Mortgage Performance and Home Sales for Damaged Homes Following Hurricane Harvey

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Abstract

We analyze loan performance and property transactions following Hurricane Harvey using a novel dataset with property-specific flood insurance and claim information. Using insurance claims to proxy for damages we find that both short-term delinquency and forbearance take-up are positively associated with damages. Loan modification is positively correlated with damages of up to 50 percent of property value and negatively correlated thereafter, suggesting that, for severely damaged homes with flood insurance, loan modifications are not an attractive remedy for delinquency concerns. By contrast, the likelihood of loan prepayment is strongly associated with large damage levels. This indicates such homeowners are likely selling their home unrepaired, making up for any shortfall between loan balance and sale price with insurance proceeds. Property transactions analysis reveals that damaged homes are less likely to sell immediately following Harvey when compared to undamaged homes. If they do sell, compared to undamaged homes, they do so at a steep price discount, sell faster and are in worse condition when sold. A pattern consistent with the homeowner behavior described above and with investors purchasing damaged homes looking to "fix and flip" the properties. We find the negative impact of large damages on sale price lingers, though at a subdued discount, at least up to two years out.

Keywords: Flood Risk, Flood Insurance, NFIP, Loan Performance, Home Sales

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1. Introduction

The frequency and severity of natural disasters events in the United States has been increasing since 1980. Specifically, Smith (2024) estimates that billion-dollar events, which account for over 85% of all costs associated with natural disasters in the US from 1980-2023, increased from an average of 3.3 events with an annual cost of $21.4 billion in the 1980s, to 20.4 events a year with an annual cost of $120.6 billion in the last five years (2019 to 2023). Costs associated with flooding are a strong component of total costs associated with natural disasters. Wing et al. (2022) estimate that as of 2020, the US's annual damages from flooding were $32.1 billion, and were expected to increase by 26% by 2050. To help cover costs associated with flood damages to building structure and contents for homeowners and renters, the U.S. federal government makes flood insurance available through the National Flood Insurance Program (NFIP) but take-up rates are low.[1] For properties located in Special Flood Hazard Areas (SFHAs), those with mortgages are generally required to purchase insurance as a condition of the loan. As such, understanding how homeowners with flood insurance may behave in the face of flood damages is critical to assessing potential impacts on mortgage performance and the housing market more generally.

Multiple papers have studied the impact of flooding events or flood risk, generally focusing on impacts to house prices.[2] The literature generally finds price decreases associated with flooding events or greater flood risk. However, the variability in magnitude of estimates across papers indicates further work is still warranted.[3] Other research has focused on credit outcomes following hurricanes (e.g., Billings et al., 2022; Du and Zhao, 2020; Gallagher and Hartley, 2017; and Kousky et al., 2020). This work tends to find adverse short-term effects on credit outcomes following storms.

Research on the role of flood insurance has been understudied due to a lack of data (Kousky, 2019). For instance, given data limitations, Kousky et al. (2020) make the simplifying assumption that properties outside SFHAs do not have flood insurance. However, some homeowners (22 percent in our data) voluntarily obtained flood insurance outside SFHAs. By using novel data that includes property-specific flood insurance and claim information for homes in Hurricane Harvey (henceforth Harvey) affected zip codes, we improve on this simplifying assumption. Our second main contribution is to examine the effect of property damage on post-storm sales patterns including prices, time on market, and property conditions at the time of sale.

Considerable economic disruption typically follows a major storm. Homeowners may be unable or unwilling to pay their mortgage due to a loss in income or sustained property damages. If homeowners have flood insurance, claim proceeds will leave them in a stronger financial position to repair their homes and resume mortgage payments or, in the case of severely damaged structures, they may elect to sell their home and use insurance proceeds to make up for any shortfall in the remaining balance on their mortgage. We

[1] FEMA (2018) estimates that the take-up rate of flood insurance outside Special Flood Hazard Area (SFHA) for homeowners with a mortgage is only about 2 percent. Kousky et al. (2018) estimate that the flood insurance take-up rate within SFHAs is about 30 percent. Kousky et al. (2018) estimate that the NFIP covers around 95% of all active insurance policies.

[2] See for example, Beracha and Prati, 2008; Bernstein et al., 2019; Bin and Landry, 2013; Bin and Polasky, 2004; Harrison et al., 2001; Kousky, 2010; Ortega and Taspinar, 2018; Murfin and Spiegel, 2020; Zhang, 2016; and Zhang and Leonard, 2019.

[3] For instance, Murfin and Spiegel (2020) did not find a change in coastal property prices due to flood risk.

find evidence of both sets of behaviors occurring. Specifically, we see that sustaining flood damages, as proxied by insurance claims—an approach we validate using inspected damages for a subset of properties—is associated with increases in short-term delinquency and forbearance take-up following a storm. We further see that the likelihood of obtaining a loan modification increases with damages up to 50 percent of property value, falling thereafter. This indicates that, for borrowers whose homes experience more significant flood damages, the option to modify their loan terms is not as appealing, as they are seen to be more likely to prepay their loan and sell their properties unrepaired, within six months of Harvey. From the sales analysis we see these unrepaired homes sold at a steep price discount of up to 17 percent, had shorter times on market, and were more likely to have a bad property condition rating at the time of sale. We further see that homes with large damages have a lingering price discount, in the order of 10 percent, up to the end of 2019 – or just over two years post-storm.

The remainder of the paper proceeds as follows: section 2 reviews the literature; section 3 describes the data; section 4 details our methodology; section 5 discusses the results; and section 6 concludes.

2. Literature Review

The majority of papers analyzing the effects of flood risk have focused on home price effects. Previous research finds a decrease in home prices after a flood event (Bin and Polasky, 2004; Carbone et al., 2006). In some markets, homes inside SFHAs sell for less than those outside SFHAs after controlling for property characteristics (Harrison et al., 2001; Ortega and Taspinar, 2018; Bernstein et al., 2019). Home price discounts are more significant in areas with a stronger belief in climate change as measured by Yale Climate Opinion Survey (Bernstein et al., 2019; Baldauf et al., 2020) or Climate Attention Index (Giglio et al., 2015). McAlpine and Porter (2018) similarly find a slower price appreciation in the areas with the highest risk from sea level rise relative to those with no such risk. The price decrease is often temporary and rebounds within a short period (Beracha and Prati, 2008; Bin and Landry, 2013). However, a recent study reports a permanent price decrease after Harvey (Ortega and Tașpınar, 2018). Zhang (2016) and Zhang and Leonard (2019) look at price differences following flooding events across SFHA status, finding price reductions of 3 to 15 percent for properties in SFHAs. One of the reasons they give for this variation in price reductions is the $250,000 upper limit on flood insurance coverage leading to differences by property value. A negative price effect driven by a flood event can also propagate to surrounding areas. Kousky (2010) finds a decline in home prices outside SFHAs even if there was no damage. However, some papers find no change in coastal property prices attributable to flood risk (Murfin and Spiegel, 2020). Overall, the literature tends to find price decreases associated with flooding events or greater flood risk. However, the variability in findings across papers suggests further work is warranted.

Although flooding is the most widely studied natural disaster, other disasters such as wildfires and earthquakes have also garnered researchers' attention. Previous research studying the effect of wildfires on home prices generally finds an immediate negative impact (Loomis, 2004; Mueller et al., 2009; McCoy and Walsh, 2018). Interestingly, Mueller et al. (2009) find a stronger effect of the second wildfire on home prices (decrease of about 23 percent) than that of the first one (decrease of about 10 percent) through a reduction in demand induced by the improved public perception of the risks. Similar to flood research, McCoy and Walsh (2018) show that home prices decreased after a wildfire and return to baseline levels within two to three years, suggesting a short-term effect. It also indicates that the risk perceptions in high-risk areas likely faded away after the event. Similarly, researchers have shown that earthquakes are associated with home price reductions (Murdoch et al., 1993; Beron et al., 1997). For instance, Murdoch et al. (1993) find about a two percent decrease in home prices after the Loam Prieta earthquake in 1989, with the effects more pronounced in areas where buyers are informed of potential earthquake risk.

