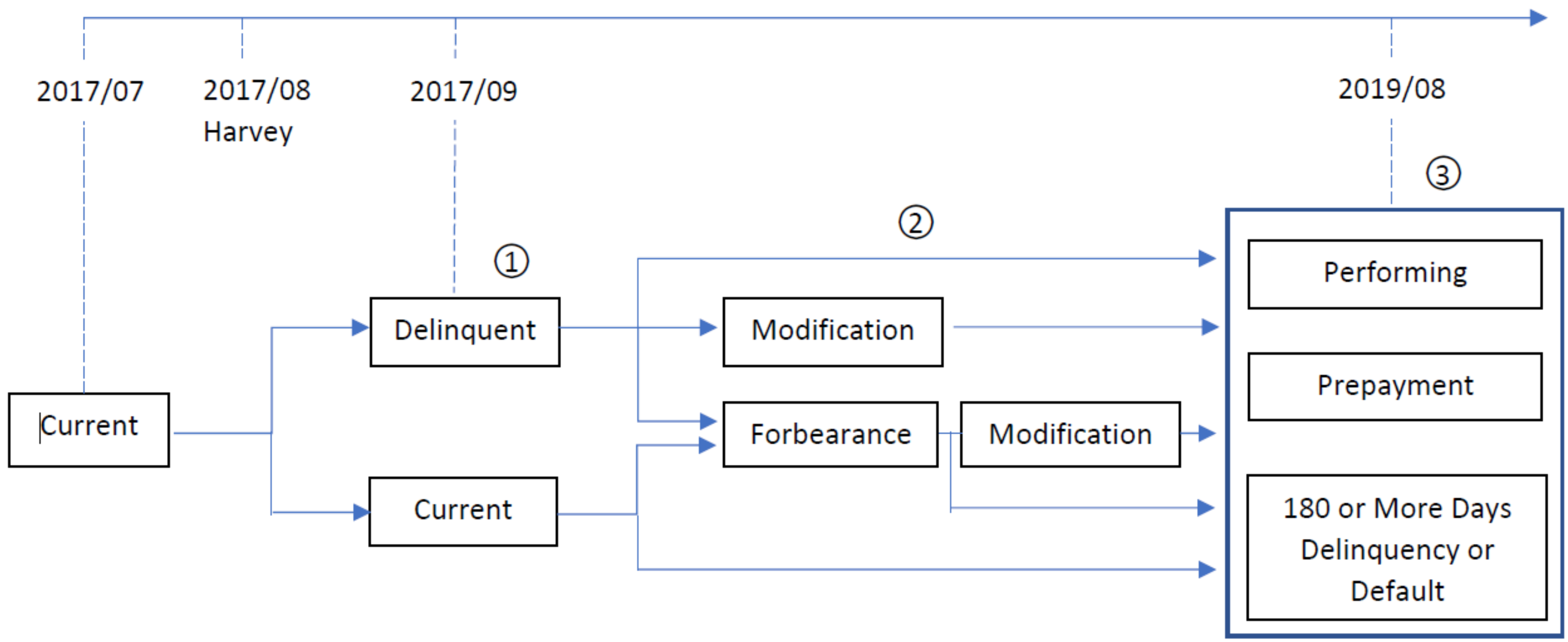
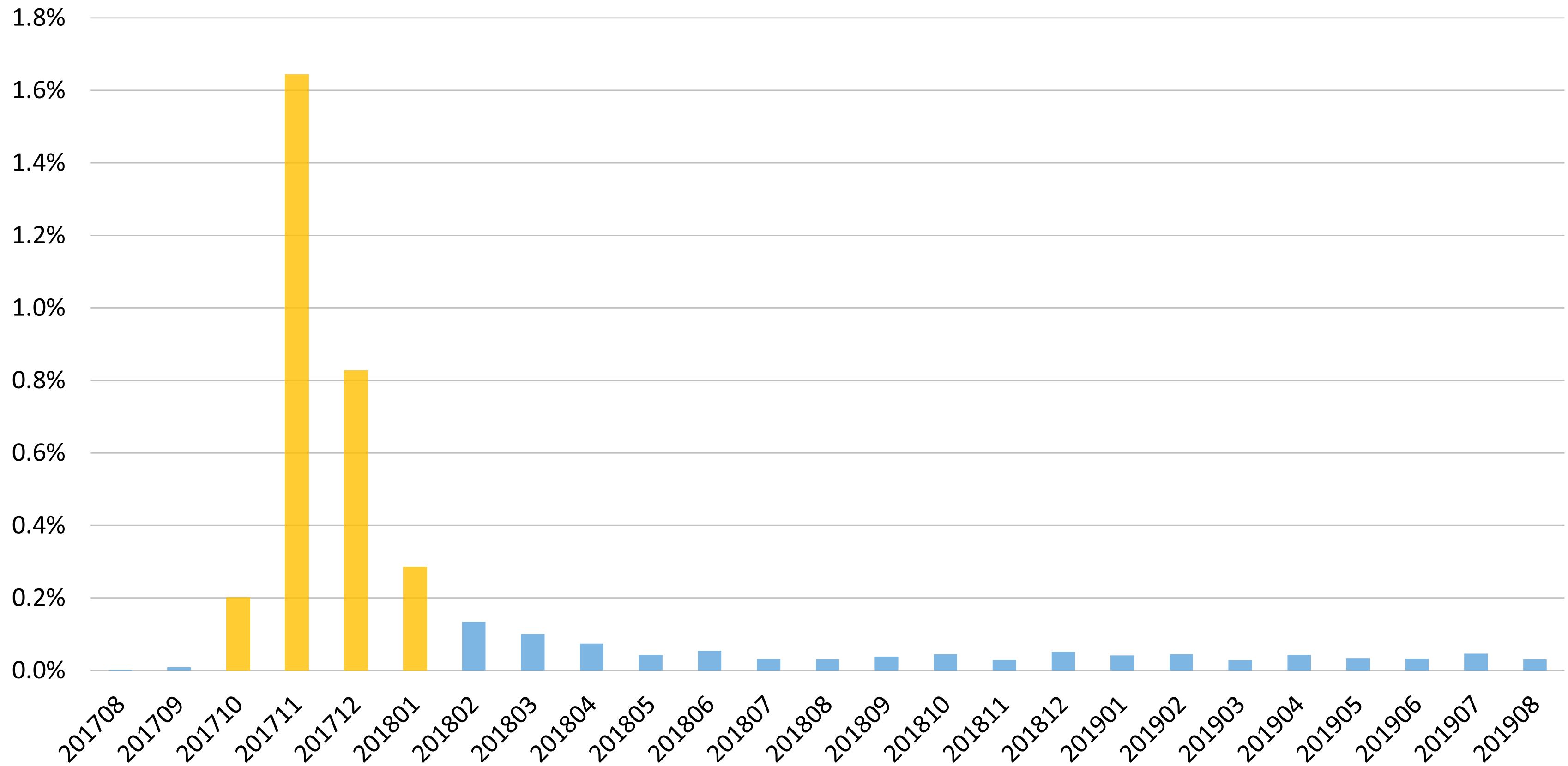