In addition to home price effects, loan performance following natural disasters is another important question, although less explored (Kousky, 2019). When a property is damaged by a flood, loan performance is likely to be worse because the property value will decrease, increasing loan-to-value ratio (LTV), and because the borrower may face a liquidity constraint, either from the need to cover costs associated with flood damages or due to possible disruptions to income if the area experiences a negative economic shock. Both increased LTV ratios and liquidity constraints have been seen to increase the likelihood of mortgage default.[4] Flood insurance can reduce this risk, as homeowners can cover the cost of repairs with proceeds from an insurance claim or pay off their mortgages. Prior research is consistent with this idea. For example, Kousky et al. (2020) show that homes damaged by Harvey are likely to have a higher 90-day delinquency rate in the short-term. In a similar manner, Du and Zhao (2020) find that the 180+ days delinquency rate of the treatment group is 10 basis points per quarter higher than the control group a year after Harvey and 91 basis points higher after Hurricane Maria. They argue that the increase in delinquency rate can be explained by damage-adjusted LTV and initial claims. However, they do not find a difference in prepayment rates between the treatment group and the control group. Gallagher and Hartley (2017) look at 90-day delinquency rates for multiple credit products following Katrina, finding that, among residents experiencing the greatest level of flooding, delinquencies were 10 percent higher than non-flooded residents in the first quarter following Katrina. Similar to the effect of a flood on home prices, this effect is not homogeneous, varying due to the differences in access to personal financial resources, government assistance, insurance payouts or loans.

Households experiencing flooding generally have three sources of federal funds: NFIP, Federal Emergency Management Agency (FEMA)'s Individual and Households Program (IHP), and Small Business Administration (SBA) loans.[5] The first is only available to insured homeowners or renters, whereas the other two programs are the primary sources of funding for uninsured homeowners and business owners. Previous work provides evidence that flooded residents tend to pay off their mortgages using flood insurance proceeds rather than rebuild in areas where reconstruction costs may be greater than home values (Gallagher and Hartley, 2017; Kousky et al., 2020). Likely for this reason, loan prepayment rates are higher for borrowers inside SFHAs than those outside SFHAs, where flood insurance is not mandatory. On the other hand, homeowners outside SFHAs tend to have a higher likelihood of loan modification and greater rates of 180 or more days of delinquency and default during the two years after Harvey (Kousky et al., 2020). One possible explanation for this result is the fewer public resources available for uninsured homeowners with damaged homes. The grants from IHP are capped at $33,300. The average grant award following Harvey was less than ten thousand dollars ($8,900), whereas the average NFIP claim was around $117,000.[6] Differences in SBA loan accessibility, also contribute to heterogeneous effects. According to Billings et al. (2022), the average SBA loan distributed to Harvey victims ($79,183) in their sample was ten times larger than the average cash grant ($7,446) from FEMA's IHP. However, SBA loans were only

[4] See Foote and Willen (2018) for a review of the literature on mortgage default.
[5] Another source of assistance for homeowners are buyout programs, see Greer and Brokopp Binder (2017) for a review.
[6] Source: https://www.fema.gov/significant-flood-events

available to borrowers with higher credit profile, generating a wedge in recovery for homeowners with lower credit profile (Begley et al., 2021).

Our study builds on the previous literature. To our knowledge, ours is the first paper to study both loan performance and subsequent sales together. We are particularly interested in the relationship between flood damages, loan performance, and subsequent sales. Our work most closely relates to Kousky et al. (2020). We improve on their measure of whether a household had flood insurance by using actual policy data from NFIP rather than assuming coverage if the properties were in SFHAs. In addition, their property-level damage measure is a qualitative estimate of damage (none, minor, moderate, or severe) rather than the actual damage amount. We improve on their approach as we can directly observe whether homeowners had flood insurance and how much they received following a successful NFIP claim. Our analysis of post-storm home sales provides additional detail on the behavior of homeowners in the housing market when facing flood damages to their property.

3. Data

We combine data from multiple sources. We first define the set of Harvey-affected zip codes in Texas around July 2017. Following Kousky et al. (2020), Harvey-affected zip codes are those with more than 20 valid registrations for FEMA's IHP following Harvey. This results in a set of 422 zip codes. From about 302,000 loans on owner-occupied detached one-unit properties in Fannie Mae's single-family book of business as of July 2017 within these Harvey-affected zip codes, we construct a final dataset for loan performance analysis of around 72,000 loans. This includes roughly 27,000 loans on properties that were inspected post-Harvey. The remaining loans are ones without a history of delinquency, which are sampled at a 1-in-10 ratio, mimicking the approach in Kousky et al. (2020).[7]

We supplement our loans dataset with NFIP flood insurance policy and claim information from FEMA. In contrast to the publicly available NFIP data on the OpenFEMA website. These data include property-level insurance policy and claims information. Specifically, our dataset contains all NFIP residential policies in effect in August 2017 for the set of Harvey-affected zip codes and any claims associated with Harvey. The claim data covers claims with a loss date between August 24th and September 13th, 2017. Note that throughout, when we reference claim or claim amount, we specifically refer to the payments made by the NFIP on a given claim.

Our data allow us to identify properties with flood insurance, even if the properties are outside SFHAs. This allows us to more accurately gauge how the presence of flood insurance is correlated with our various outcome measures, whereas previous research has relied on a property being located inside an SFHA as indicating they likely had flood insurance (e.g. Kousky et al. 2020). Figure 1 highlights the fact that proxying for flood insurance status with a property being in an SFHA will underestimate flood insurance prevalence. 25.4 percent of properties in our sample were matched to an NFIP insurance policy, but 20.1 percent of properties have insurance and are outside of an SFHA. Put another way, 79 percent of properties with insurance in our sample are located outside of an SFHA (20.1 of the 25.4 percent with insurance). Figure 1 also evidences the fact that not all the properties we estimate to be in an SFHA are matched to an

[7] Loans in zip codes with less than 20 total loans are sampled at a 1-in-2 ratio. Loan performance regression results throughout make use of sample weights to reflect differing likelihood of a loan being in our estimation sample.

NFIP insurance policy, 0.8 percent of all properties in the sample are deemed to be in an SFHA and have no NFIP insurance information. This may happen due to an inaccurate determination of SFHA status, or due to imprecision in the address field used to match properties between our loan dataset and the NFIP insurance dataset, for more details please refer to Appendix 1. Another salient feature of Figure 1 is that the share of properties with a positive claim amount, among those with insurance, is higher for properties located in SFHAs than for those outside SFHAs. This is a finding we will see echoed in our loan performance measures, where we generally see more property damage and more negative loan performance outcomes for properties in SFHAs. Note that a claim is defined as large if it is above the median, whereas a claim is small if it is below the median (around $125,000).

Following Kousky et al. (2020) we look at five different loan performance measures, with different time-horizons following Harvey. Short-term loan performance is gauged by the prevalence of loans becoming 90 or more days delinquency within five months after Harvey. Medium-term performance is measured via forbearance take-up and the incidence of loan modifications within 18 months after Harvey. Long-term loan performance is measured via the incidence of loans becoming 180 or more days delinquency (henceforth defaulting), or loans prepaying within 24 months of Harvey.[8] Summary statistics for these loan outcomes by NFIP policy status are displayed on the top of Table 1A. The group without a policy had higher short-term delinquency, forbearance, and modification rates, but the prepayment rate was higher for the former group. No difference is evident in the default rate across these two groups.

Our main explanatory variables for the loan performance regressions are the presence of flood insurance ("policy" variable in Table 1A) and the presence and size of insurance claims associated with Harvey ("claim size" variable in Table 1A). From Table 1A we see that 22.5 percent of loans with a policy had a claim associated with Harvey (3,823 out of 17,001 loans with a policy). We take the claim amount as a proxy for flood damages sustained by the property. In order to validate this approach, in Figure 2 we contrasted the claim-to-value ratio (ratio of claim amount to mark-to-market property value as of July 2017) to the assessed damages for the properties that were inspected post-Harvey. There is a clear correlation between claim amounts for properties with insurance and assessed damages as assigned by the inspector. As we move from no damage to severe damage (second to fourth bars in Figure 2) we observe that a greater share of properties have claims, and that those claims tend to be larger relative to property value. In fact, for the set of properties assessed to have severe damage, only eight percent of properties with insurance had no claim. Figure 2 also highlights the differences in the share of properties with insurance (black line in Figure 2) across inspected damage groups. We note that properties with greater assessed damage were more likely to have insurance (reflecting the fact that these were more likely to be located in SFHAs). From Table 1A, we also observe that among the set of inspected properties those with insurance are more likely to have non-zero assessed damages, again reflecting the greater likelihood of properties with a policy being located in SFHAs, which generally correlates with higher flood damages from Harvey.

We are also interested in how receipt of FEMA IHP grants may affect loan performance. Since we do not observe the property-level IHP registration, we use the IHP registration numbers relative to the population at the zip code-level using the 2015-2019 American Community Survey (ACS) 5-year population estimates. IHP registrations per capita can be seen as a measure of the relative economic disruption due to the storm in a given zip code. In Table 1A we present the summary statistics for the IHP Ratio, which is measured as the zip-code total IHP registrations per capita multiplied by 100 (for ease of exposition). We

[8] Please refer to Appendix Figure A2 for a depiction of the timing of loan performance measures.

observe that loans with an NFIP policy had a higher IHP ratio, indicating that properties with these loans tended to be located in areas where the economic disruption following Harvey was higher.

We control for a set of loan characteristics in our regressions; these are detailed in Table 1A. Some of these characteristics are measured as of July 2017 (the month before Harvey), namely loan age in months and mark-to-market combined loan-to-value ratio (MTMCLTV) as of July 2017. Other characteristics are measured at the time of origination, these are: debt-to-income (DTI) ratio, credit score (FICO), single borrower status, 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 (as indicators for less than six months, six to eleven months, or more than eleven months of reserves).[9] From Table 1A we see that loans with an NFIP policy generally had higher credit score borrowers, higher home values, and higher borrower incomes, but lower DTI.

To investigate sale outcomes for properties in Harvey impacted zip codes, we make use of data for approximately 392,000 arms-length sale transactions occurring between the start of January 2016 and the end of December 2019. These sale transaction data come from Fannie Mae's Collateral Underwriter (CU) comparable transactions dataset and closely matches other estimates of overall sales volumes.[10] This dataset includes a rich set of property attributes that we can control for in the regressions, detailed in the next paragraph. Further, the transactions dataset includes transactions for properties that are not part of our loan analysis sample, hence we have a broader view of the home purchase market for this subset of our analysis. The transactions outcomes that we focus on are sales price, days on market, and property condition. Table 1B details provides summary statistics for these sale outcome variables by NFIP policy status. Note the larger sample size in Table 1B than in Table 1A, per the point above about Table 1B including sales for properties which we do not see in our loan performance dataset. We observe that properties with a policy tend to sell at a higher price but there are no meaningful differences in days on market. The higher price can partly be explained by these properties being more likely to be located in SFHAs, hence more likely to be coastal properties with a price premium.

The set of property attributes visible at the time of a sale that we control for in the sale outcome regressions are detailed in Table 1B. These include home age, gross living area (GLA), number of bathrooms, number of bedrooms, property condition and quality ratings, and location and view ratings. Condition and quality ratings are appraiser-indicated and are descending in quality or condition, i.e.: a rating of 1 indicates the highest quality or condition, a rating of 6 the lowest.[11] In Table 1B, we see that homes with a policy are less likely to have a condition rating of C1 at the time of sale, which denotes a new or fully renovated home, than homes without a policy. This effect is partly mechanical due to the way in which we define the group with a policy. More specifically, since we define the group with a policy based off whether they had a

[9] Following the specifications in Kousky et al. (2020), some variables are included in the regressions as splines, and others as indicator variables. Variables included as splines are loan age (with knots 3, 12, 60, 96), MTMCLTV (knots at 30%, 80%, 100%), FICO (knots at 620, 820), and DTI (knots at 36%, 45%). In cases where the information is missing from the time of origination, an indicator for value missing is included in the regression.

[10] This sales transactions data is a subset of that used in McClain and Mota (2024), which closely matched estimates of total sales volumes in Texas, produced by the Texas Real Estate Research Center - https://www.recenter.tamu.edu/data/housing-activity/#!/activity/State/Texas

[11] For more details on condition and quality ratings please refer to https://selling-guide.fanniemae.com/Selling-Guide/Origination-thru-Closing/Subpart-B4-Underwriting-Property/Chapter-B4-1-Property-Assessment-and-Valuation/Section-B4-1-3-Appraisal-Report-Assessment/1032992471/B4-1-3-06-Property-Condition-and-Quality-of-Construction-of-the-Improvements-03-01-2023.htm

policy in effect in August 2017, then track sales for those same addresses for the entire period, the only way these homes would show up as a C1 in future transactions is if the homes are fully renovated. By contrast, for the group with no policy, any new construction can appear post-2017, both new constructions at new addresses and full renovations at the same address. It is for this reason that when we assess property condition as an outcome, we do not look at average condition but instead at the likelihood a property has a bad condition rating (C5 or C6). From Table 1B we also observe that homes with a flood insurance policy tend to be slightly older and larger and are more likely to have a beneficial location and view.

4. Methodology

In our loan performance tests, we use logit or multinomial logit models to assess the impact of flood insurance on loan performance, per equation (1).

$$\Pr(performance\ outcome_i) = f(X_i\beta + Z_i\alpha) \tag{1}$$

Since our data includes individual loan records at a point in time (not a panel), it does not have a time operator. In the model, i indicates a loan. The dependent variables can be divided into two groups. The short- and intermediate-term outcomes are 90-day delinquency, forbearance, and modification. The long-term outcomes include both loan prepayment and default. We use the logit model for the short-/intermediate-term outcomes and the multinomial logit model for the long-term outcomes. Our main interest lies in the coefficient of vector Z, which includes indicators for SFHAs, NFIP policy, NFIP claim size category, and interactions of these variables. X_i indicates the remaining independent variables included in our models, as shown in Table 1A.

In the sale outcomes regressions we use an event study model that contrasts the evolution of the dependent variables post-Harvey over time, per equation (2).

$$Sale\_Outcome_i = \theta\ Policy\_Claim\_Group_i * Qtr_t + \beta G_i + \mu + \epsilon_i \tag{2}$$

Where Qtr_t is a vector of indicator variables for the year and quarter from 2016 Q1 to 2019 Q4, G_i is the vector of property attributes detailed in Table 1B, μ are zip code fixed effects, and ϵ_i is the error term. The sale outcomes we model in this manner are price (log of price in regressions), days on market, and property condition at the time of sale. Note that since we are trying to isolate differences pre- and post-Harvey, we split the 2017 Q3 indicator into two parts: one including the month of July 2017, the period immediately before Harvey; and another capturing the months of August and September 2017, the two initial months post-Harvey. Note as well that in the property condition regressions, we do not include the condition indicators as explanatory variables in the regressions.

5. Results

5.1. Loan Performance Outcomes

Short-Term Loan Performance

Our short-term loan performance measure is an indicator of a loan experiencing a 90 or more days delinquency within five months of Harvey. Table 2 shows odds ratios for our main variables of interest obtained from estimating a logistic regression per the specification in equation (1) for this outcome. In column (1) we separately control for the loan being for a property in an SFHA and for the presence of insurance and size of claim; in column (2) we interact SFHA status with insurance and claim status. This table layout is emulated for all other loan performance results tables. All models control for the full set of property characteristics detailed in Table 1A as well as for the IHP ratio.

Focusing initially on the results displayed in column (1) of Table 2, we see that homeowners inside SFHAs were 1.48 times more likely to have a 90-day delinquency compared to those outside SFHA. This is similar to the finding in Kousky et al. (2020) of SFHA homes being 1.40 times more likely to have a 90-day delinquency. Since SFHAs tends to have a higher flood risk than non-SFHAs, this result is not surprising. One difference between homes in SFHAs and non-SFHAs is the mandatory flood insurance requirement for homeowners with federally backed loans inside SFHAs. If the difference in performance for loan associated with properties inside SFHAs relative to outside SFHAs were purely driven by the differential likelihood of having insurance, then the inclusion of the insurance indicator in the regression should make the statistical significance of *SFHAs* disappear. Yet, that is not the case.

Focusing on the coefficients on insurance policy and claim status in column (1) of Table 2, we can observe that higher claims, hence higher damages, are associated with greater short-term delinquency. This finding is consistent with that in Kousky et al. (2020). Specifically, borrowers with a large insurance claim are 3.5 times likelier to become 90 or more days delinquent on their mortgage, than are borrowers without insurance. A claim is defined as large if it is above the median, whereas a claim is small if it is below the median (around $125,000).[12] We also note that borrowers with insurance, but no claim associated with Harvey were half as likely to become 90-day delinquent following Harvey. This lower delinquency rate can reflect the fact that homes with no insurance claims were less likely to have any flood damages than those without insurance, per Figure 2. Another possible explanation pertains to the fact that borrowers who choose to purchase flood insurance may be more financially aware or financially resilient, hence less likely to enter delinquency. This latter point is one we can explore further by looking at the results in column (2) of Table 2.