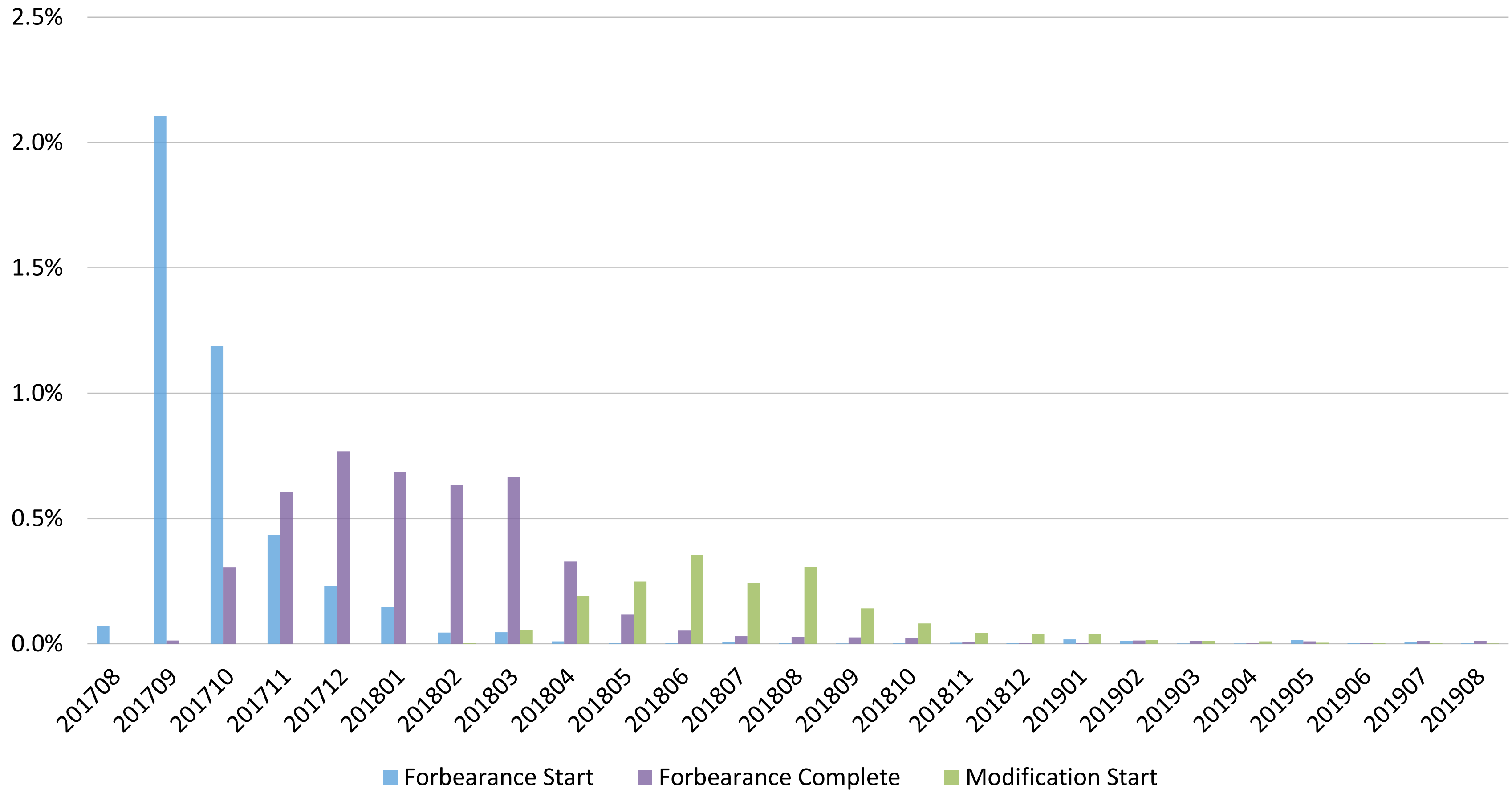