In the column (2) regression specification of Table 2 we interact SFHA, policy, and claim status. This allows us to contrast the effects of insurance presence and claim size across SFHA status. We can therefore gauge differences in these effects for borrowers required to obtain flood insurance versus those that do so voluntarily. The main finding from these column (2) results are that the patterns of increased delinquency for larger claim amounts and lesser likelihood of delinquency for borrowers without a claim than those without insurance are evident both inside and outside of SFHAs. We also see that the odds ratios for all policy and claim status groups are always higher for properties in SFHAs, consistent with the general

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[12] We also conducted the analysis using the ratio of claim amount to property value to define small and large claims. Results are comparable to those obtained when the definition is based on the dollar value of claims.

finding of higher delinquency in SFHAs visible in column (1). Note that all loans associated with properties in SFHAs in our sample must, by requirement, have insurance, hence the group with no insurance but within SFHA likely indicates an imperfect match between our loans dataset and the NFIP's insurance dataset. As such, we can assume that this set of loans with no NFIP match within SFHAs actually do have insurance. Hence the difference in performance between this set of loans and those with insurance but no claim is probably driven by the differences in flood damages. Thus showing that this pattern of lower delinquency for borrowers with no claim relative to those without insurance, visible in column (1), does not simply reflect unobserved differences between borrowers who choose to purchase insurance and those that choose to not.

In Panel A of Figure 3, we can assess whether there are non-linearities evident in the impact of flood damages on short-term delinquency. This figure again shows that homes with a zero claim-to-value ratio had a lower likelihood of delinquency than homes with no insurance, as was seen in Table 2. Further, we can observe that the positive correlation between damages and short-term delinquency appears to plateau around a claim-to-value ratio of 0.5. Put another way, once flood damages are greater than or equal to 50 percent of our estimated property value, we see no added increase in the likelihood of delinquency following Harvey. Together, results in Table 2 and in Panel A of Figure 3 clearly indicate that higher flood damages are associated with a higher likelihood of short-term delinquency following Harvey.

Medium-Term Loan Performance

To assess medium-term loan performance, our dependent variables are indicators of loans entering forbearance or a loan modification occurring within 18 months of Harvey. Table 3 presents the regression results from estimating a logistic regression using the specification in equation (1) for the outcome of forbearance. The impacts of being in an SFHA, and insurance policy and claim status on forbearance are very similar to those seen for short-term delinquency. Since 84 percent of loans with short-term delinquency following Harvey enter forbearance, the similarity in impacts across these two outcomes is perhaps unsurprising. Nonetheless, 43 percent of loans that enter forbearance do so without ever experiencing a short-term delinquency, as measured in this paper, following Harvey. In fact, loans may enter and exit forbearance following Harvey and never experience any other of the short-, medium-, or long-term outcomes that we analyze in this paper. Per Figure 4, this is the third most common loan trajectory within 24 months of Harvey. Given this, the similarity in the impacts of damages on short-term delinquency and forbearance is striking.

Panel B of Figure 3 displays logistic regression odds-ratios for the impact of claim-to-value ratio on the outcome of forbearance within 18 months of Harvey. As discussed above for Table 2 results, we again see a remarkably similar set of coefficients for 90-day delinquency and forbearance. Specifically, we observe that borrowers with no claim had a lower likelihood of forbearance than did borrowers with no insurance policy. Again, likely reflecting the fact that borrowers with no policy are more likely to have damages than those with no claims, per Figure 2. We see that the positive relationship between the claim-to-value ratio increases up to a ratio of 0.5 and plateaus thereafter. That being said, there is a pronounced uptick in the likelihood of forbearance for borrowers with a claim-to-value ratio of 1 relative to those just with a ratio just below that value.

Turning our attention to our other measure of medium-term loan performance, Table 4 presents the regression results from estimating a logistic regression using the specification in equation (1) for the outcome of loan modification. Akin to the findings in Tables 2 and 3, for short-term delinquency and forbearance, respectively, we again see evidence of larger flood damages being associated with a greater likelihood of loan modification. Further, we again see that borrowers with no insurance claim had a lower likelihood of loan modification than did borrowers without insurance. We also see no meaningful difference in the pattern of damage impact on loan modification by SFHA status. These results are echoed in the common loan path trajectories visible in Figure 4. In that figure we tend to see that for common trajectories which include a loan modification, the largest share of loans in these trajectories tends to be those for properties with large insurance claims. We do however note that for the loan trajectory which includes entering forbearance and obtaining a loan modification, without having experienced a 90-day delinquency within five months of Harvey, the group with the largest share of loans experiencing this trajectory is that of borrowers with a small claim. This is notable given the findings in Figure 3 Panel C, discussed in the next paragraph.

By contrast to the results visible in Table 4, which denoted a strong similarity in the impact of damages on loan modification relative to the impact of damages on early delinquency and forbearance, the impact of insurance claim-to-value ratio on loan modification is markedly different than for the other two outcomes assessed thus far. Panel C of Figure 3 presents these odds ratios for the impact of claim-to-value ratio on loan modification and shows the odds ratios increasing up to a claim-to-value ratio of 0.5 and decreasing thereafter. In fact, for borrowers with a claim-to-value ratio of 0.9 or greater we see no meaningful difference in the likelihood of obtaining a loan modification relative to the reference group of borrowers with no flood insurance policy. These results suggest that borrowers whose homes experience larger damages may make the decision that a loan modification is not helpful since they are more likely to sell the property and use flood insurance proceeds to pay off their loan. This is a point we will return to when assessing loan prepayment and property sales following Harvey. By contrast, for borrowers whose homes had less extensive damage and may be facing some challenges in making mortgage payments taking the option of undergoing a loan modification is appealing.

Long-Term Loan Performance

We now consider long-term loan performance within 24 months of Harvey. The two outcomes are default and prepayment and we employ a multinomial logistic regression model to assess these competing risks. Tables 5 and 6 show the regression results. Table 5 presents the results for the outcome of default. In column (1), we observe that none of the policy and claim status indicators have an association with default likelihood. We see that SFHA status is associated with a greater likelihood of default, as is the IHP ratio. These indicate that loans for homes in areas likely to have experienced greater flood damages and economic impact are more likely to default. That being said, there is no discernible impact of loan-level damage estimates on default.

The one policy and claim status odds ratio that shows up as statistically significant in Table 5 is that for properties within SFHAs with no insurance claim. Per Figure 2, most loans associated with properties within SFHAs did not have an insurance claim, hence this particular odds ratio showing up as statistically significant is likely just picking up the general SFHA effect on default. Again, this emphasizes that property-specific flood damages are not seen to have a statistically significant impact on the likelihood of default. Results in Table 5 also emphasize the importance of both loan modifications and forbearance on the outcome of default. A successful modification is associated with a lower likelihood of default (odds ratio of 0.20) and a forbearance with a higher likelihood (odds ratio of 13.7). This association with modifications is an expected one and shows the value of borrowers being able to carry out a loan modification in order to keep up with mortgage payments, or return to a non-delinquent state, and remain in their homes. The correlation with forbearance likely reflects the fact that if a borrower enters forbearance they either may already be experiencing difficulty making mortgage payments or forecast difficulties making these payments in the future, hence they are also more likely to eventually default.

Panel D of Figure 3 presents the odds ratios associated with various values of the claim-to-value ratio for the outcome of default. Consistent with the findings described above, most of the odds ratios are not statistically different from 1 at the 95 percent confidence level. The only estimate that is markedly different from 1 is that for properties with a claim-to-value ratio greater than 1, i.e. those for which NFIP claim payment exceeded the estimated property value. For this particular claim-to-value ratio there is a negative association with the likelihood of default, relative to the no insurance group. As we will see in the subsequent discussion, properties with higher damages are significantly more likely to prepay, hence this negative impact on default may just be the complement to the added likelihood of prepayment. Overall, we fail to find conclusive evidence that property-specific flood damages are associated with a greater likelihood of default within 24 months of Harvey.

We next focus on the outcome of prepayment, for which multinomial logistic regression results are displayed in Table 6 and in Panel E of Figure 3. Table 6 shows that borrowers with a claim were more likely to prepay their loans and that borrowers with large claims were twice as likely to prepay than borrowers with no insurance or with insurance but no claim. Table 6 further shows that there is very little difference in this association between damages and prepayment across SFHA status. This clear association between flood damages and the likelihood of prepayment is emphasized in Panel E of Figure 3, where we observe the odds ratios increasing as the claim-to-value ratio increases. There is also an interesting non-linearity evident in this relationship, with markedly larger odds ratio for borrowers with a claim-to-value ratio of 0.9 or higher than those with ratio values of 0.8 or lower. Table 6 also reveals that loan modifications were associated with a lower likelihood of prepayment. This again emphasizes that borrowers will weigh up the options of modification or paying off their mortgages when deciding whether to carry out a loan modification.

The common loan performance trajectories shown in Figure 4 provide further evidence of the association between damages and prepayment. In Figure 4 we see that for the most common trajectory other than the loan remaining current, which is that a loan prepays within 24 months, there is a clearly higher share of loans with this outcome among loans for properties with a large insurance claim. So not only is the association with prepayment and damages clear, but prepayment is also the most common non-current outcome that occurs within 24 months of Harvey. These results emphasize the fact that for borrowers whose homes may have suffered severe flood damages the optimal decision may be to sell the home and use the insurance proceeds to pay off the loan and move elsewhere, instead of using insurance proceeds to rebuild their home. Further signs of this behavior occurring are evident when we assess sale outcomes, in section 5.2.

Differences in Impact of Damages by Presence of Flood Insurance Policy

In this section of the analysis, we make use of the subsample of loans for which we have property inspected damage levels. We use these to gauge how the association of inspected damages with the various loan outcomes differs for properties with and without flood insurance. Note that Kousky et al. (2020) found there were differences in the association of inspected damages with the outcomes of loan modification and prepayment between properties inside and outside of SFHAs. In our results, using actual flood insurance status instead of proxying for it using property location within SFHAs, we similarly find that differences in damage impacts across flood insurance status are only visible for these two outcomes.

Figure 5 displays the odds ratios associated with inspected damage levels for the outcomes of loan modification and prepayment. The odds ratios associated with inspected damage levels for the remaining loan outcomes do not differ by flood insurance status, hence are not displayed. For these other outcomes, the overall patterns by inspected damage amount tend to follow the patterns by claim amount presented in the various panels of Figure 3.

For the outcome of loan modification, seen in Panel A of Figure 5, we observe that borrowers in properties without flood insurance with severe damages were more likely to obtain a loan modification. This effect is not visible for borrowers in properties with flood insurance. Kousky et al. (2020) similarly found this effect of severe damages on loan modification only being visible for properties outside SFHAs. Not finding an association between severe damages and loan modification for properties with flood insurance mimics the results visible in Panel C of Figure 3, where we see that damages are positively associated with loan modification up to claim-to-value ratios of 0.5, with the association decreasing for higher claim-to-value ratios.

The prepayment results above suggest that in the case of severe damages, having flood insurance proceeds makes borrowers less likely to seek a loan modification, possibly because they are more likely to prepay and sell their home. In Panel E of Figure 3 we indeed see that greater claim-to-value ratios are associated with an increased likelihood of prepayment. Turning to the sample of inspected properties, in Figure 5 Panel B, we see that among homes with flood insurance we indeed see moderate or severe inspected damage levels are associated with an increased likelihood of prepayment. By contrast, for homes without flood insurance we see that minimal and moderate inspected damage levels are associated with a lower likelihood of prepayment (with no statistically significant difference in prepayment likelihood for loans to properties with severe assessed damage). This result again emulates Kousky et al. (2020)'s findings using property location within SFHAs to proxy for flood insurance status. Together, our results and those of Kousky et al. (2020) suggest that flood insurance allows borrowers to either be more likely to fix their homes with insurance proceeds and sell, or to sell at lower sale prices without fixing their homes and make up for the differences between their mortgage balance and sale revenue using flood insurance proceeds. Thus, flood insurance may have a positive impact on homeowners' ability to move following a major storm. These potential behaviors are ones we can gauge with our analysis of sale outcomes, in section 5.2.

5.2. Sale Outcomes

Figures 6 through 9 present results from the analysis of sale outcomes. As indicated in the data section, this portion of the analysis makes use of sale transactions information for Harvey-impacted zip codes for a wider set of properties than those that were included in our loan performance analysis. As such, it provides us with a wider view of the market than if we were to focus exclusively on sales of properties associated with loans that were included in our loan performance analysis set. Figure 6 assesses how the number of sales in a given quarter from the start of 2017 until end of 2019, compares to the 2012-2016 average number of sales in that same quarter of the year. This allows us to gauge whether the number of sales post-Harvey markedly differed from the usual number of sales for a given quarter in the four years prior to Harvey. The analysis splits properties up based off whether they were matched to our NFIP insurance information sample, whether the NFIP record had a claim associated with Harvey, and whether that claim was above ("large" claim) or below ("small" claim) 50 percent of total flood insurance coverage.

From Figure 6 we can observe that there is a clear dip in the number of sales in the third quarter of 2017, which is when Harvey hit, for all policy and claim status groups of properties. The dip is markedly more pronounced for properties with small and large claims and for these two sets of properties the dip remains evident through the fourth quarter of 2017, with the number of sales depressed by about 40 percent for these two quarters, echoing the findings in Gallagher and Hartley (2017). From 2018 onwards, we see that for homes with a large claim the number of sales is markedly elevated relative to either the "no policy" or the "no claim" groups. For properties matched to an NFIP insurance policy but with no Harvey claim we also see a dip in the sales volume, but the pattern of the number of sales post-Harvey matches with those for properties with no insurance, just at a lower level. This reflects the fact that among properties matched with an NFIP policy we cannot see new addresses (or sales for newly built homes) show up following the classification of properties, i.e., following Harvey. By contrast, for properties with no insurance match, any sale at a new address (from a newly built home) still counts as a sale in the post-Harvey period. Hence the lower level but similar trajectory in terms of the number of sales for properties with insurance but no claim when compared to those with no insurance. Together, the results in Figure 6 indicate a lesser likelihood of a sale occurring for homes with greater damages within six months of Harvey and possibly a higher likelihood of a sale occurring for homes with larger claims after that.

Having seen there is a change in the likelihood of sales occurring for homes with flood damages, the remaining sections of the sale analysis focus on outcomes for the sale. In looking at these sale outcomes it is important to remember that the likelihood of sale does differ by flood damage, hence all results should be viewed through this lens. Specifically, Figures 7 through 9 present event study results by displaying year-and-quarter indicator regression coefficients for various policy and claim status groups of properties relative to properties with no insurance. Throughout, these regressions control for a wide array of property and location characteristics, detailed in Table 1B.

Figure 7 presents the event study results for the outcome of transaction price (specifically the log of transaction price). The first thing to note is that for properties with no claim there is no meaningful difference in the evolution of prices post-Harvey relative to the group of properties with no insurance. Secondly, we observe that for properties with a small claim amount we generally find an elevated level of prices relative to the no insurance group. Further, while the point estimates show some fluctuations around that elevated level immediately following Harvey, none of those estimates differ statistically from the general elevated level evident throughout the entire period. By contrast to the groups referenced above, for properties with large claims there is a very clear relative drop in transaction prices. The drop in prices, is most pronounced immediately following Harvey, reaching a negative coefficient of 0.19 (or 17 percent lower) in the fourth quarter of 2017 (first full quarter post-Harvey), then leveling out at a new depressed level of about negative 0.1 (or 10 percent lower).

The immediate and strongly negative impact on prices likely indicates homes with large claims that sold without being repaired; a point we will provide further evidence of when assessing time on market and property condition at the time of sale. The lingering negative impact on prices, though more modest relative to the initial effect, may indicate a persistent relative price drop for properties with large flood damages due to buyers being aware of the history of flooding for the property. A couple of factors may contribute to this persistent relative price drop. Harvey was a very large storm which would remain at the forefront of people's minds in the subsequent years. Additionally, Texas' flood disclosure laws, in place at the time Harvey hit and revised in September 2019 to place further emphasis on history of flood damages and flood risk, may heighten buyer awareness of previous flooding and hence make it more likely there would be a lingering negative impact on price.

Having seen there is a strong negative impact on prices for properties with large claims sold within the first two quarters following Harvey, the next section assesses whether these properties sold any faster or were more likely to be left unrepaired. Figures 8 and 9 show the results of the event studies for days on market and the likelihood of properties having a bad condition rating, respectively, using the specification shown in equation (2). Together, these two tables indeed indicate that homes with a large claim had a markedly shorter time on market and were significantly more likely to have a bad condition rating when sold. Both these findings are consistent with homeowners taking the insurance proceeds, selling their home quickly and paying off their mortgage (per increased prepayment likelihood for borrowers with large claims, seen in Panel E of Figure 3). The findings are also consistent with these likely being properties that are purchased by investors at a discount in order to "fix and flip." Homeowners that receive insurance proceeds, which can make up for any shortcomings between the sale price and the amount due on their mortgage, appear less likely to wait around for a better offer and appear to just want to sell the home fast and move on, hence the lower prices, faster sales, for these unrepaired properties.

6. Conclusion

Using a novel dataset which enabled us to gauge property-specific flood insurance and claim status and combining it with loan performance data and property transaction records, we investigated loan performance and property sales following Hurricane Harvey. Specifically, taking insurance claims as a proxy for damages—an approach we were able to validate using a set of properties for which we had assessed damage information—we investigated the association of flood damages with a series of loan performance and sale outcomes. For both short-term (90-day delinquency within five months of Harvey) and medium-term (forbearance or loan modification within eighteen months of Harvey) loan performance outcomes we see a clear association between flood damages and these outcomes.