Figure 4. Rate of Loans Entering 90 days Delinquency After Harvey by Month



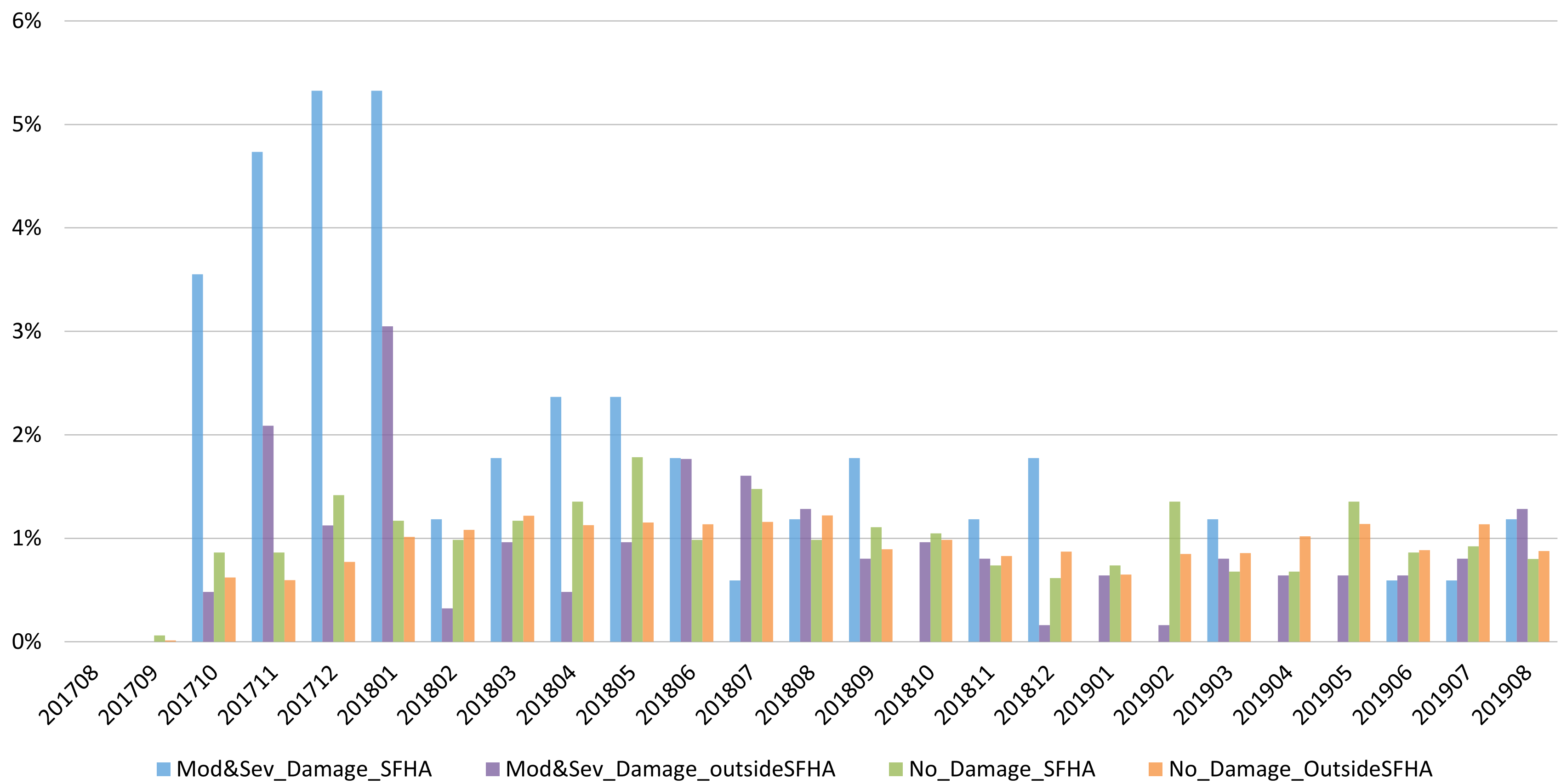
Note: Population is the loans that were current as of July 2017 and the properties are owner-occupied detached one-unit single-family houses that are located in Harvey-affect area.

Figure 5. Rate of Loans Entering Forbearance, Completing Forbearance and Starting Modification After Harvey by Month



Note: Population is the loans that were current as of July 2017 and the properties are owner-occupied detached one-unit single-family houses that are located in Harvey-affect area.

Figure 6. Prepayment Rate by Property Damage Level and by the SFHA Indicator



Note: Population is the loans that were current as of July 2017 and the properties are owner-occupied detached one-unit single-family houses that are located in Harvey-affect area and were inspected after Harvey.

Table 1. Variable Definitions and Summary Statistics

Variables	Description	Full Sample (obs=71,949)		Inspection Sample (obs=27,061)	
		Mean	Standard Deviation	Mean	Standard Deviation
SFHA	The property is located in the SFHA	6.58%	0.51	6.94%	0.25
90 Days Delinquency	Becoming 90 days delinquent up to five months after Harvey	2.93%	0.35	5.45%	0.23
Forbearance	Forbearance up to 18 months after Harvey	4.30%	0.42	5.04%	0.22
Modification	Disaster Modification up to 18 months after Harvey	1.76%	0.27	3.31%	0.18
180 Or More Days Delinquency or Default	Becoming 180 or more days past due or default up to 24 months after Harvey	0.19%	0.09	0.32%	0.06
Default	Becoming default up to 24 months after Harvey	0.05%	0.05	0.09%	0.03
Prepayment	Prepayment up to 24 months after Harvey	22.44%	0.86	22.31%	0.42
Loan Age	Count of months between origination and July 2017	59.71	105.09	73.54	53.09
MTMCLTV	Mark-to-market combined loan-to-value ratio as of July 2017	52.65	44.87	49.97	20.33
Credit Score	The lower of borrower and co-borrower's credit scores as of loan origination	733.77	116.4	721.56	65.12
DTI	The total combined monthly debt to monthly income ratio at origination	0.34	0.24	0.35	0.13
Number of Borrowers	One Borrower (as opposed to two more borrowers)	52.42%	1.03	55.90%	0.50
Product Type	FRM15: 15 and 20 year fixed-rate mortgage	60.92%	1.00	58.57%	0.49
	FRM30: 25, 30 and 40 year fixed-rate mortgage	37.27%	1.00	39.26%	0.49
	ARM: adjustable-rate mortgage	1.80%	0.27	2.17%	0.15
Loan Purpose	Cash-out refinance	15.30%	0.74	13.74%	0.34
	Rate and term refinance	37.74%	1.00	43.09%	0.50
	Purchase Money	46.96%	1.03	43.17%	0.50
Third Party Origination	The mortgage is initiated through a broker or a correspondent	41.19%	1.01	42.15%	0.49
Reserves	Months of Reserves as Loan Origination	19.95	138.08	17.19	57.85
MTM Home Value	Mark-to-market home value	303467.32	518978.27	281266.78	177381.43
Borrowers' Income	Borrower's Annual Income as of loan origination in 2017 dollar	110239.40	182609.01	101891.98	77615.13