Greater flood damages, as proxied by claim amounts, are associated with higher likelihoods of short-term delinquency and forbearance take-up, with the effects appearing to plateau once the damages are greater than about 50 percent of estimated property value. The association of claims with the likelihood of loan modification similarly increases up to claims of about 50 percent of estimated property value but the association then diminishes in strength for higher claim levels relative to property amount. This finding indicates that, for borrowers with properties that are more severely damaged, the option to take up a loan modification is likely to not be as appealing as they probably plan to take insurance proceeds, sell their home unrepaired and prepay their loan, using insurance proceeds to make up for any shortfall between sale price and outstanding mortgage balance. Indeed, we find a strong association between higher insurance claim amounts and the likelihood of loan prepayment, one of our two long-term loan performance outcomes; with the effect particularly striking for properties where damages are close to or exceed the estimated property value. For our other long-term loan performance outcome of default (180-day delinquency within 24 months of Harvey) we fail to see a statistically significant correlation with insurance claim amounts. This finding suggests that the effect of increased prepayment for damaged homes dominates any potential impact on default. It is important to note that for the subsample of properties where we are able to observe inspected damage amounts, we can contrast the association of inspected damages with the various loan outcomes by flood insurance status. In so doing, we observe that the positive association between damages and loan prepayment likelihood is not visible among homes without flood insurance, indeed if anything, damages are associated with a lower likelihood of prepayment. This suggests flood insurance may have a positive impact on borrower mobility after a major storm, allowing homeowners to "get back on their feet" from a financial point of view and move elsewhere if they so desire.

From our analysis of post-Harvey property transactions, we see that homes with larger claim amounts are less likely to be sold and, those that do sell, do so at a price discount. We see evidence of severely damaged homes being sold unrepaired within two quarters of Harvey and that, during this timeframe, they sell at a steep price discount of around 17 percent, sell faster, and are markedly more likely to have a bad property condition rating at the time of sale. These properties might be picked up by investors looking to "fix and flip." However, we find that even when sales occur at a later time period (up to two years post-Harvey, the end-point of our sample), the relative price discount for homes with a large claim amount, though markedly subdued at 10 percent, remains. This suggests that a lingering negative price impact for homes that previously suffered flood damages exists. This effect may reflect the high visibility of such a large storm as Harvey and Texas' relatively strong home sale disclosures pertaining to a property's flood history and flood risk when compared to other states, which both may contribute towards flood history and risk being present in buyer's minds.

Together, our results highlight that flood damages have a real, though apparently short-term impact on loan performance and property sales. We further find that a lingering negative impact on home prices for damaged homes is evident, likely highlighting the role for flood disclosures in increasing homebuyer awareness of flood history and flood risk. We also see evidence consistent with investors purchasing homes that were damaged within first the two months following Harvey; which may lead to the displacement of current residents. Further research on how damaged homes may fare in the housing market post-major storms, in particular how flood disclosure requirements may factor into the equation is certainly warranted. The topic of borrower displacement following storms, or more generally climate risk induced migration, is another fruitful avenue for future research. Finally, our failing to find a statistically significant impact on defaults is a topic that may be worth pursuing in future research. Is the failure to find an impact a function of Harvey having been a major storm, which attracted a substantial amount of state and federal government assistance for the impacted populations? If so, analyzing smaller flooding events, or less impactful hurricanes, may be a productive future research endeavor.

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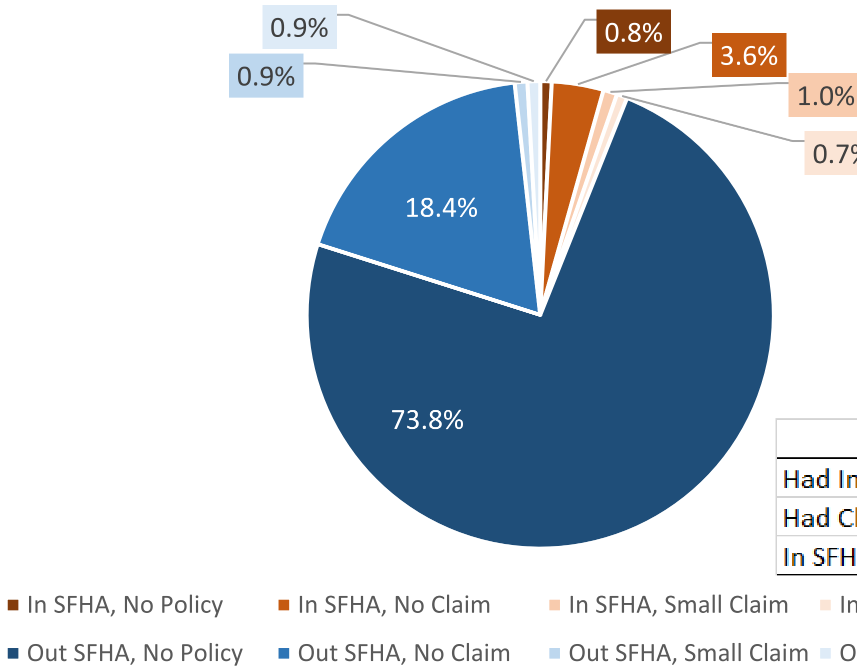
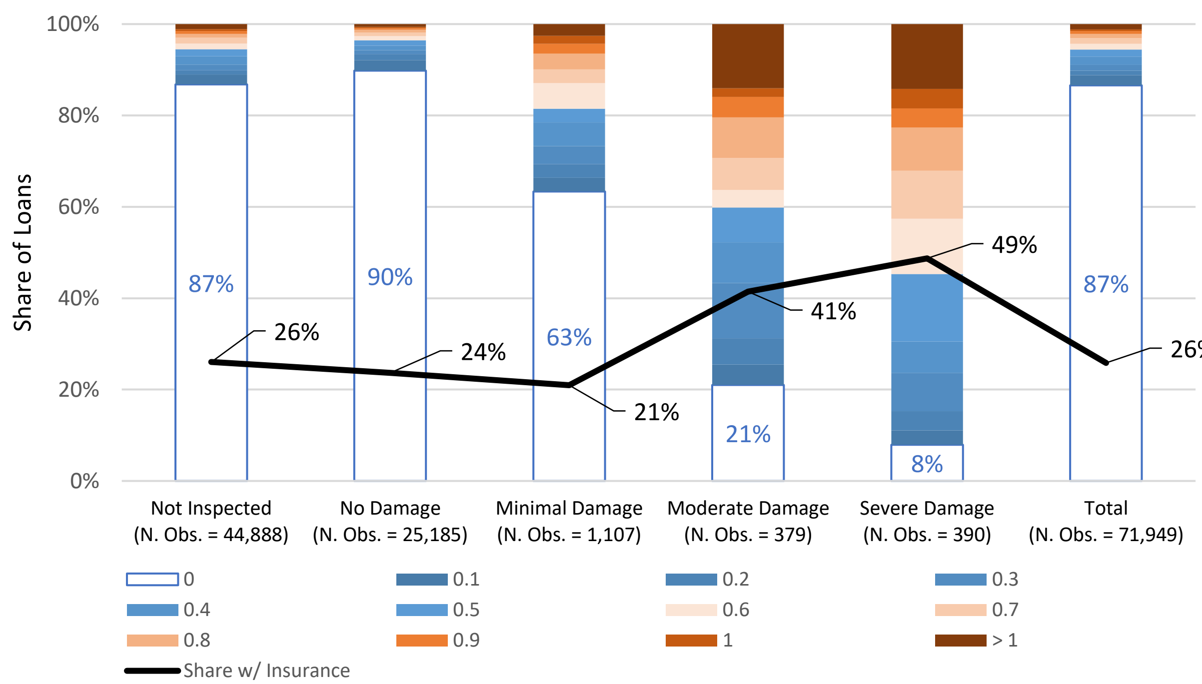
Figure 1. Share of Loans by SFHA, Insurance Policy, and Claim Status



	Share of Loans
Had Insurance	25.4%
Had Claims	3.4%
In SFHA	6.1%

Note: A claim is defined as large if it is above the sample median amount of around $125,000, small if it is below the median.