Note: Population is the loans that were current as of July 2017 and the properties are owner-occupied detached one-unit single-family houses that are located in Harvey-affect area.

Table 2. Distribution of Actual and Predicted Property Damages

Actual Inspection Outcomes	Actual (1)	Predicted (2)	Predicted (3)	Predicted Loss Ratio
None	93.07	91.29	90.73	0
Minimal	4.10	4.78	4.96	0-10%
Moderate to Severe	2.83	4.06	4.32	>10%
Sample	**Inspection**	**Inspection**	**Full**	
Number of Observation	27,061	27,061	71,949	
Weighted Number of Observation	27,061	27,061	301,576	

Table 3. Actual Property Damage VS Predicted Property Damage

		Catastrophe Model Predicted Damage	
		Yes	**No**
Actual Damage	**Yes**	1.49%	5.67%
	No	7.22%	85.62%

Note: Population are the loans that were current as of July 2017 and the properties are owner-occupied detached one-unit single-family houses that are located in Harvey-affect area and were inspected after Harvey.

Table 4. Odds Ratio of Entering 90 Days Delinquency Up to Five Months After Hurricane Harvey (Post-Harvey Inspection Sample)

Logit Model			90-day Delinquency in Oct, 2017 - Jan, 2018				
Variables	**Categories**		**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
SFHA	Yes			1.52***	1.40***		
	No			1	1		
Inspected Outcome	Moderate or Severe				2.94***		
	Minor				0.99		
	No				1		
Inspected Outcome	Moderate or Severe	SFHA = Yes				3.61***	2.60***
	Minor					1.83*	1.31
	No					1.39***	1
	Moderate or Severe	SFHA = No				3.03***	2.18***
	Minor					0.95	0.68**
	No					1	0.72***
Number of Observations			27,061	27,061	27,061	27,061	27,061
Number of Events			1,502	1,502	1,502	1,502	1,502
Gini			0.575	0.578	0.589	0.589	0.589

Note:

1. Population is the loans that were current as of July 2017 and the properties are owner-occupied detached one-unit single-family houses that are located in Harvey-affect area and were inspected after Hurricane Harvey.
2. The control variables include loan age and MTMCLTV as of July 2017, origination DTI, credit score and number of months of reserves as of origination, number of borrowers, product type, loan purpose, third-party origination indicators.
3. Columns (4) and (5) use the same model specification except that column (4) uses the no-damage homes outside the SFHA while column (5) uses the no-damage homes inside the SFHA as the reference group.
4. *10%,**5%,***1% Significance Levels

Table 5. Odds Ratio of Obtaining Forbearance Up to 18 Months After Hurricane Harvey (Post-Harvey Inspection Sample)

Logit Model			Forbearance				
Variables	**Categories**		**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
SFHA	Yes			1.85***	1.78***		
	No			1	1		
Inspected Outcome	Moderate or Severe				1.38**		
	Minor				1.74***		
	No				1		
Inspected Outcome	Moderate or Severe	SFHA = Yes				1.93**	1.12
	Minor					4.47***	2.58***
	No					1.73***	1
	Moderate or Severe	SFHA = No				1.48**	0.86
	Minor					1.61***	0.93
	No					1	0.58***
Number of Observations			27,061	27,061	27,061	27,061	27,061
Number of Events			1,374	1,374	1,374	1,374	1,374
Gini			0.590	0.595	0.601	0.601	0.601

Note:

1. Population is the loans that were current as of July 2017 and the properties are owner-occupied detached one-unit single-family houses that are located in Harvey-affect area and were inspected after Hurricane Harvey.
2. The control variables include loan age and MTMCLTV as of July 2017, origination DTI, credit score and number of months of reserves as of origination, number of borrowers, product type, loan purpose, third-party origination indicators.
3. Columns (4) and (5) use the same model specification except that column (4) uses the no-damage homes outside the SFHA while column (5) uses the no-damage homes inside the SFHA as the reference group.4. *10%,**5%,***1% Significance Levels.

Table 6. Odds Ratio of Being Modified Up to 18 Months After Hurricane Harvey (Post-Harvey Inspection Sample)

Logit Model			Disaster-Modification				
Variables	**Categories**		**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
SFHA	Yes			1.27*	1.23		
	No			1	1		
Inspected Outcome	Moderate or Severe				1.83***		
	Minor				0.36***		
	No				1		
Inspected Outcome	Moderate or Severe	SFHA = Yes				1.32	0.98
	Minor	SFHA = Yes				0.31	0.23
	No	SFHA = Yes				1.34**	1
	Moderate or Severe	SFHA = No				2.06***	1.53*
	Minor	SFHA = No				0.38***	0.28***
	No	SFHA = No				1	0.74**
Number of Observations			27,061	27,061	27,061	27,061	27,061
Number of Events			904	904	904	904	904
Gini			0.663	0.663	0.670	0.670	0.670

Note:

1. Population is the loans that were current as of July 2017 and the properties are owner-occupied detached one-unit single-family houses that are located in Harvey-affect area and were inspected after Hurricane Harvey.
2. The control variables include loan age and MTMCLTV as of July 2017, origination DTI, credit score and number of months of reserves as of origination, number of borrowers, product type, loan purpose, third-party origination indicators.
3. Columns (4) and (5) use the same model specification except that column (4) uses the no-damage homes outside the SFHA while column (5) uses the no-damage homes inside the SFHA as the reference group.
4. *10%,**5%,***1% Significance Levels.

Table 7. Odds Ratio of Becoming 180 or more days Delinquent or Defaulting as of the 24th Month After Hurricane Harvey (Post-Harvey Inspection Sample)

Multinomial Logit Model			Becoming 180-days delinquent or Worse				
Variables	**Categories**		**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
SFHA	Yes			1.24	1.15		
	No			1	1		
Inspected Outcome	Moderate or Severe				2.59**		
	Minor				1.31		
	No				1		
Inspected Outcome	Moderate or Severe	SFHA = Yes				2.96	2.26
	Minor	SFHA = Yes				0.94	0.71
	No	SFHA = Yes				1.31	1
	Moderate or Severe	SFHA = No				2.63**	2.00
	Minor	SFHA = No				1.44	1.10
	No	SFHA = No				1	0.76
Forbearance			9.70***	9.60***	9.34***	9.38***	9.38***
Modification			0.21**	0.21**	0.20**	0.20**	0.20**
Number of Observations			27,061	27,061	27,061	27,061	27,061
Number of Events			89	89	89	89	89

Note:

1. Population is the loans that were current as of July 2017 and the properties are owner-occupied detached one-unit single-family houses that are located in Harvey-affect area and were inspected after Hurricane Harvey.
2. The control variables include loan age and MTMCLTV as of July 2017, origination DTI, credit score and number of months of reserves as of origination, number of borrowers, product type, loan purpose, third-party origination indicators.
3. Columns (4) and (5) use the same model specification except that column (4) uses the no-damage homes outside the SFHA while column (5) uses the no-damage homes inside the SFHA as the reference group.
4. *10%,**5%,***1% Significance Levels.

Table 8. Odds Ratio of Prepayment as of the 24th Month After Hurricane Harvey (Post-Harvey Inspection Sample)

Multinomial Logit Model			Prepayment				
Variables	Categories		(1)	(2)	(3)	(4)	(5)
SFHA	Yes			1.22***	1.20***		
	No			1	1		
Inspected Outcome	Moderate or Severe				1.20**		
	Minor				0.91		
	No				1		
Inspected Outcome	Moderate or Severe	SFHA = Yes				2.37***	2.14***
	Minor					1.27	1.15
	No					1.11	1
	Moderate or Severe	SFHA = No				1.01	0.91
	Minor					0.89	0.80**
	No					1	0.9
Forbearance			1.09	1.08	1.09	1.08	1.08
Modification			0.49***	0.49***	0.49***	0.49***	0.49***
Number of Observations			27,061	27,061	27,061	27,061	27,061
Number of Events			6,022	6,022	6,022	6,022	6,022

Note:

1. Population is the loans that were current as of July 2017 and the properties are owner-occupied detached one-unit single-family houses that are located in Harvey-affect area and were inspected after Hurricane Harvey.
2. The control variables include loan age and MTMCLTV as of July 2017, origination DTI, credit score and number of months of reserves as of origination, number of borrowers, product type, loan purpose, third-party origination indicators.
3. Columns (4) and (5) use the same model specification except that column (4) uses the no-damage homes outside the SFHA while column (5) uses the no-damage home inside the SFHA as the reference group.
4. *10%,**5%,***1% Significance Levels.

Table 9. Odds Ratio of Entering 90 Days Delinquency
Up to Five Months After Hurricane Harvey
(Full Sample)

Logit Model			**90-day DLQ in Oct, 2017 - Jan, 2018**			
Variables	**Categories**		**(1)**	**(2)**	**(3)**	**(4)**
SFHA	Yes		1.26**	1.35***		
	No		1	1		
Predicted Property Damage	>=10%		2.58***	2.29***		
	<10%		1.63***	1.75***		
	0		1	1		
Predicted Property Damage	>=10%	SFHA = Yes			3.62***	2.85***
	<10%				2.18***	1.71***
	0				1.27***	1
	>=10%	SFHA = No			2.12***	1.66***
	<10%				1.80***	1.41***
	0				1	0.79***
Sample			Inspected	Full		
Number of Observations			27,061	71,949	71,949	71,949
Weighted Number of Observations			27,061	301,576	301,576	301,576
Number of Events			1,502	9,053	9,053	9,053
Weighted Number of Events			1,502	9,053	9,053	9,053
Gini			0.589	0.447	0.447	0.447

Note:

1. Population is the loans that were current as of July 2017 and the properties are owner-occupied detached one-unit single-family houses that are located in Harvey-affect area and were inspected after Hurricane Harvey.
2. The control variables include loan age and MTMCLTV as of July 2017, origination DTI, credit score and number of months of reserves as of origination, number of borrowers, product type, loan purpose, third-party origination indicators.
3. Columns (3) and (4) use the same model specification except that column (3) uses the no-damage homes outside the SFHA while column (4) uses the no-damage home inside the SFHA as the reference group.
4. *10%,**5%,***1% Significance Levels.