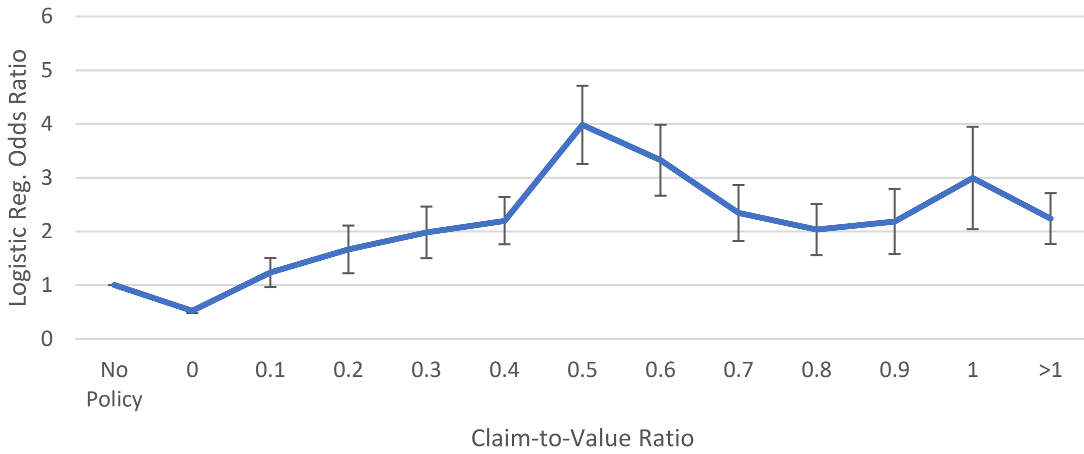
Figure 2. Claim-to-Value Ratio and Share with Insurance Policy by Inspected Damage Category



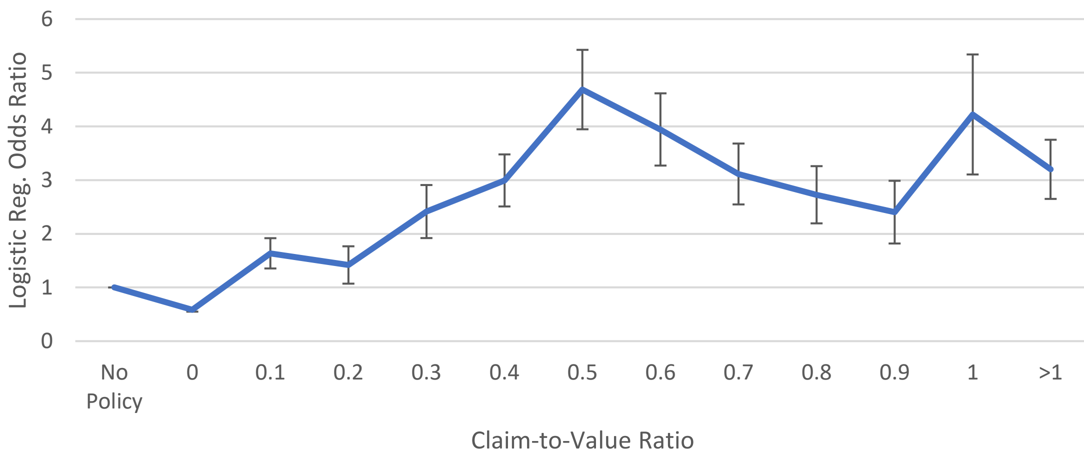
Note: Insurance claim-to-value ratio is the ratio of insurance claim amount to MTM property value as of July 2017. A value of zero indicates no claim. Values above 1 indicate that the claim amount is larger than the MTM property value.

Figure 3. Odds Ratios for Claim-to-Value Ratio from Loan Performance Regressions

Panel A - 90 day delinquency within 5 mths.



Panel B - forbearance within 18 mths.



Panel C - modification within 18 mths.

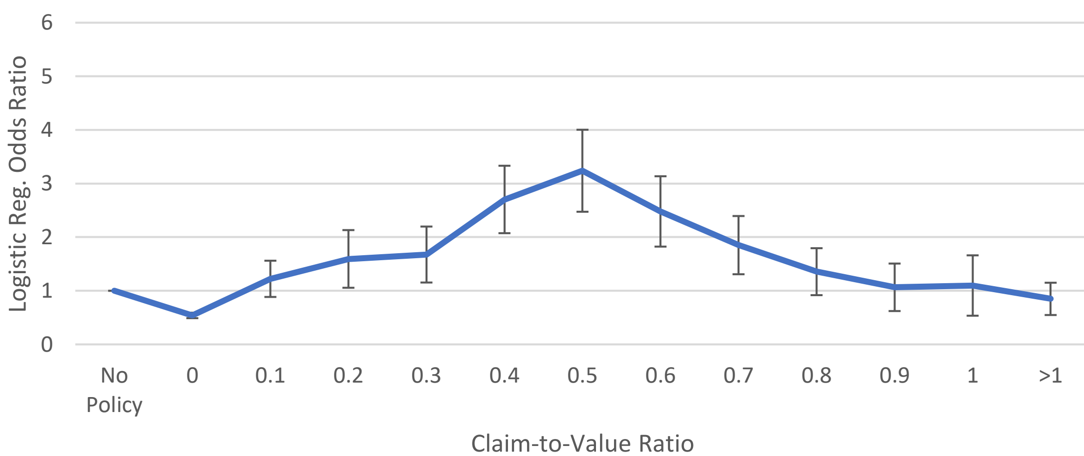
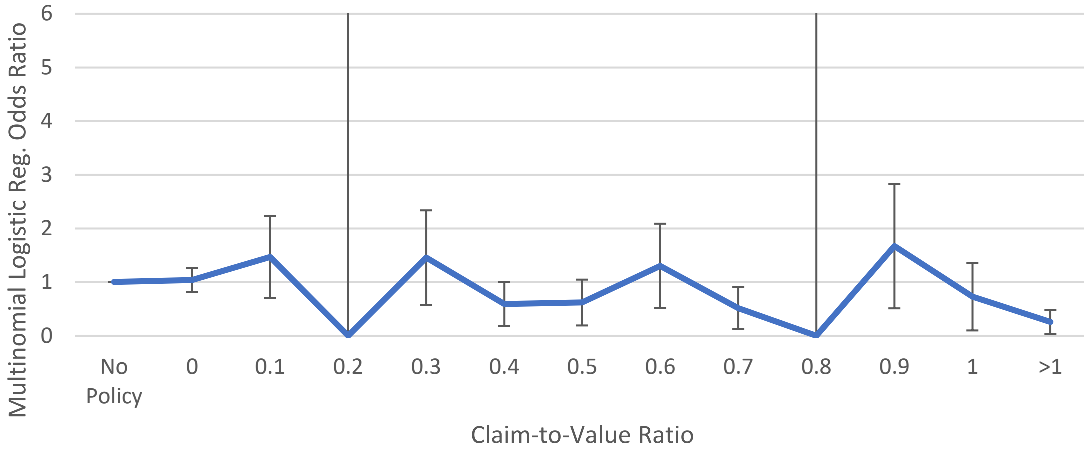
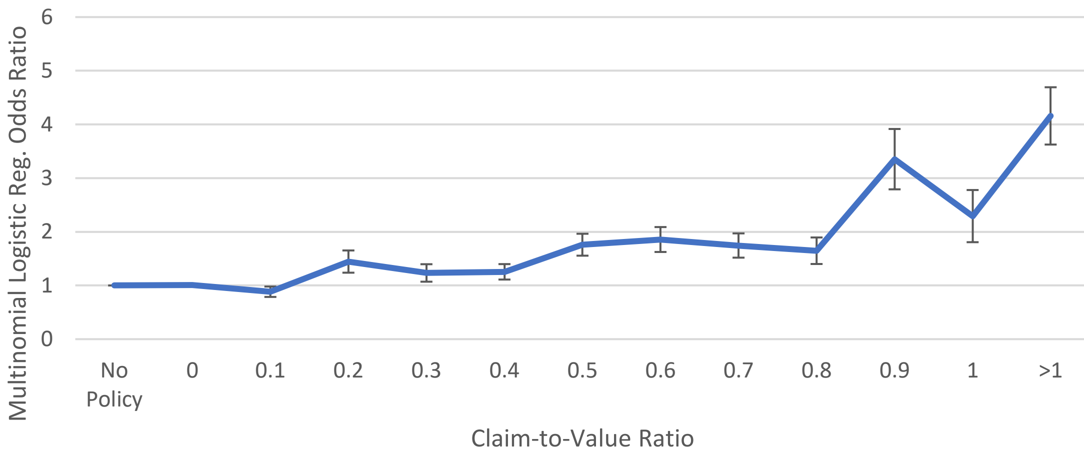


Figure 3. Odds Ratios for Claim-to-Value Ratio from Loan Performance Regressions (Continued)

Panel D - default within 24 mths.