Table 10. Odds Ratio of Obtaining Forbearance Up to 18 Months After Hurricane Harvey (Full Sample)

Logit Model			Forbearance			
Variables	Categories		(1)	(2)	(3)	(4)
SFHA	Yes		1.66***	1.59***		
	No		1	1		
Predicted Property Damage	>=10%		1.77***	2.25***		
	<10%		1.41***	1.80***		
	0		1	1		
Predicted Property Damage	>=10%	SFHA = Yes			3.96***	2.52***
	<10%				2.62***	1.67***
	0				1.57***	1
	>=10%	SFHA = No			2.13***	1.36***
	<10%				1.87***	1.19***
	0				1	0.64***
Sample			Inspected	Full		
Number of Observations			27,061	71,949	71,949	71,949
Weighted Number of Observations			27,061	301,576	301,576	301,576
Number of Events			1,374	12,788	12,788	12,788
Weighted Number of Events			1,374	13,266	13,266	13,266
Gini			0.674	0.545	0.545	0.545

Note:

1. Population is the loans that were current as of July 2017 and the properties are owner-occupied detached one-unit single-family houses that are located in Harvey-affect area and were inspected after Hurricane Harvey.
2. The control variables include loan age and MTMCLTV as of July 2017, origination DTI, credit score and number of months of reserves as of origination, number of borrowers, product type, loan purpose, third-party origination indicators.
3. Columns (3) and (4) use the same model specification except that column (3) uses the no-damage homes outside the SFHA while column (5) uses the no-damage homes inside the SFHA as the reference group.
4. *10%,**5%,***1% Significance Levels.

Table 11. Odds Ratio of Being Modified Up to 18 Months After Hurricane Harvey (Full Sample)

Logit Model			Disaster Modification			
Variables	Categories		(1)	(2)	(3)	(4)
SFHA	Yes		1.07	1.17***		
	No		1	1		
Predicted Property Damage	>=10%		2.42***	1.90***		
	<10%		1.34*	1.51***		
	0		1	1		
Predicted Property Damage	>=10%	SFHA = Yes			2.34***	1.86***
	<10%				1.42***	1.13
	0				1.26***	1
	>=10%	SFHA = No			1.87***	1.48***
	<10%				1.63***	1.29***
	0				1	0.79***
Sample			Inspected	Full		
Number of Observations			27,061	71,949	71,949	71,949
Weighted Number of Observations			27,061	301,576	301,576	301,576
Number of Events			904	5,273	5,273	5,273
Weighted Number of Events			904	5,391	5,391	5,391
Gini			0.672	0.563	0.563	0.563

Note:

1. Population is the loans that were current as of July 2017 and the properties are owner-occupied detached one-unit single-family houses that are located in Harvey-affect area and were inspected after Hurricane Harvey.
2. The control variables include loan age and MTMCLTV as of July 2017, origination DTI, credit score and number of months of reserves as of origination, number of borrowers, product type, loan purpose, third-party origination indicators.
3. Columns (3) and (4) use the same model specification except that column (3) uses the no-damage homes outside the SFHA while column (4) uses the no-damage homes inside the SFHA as the reference group.
4. *10%,**5%,***1% Significance Levels.

Table 12. Odds Ratio of Becoming 180 or More Days Delinquent or Defaulting as of the 24th Month After Hurricane Harvey (Full Sample)

Multinomial Logit Model			**Becoming 180-days DLQ or Worse**			
Variables	**Categories**		**(1)**	**(2)**	**(3)**	**(4)**
SFHA	Yes		1.06	1.37**		
	No		1	1		
Predicted Property Damage	>=10%		3.24***	1.30		
	<10%		1.08	1.22		
	0		1	1		
Predicted Property Damage	>=10%	SFHA = Yes			2.35***	1.36
	<10%				0.24**	0.14***
	0				1.72***	1
	>=10%	SFHA = No			1.17	0.68
	<10%				1.81***	1.05
	0				1	0.58***
Forbearance			9.66**	13.74***	13.75***	13.75***
Modification			0.20***	0.20***	0.20***	0.20***
Sample			Inspected	Full		
Number of Observations			27,061	71,949	71,949	71,949
Weighted Number of Observations			27,061	301,576	301,576	301,576
Number of Events			89	439	439	439
Weighted Number of Events			89	602	602	602

Note:

1. Population is the loans that were current as of July 2017 and the properties are owner-occupied detached one-unit single-family houses that are located in Harvey-affect area and were inspected after Hurricane Harvey.
2. The control variables include loan age and MTMCLTV as of July 2017, origination DTI, credit score and number of months of reserves as of origination, number of borrowers, product type, loan purpose, third-party origination indicators.
3. Columns (3) and (4) use the same model specification except that column (3) uses the no-damage homes outside the SFHA while column (4) uses the no-damage homes inside the SFHA as the reference group.
4. *10%,**5%,***1% Significance Levels.

Table 13. Odds Ratio of Prepayment as of the 24th Month After Hurricane Harvey (Full Sample)

Multinomial Logit Model			Prepayment			
Variables	Categories		(1)	(2)	(3)	(4)
SFHA	Yes		1.20***	1.22***		
	No		1	1		
Predicted Property Damage	>=10%		1.17**	1.14***		
	<10%		1.09	1.04**		
	0		1	1		
Predicted Property Damage	>=10%	SFHA = Yes			1.97***	1.83***
	<10%				1.28***	1.19***
	0				1.08***	1
	>=10%	SFHA = No			0.99	0.92**
	<10%				1.03	0.96
	0				1	0.93***
Forbearance			1.08	1.12***	1.12***	1.12***
Modification			0.48***	0.43***	0.44***	0.44***
Sample			Inspected	Full		
Number of Observations			27,061	71,949	71,949	71,949
Weighted Number of Observations			27,061	301,576	301,576	301,576
Number of Events			6,022	15,651	15,651	15,651
Weighted Number of Events			6,022	67,257	67,257	67,257

Note:

1. Population is the loans that were current as of July 2017 and the properties are owner-occupied detached one-unit single-family houses that are located in Harvey-affect area and were inspected after Hurricane Harvey.
2. The control variables include loan age and MTMCLTV as of July 2017, origination DTI, credit score and number of months of reserves as of origination, number of borrowers, product type, loan purpose, third-party origination indicators.
3. Columns (4) and (5) use the same model specification except that column (4) uses the no-damage homes outside the SFHA while column (5) uses the no-damage homes inside the SFHA as the reference group.
4. *10%,**5%,***1% Significance Levels.

Table 14. Odds Ratio of Becoming 180 or More Days Delinquent or Defaulting as of the 24th Month After Hurricane Harvey by Home Value (Full Sample)

Multinomial Logit Model			Becoming 180-days DLQ or Worse			
Variables	Categories		home value <=$350k		home value >$350k	
			(1)	(2)	(3)	(4)
Predicted Property Damage	>=10%	SFHA = Yes	2.25**	1.07	2.20*	4.63***
	<10%		0.19*	0.09**	0.27	0.55
	0		2.10***	1	0.47	1
	>=10%	SFHA = No	0.93	0.44**	1.08	2.27
	<10%		2.11***	1.00	1.16	2.44
	0		1	0.48***	1	2.11
Forbearance			10.43***	10.43***	34.21***	34.21***
Modification			0.20***	0.20***	0.16***	0.16***
Number of Observations			53,697	53,697	18,252	18,252
Weighted Number of Observations			215,118	215,118	86,458	86,458
Number of Events			327	327	112	112
Weighted Number of Events			453	453	149	149

Note:

1. Population is the loans that were current as of July 2017 and the properties are owner-occupied detached one-unit single-family houses that are located in Harvey-affect area and were inspected after Hurricane Harvey.
2. The control variables include loan age and MTMCLTV as of July 2017, origination DTI, credit score and number of months of reserves as of origination, number of borrowers, product type, loan purpose, third-party origination indicators.
3. Columns (1) and (3) use no-damage homes outside the SFHA while columns (2) and (4) use no-damage homes inside the SFHA as the reference group.
4. *10%,**5%,***1% Significance Levels.

Table 15. Odds Ratio of Becoming 180 or More Days Delinquent or Defaulting as of the 24th Month After Hurricane Harvey by Borrowers' Incomes (Full Sample)

Multinomial Logit Model			Becoming 180-days DLQ or Worse			
Variables	**Categories**		**<=median income**		**>median income**	
			(1)	**(2)**	**(3)**	**(4)**
Predicted Property Damage	>=10%	SFHA = Yes	2.52**	0.85	2.25**	2.51*
	<10%		0.00	0	0.46	0.52
	0		2.97***	1	0.90	1
	>=10%	SFHA = No	1.06	0.36**	1.20	1.34
	<10%		2.40***	0.81	1.25	1.39
	0		1	0.34***	1	1.11
Forbearance			8.60***	8.60***	17.93***	17.93***
Modification			0.21***	0.21***	0.19***	0.19***
Number of Observations			38,142	38,142	33,807	33,807
Weighted Number of Observations			150,248	150,248	151,328	151,328
Number of Events			243	243	196	196
Weighted Number of Events			315	315	287	287

Note:

1. Population is the loans that were current as of July 2017 and the properties are owner-occupied detached one-unit single-family houses that are located in Harvey-affect area and were inspected after Hurricane Harvey.
2. The control variables include loan age and MTMCLTV as of July 2017, origination DTI, credit score and number of months of reserves as of origination, number of borrowers, product type, loan purpose, third-party origination indicators.
3. Columns (1) and (3) use no-damage homes outside the SFHA while columns (2) and (4) use no-damage homes inside the SFHA as the reference group.
4. *10%,**5%,***1% Significance Levels.

Table 16. Odds Ratio of Becoming 180 or More Days Delinquent or Defaulting as of the 24th Month After Hurricane Harvey by Borrowers' Credit Scores (Full Sample)

Multinomial Logit Model			Becoming 180-days DLQ or Worse			
Variables	Categories		Credit Score <=720		Credit Score>720	
			(1)	(2)	(3)	(4)
Predicted Property Damage	>=10%	SFHA = Yes	2.12**	0.99	2.68**	3.48**
	<10%		0.35*	0.16**	0.00	0
	0		2.15***	1	0.77	1
	>=10%	SFHA = No	1.02	0.48**	1.52	1.97
	<10%		1.42	0.63*	2.57***	3.34**
	0		1	0.46***	1	1.3
Forbearance			9.90***	9.90***	38.43***	38.43***
Modification			0.20***	0.20***	0.20***	0.20***
Number of Observations			34,755	34,755	37,194	37,194
Weighted Number of Observations			115,919	115,919	185,657	185,657
Number of Events			333	333	106	106
Weighted Number of Events			424	424	178	178

Note:

1. Population is the loans that were current as of July 2017 and the properties are owner-occupied detached one-unit single-family houses that are located in Harvey-affect area and were inspected after Hurricane Harvey.
2. The control variables include loan age and MTMCLTV as of July 2017, origination DTI, credit score and number of months of reserves as of origination, number of borrowers, product type, loan purpose, third-party origination indicators.
3. Columns (1) and (3) use no-damage homes outside the SFHA while columns (2) and (4) use no-damage homes inside the SFHA as the reference group.
4. *10%,**5%,***1% Significance Levels.

Appendix

Background on Event Reconstruction using the RMS Catastrophe Model

RMS developed a method of event reconstruction for the precipitation-induced inundation from Hurricane Harvey (2017), which was used as the basis of flood hazard in this analysis, along with the proprietary RMS building damage component to determine flood damage for the Fannie Mae loans. To create the reconstruction, RMS used event precipitation data from the Climate Prediction Center as an input to the RMS U.S. Inland Flood HD Model to simulate the rainfall, run-off, and pluvial and fluvial flows across Texas and Louisiana. In addition, RMS utilized meteorological forcing data in the simulation, including a period preceding the event, used to set the antecedent conditions prior to the event. The derived river flows and run-off values were used to drive the inundation model component that underpins the inland flood model, to create a bespoke hazard reconstruction for Hurricane Harvey. RMS validated the simulated event flood extent and depths by comparing them to i) USGS gauge discharges, ii) USGS water surface elevation values, iii) water depth observations from RMS field reconnaissance, and iv) available satellite and areal imagery.

Table A1. Odds Ratio of Prepayment
as of the 24th Month After Hurricane Harvey by Home Value
(Full Sample)

Multinomial Logit Model			Prepayment			
Variables	**Categories**		**home value <=$350k**		**home value >$350k**	
			(1)	**(2)**	**(3)**	**(4)**
Predicted Property Damage	>=10%	SFHA = Yes	2.00***	1.74***	1.97***	2.26***
	<10%		1.27***	1.11*	1.30***	1.49***
	0		1.15***	1	0.87***	1
	>=10%	SFHA = No	0.93**	0.81***	1.06	1.22***
	<10%		1.09***	0.95	0.98	1.13**
	0		1	0.87***	1	1.15***
Forbearance			1.06***	1.06***	1.36***	1.36***
Modification			0.44***	0.44***	0.42***	0.42***
Number of Observations			53,697	53,697	18,252	18,252
Weighted Number of Observations			215,118	215,118	86,458	86,458
Number of Events			11,692	11,692	3,959	3,959
Weighted Number of Events			48,574	48,574	18,683	18,683

Note:

1. Population is the loans that were current as of July 2017 and the properties are owner-occupied detached one-unit single-family houses that are located in Harvey-affect area and were inspected after Hurricane Harvey.
2. The control variables include loan age and MTMCLTV as of July 2017, origination DTI, credit score and number of months of reserves as of origination, number of borrowers, product type, loan purpose, third-party origination indicators.
3. Columns (1) and (3) use no-damage homes outside the SFHA while columns (2) and (4) use no-damage homes inside the SFHA as the reference group.
4. *10%,**5%,***1% Significance Levels.

Table A2. Odds Ratio of Prepayment
as of the 24th Month After Hurricane Harvey by Borrowers' Income
(Full Sample)

Multinomial Logit Model			**Prepayment**			
Variables	**Categories**		**<=median income**		**>median income**	
			(1)	**(2)**	**(3)**	**(4)**
Predicted Property Damage	>=10%	SFHA = Yes	2.25***	1.89***	1.69***	1.77***
	<10%		1.29***	1.08	1.27***	1.33***
	0		1.19***	1	0.96	1
	>=10%	SFHA = No	1.13***	0.95	0.88***	0.92*
	<10%		1.06	0.89**	0.99	1.04
	0		1	0.84***	1	1.05
Forbearance			1.12***	1.12***	1.25***	1.25***
Modification			0.44***	0.44***	0.42***	0.42***
Number of Observations			38,142	38,142	33,807	33,807
Weighted Number of Observations			150,248	150,248	151,328	151,328
Number of Events			7,978	7,978	7,673	7,673
Weighted Number of Events			32,670	32,670	34,587	34,587

Note:

1. Population is the loans that were current as of July 2017 and the properties are owner-occupied detached one-unit single-family houses that are located in Harvey-affect area and were inspected after Hurricane Harvey.
2. The control variables include loan age and MTMCLTV as of July 2017, origination DTI, credit score and number of months of reserves as of origination, number of borrowers, product type, loan purpose, third-party origination indicators.
3. Columns (1) and (3) use no-damage homes outside the SFHA while columns (2) and (4) use no-damage homes inside the SFHA as the reference group.
4. *10%,**5%,***1% Significance Levels.

Table A3. Odds Ratio of Prepayment as of the 24th Month After Hurricane Harvey by Borrowers' Credit Scores (Full Sample)

Multinomial Logit Model			Prepayment			
Variables	Categories		Credit Score <=720		Credit Score>720	
			(1)	(2)	(3)	(4)
Predicted Property Damage	>=10%	SFHA = Yes	2.48***	2.37***	1.68***	1.50***
	<10%		1.14**	0.90	1.37***	1.23***
	0		1.05	1	1.12**	1
	>=10%	SFHA = No	1.36***	1.30**	0.83***	0.74***
	<10%		1.06	1.01	1.02	0.91**
	0		1	0.96	1	0.89**
Forbearance			0.97	0.97	1.55***	1.55***
Modification			0.46***	0.46***	0.37***	0.37***
Number of Observations			34,755	34,755	37,194	37,194
Weighted Number of Observations			115,919	115,919	185,657	185,657
Number of Events			7,424	7,424	8,227	8,227
Weighted Number of Events			26,966	26,966	40,291	40,291

Note:

1. Population is the loans that were current as of July 2017 and the properties are owner-occupied detached one-unit single-family houses that are located in Harvey-affect area and were inspected after Hurricane Harvey.
2. The control variables include loan age and MTMCLTV as of July 2017, origination DTI, credit score and number of months of reserves as of origination, number of borrowers, product type, loan purpose, third-party origination indicators.
3. Columns (1) and (3) use no-damage homes outside the SFHA while columns (2) and (4) use no-damage homes inside the SFHA as the reference group.
4. *10%,**5%,***1% Significance Levels.