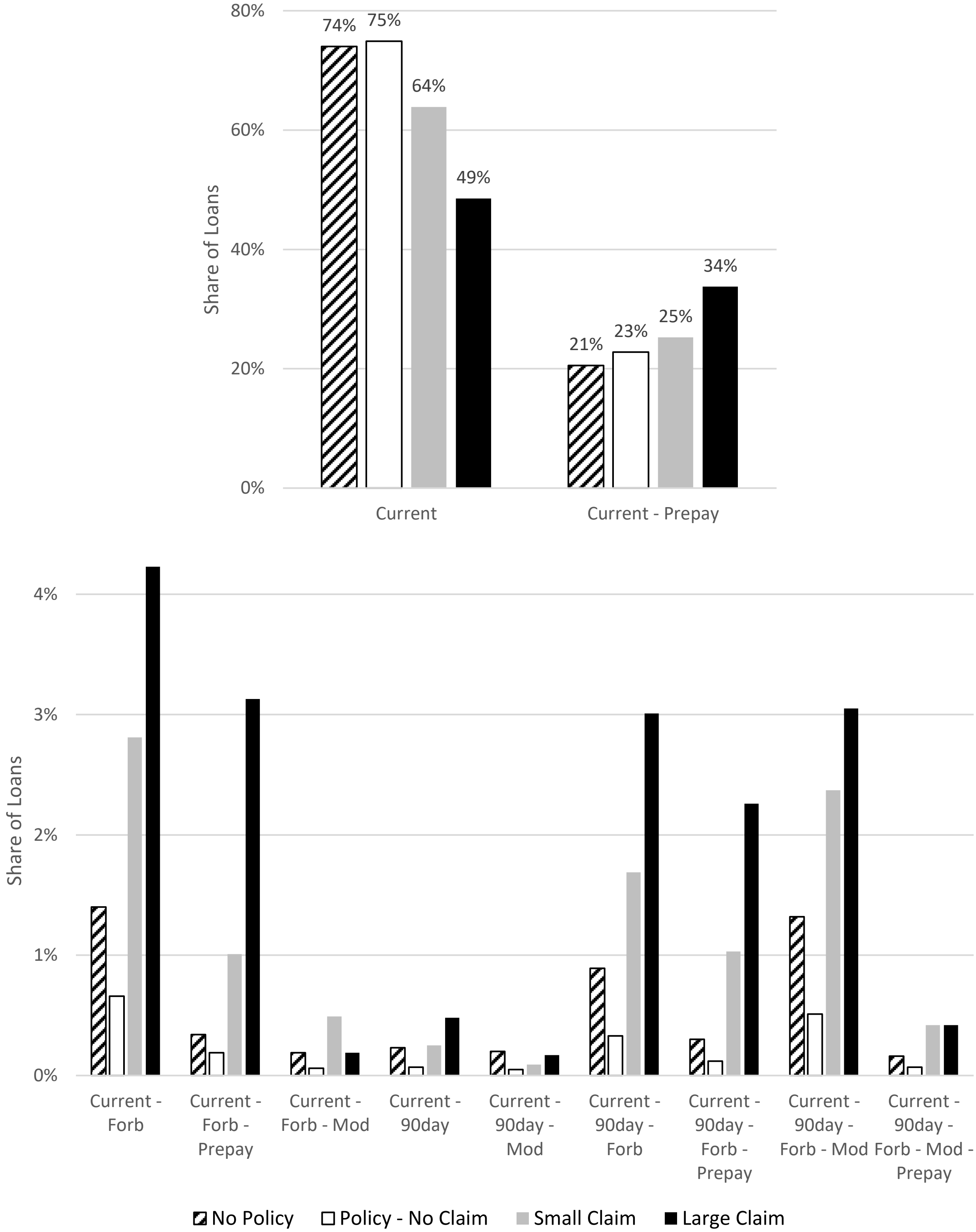


Panel E - prepayment within 24 mths.



Note: Odds ratios displayed in these figures are obtained from running logistic or multinomial logistic regressions for the various outcomes with the full set of controls detailed in Table 1A. Error bars denote the 95% confidence bands around the estimated odds ratios. In Panel D no loans with a claim-to-value ratio of 0.2 or 0.8 experienced a default, hence the estimated odds ratio of zero and the 95% confidence bands covering the entirety of the scale.

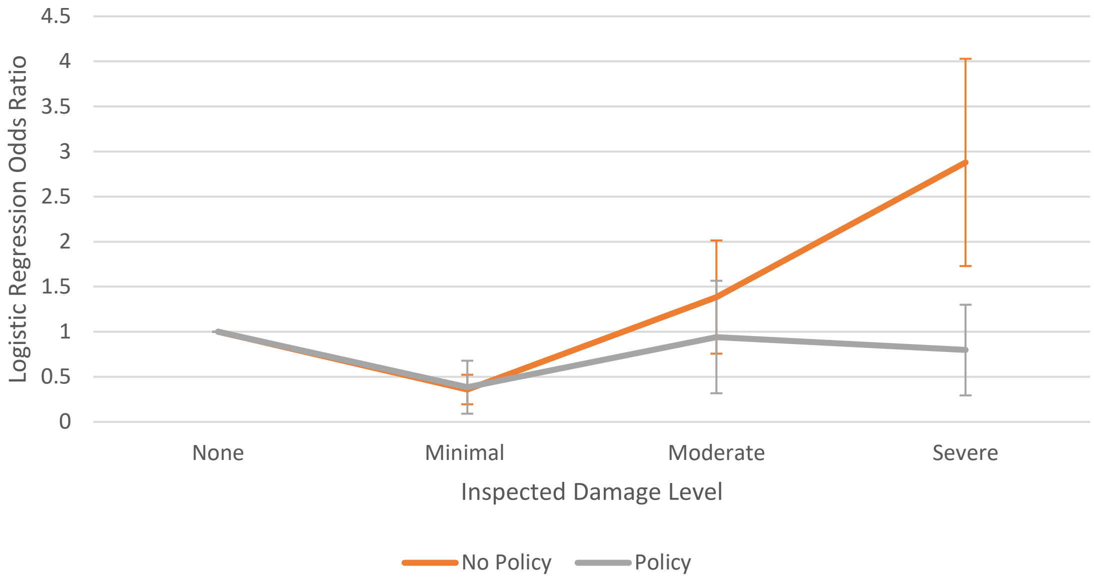
Figure 4. Common Loan Performance Trajectories by Policy and Claim Status



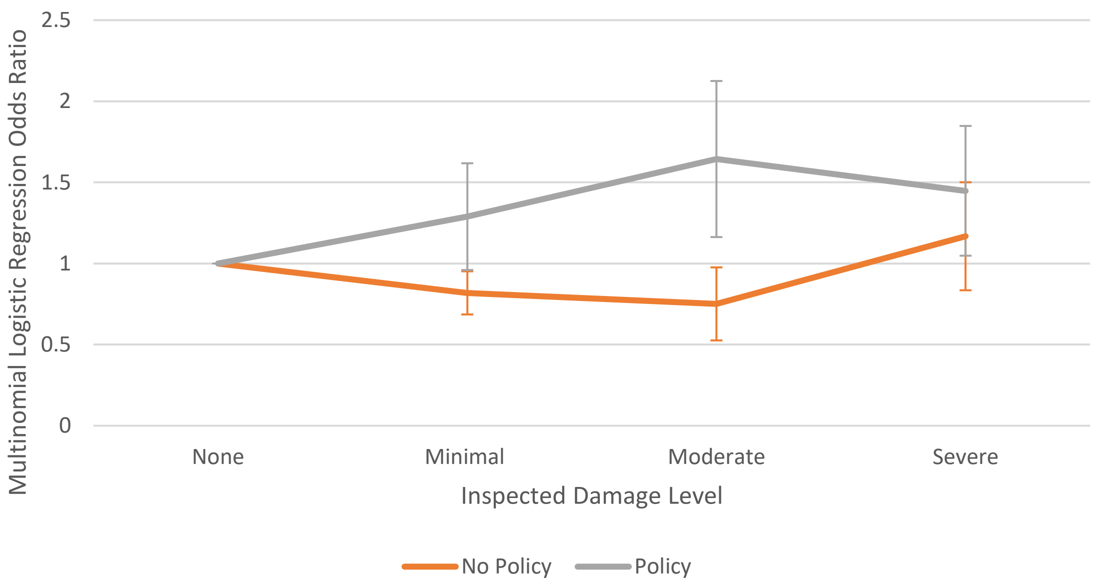
Note: The chart above displays the share of loans remaining current through the 24-month window following Harvey and the top 10 most common non-current loan trajectories. A claim is defined as large if it is above the sample median amount of around $125,000, small if it is below the median.

Figure 5. Odds Ratios for Inspected Damage Level by Insurance Policy Status from Loan Performance Regressions

Panel A - modification within 18 mths.

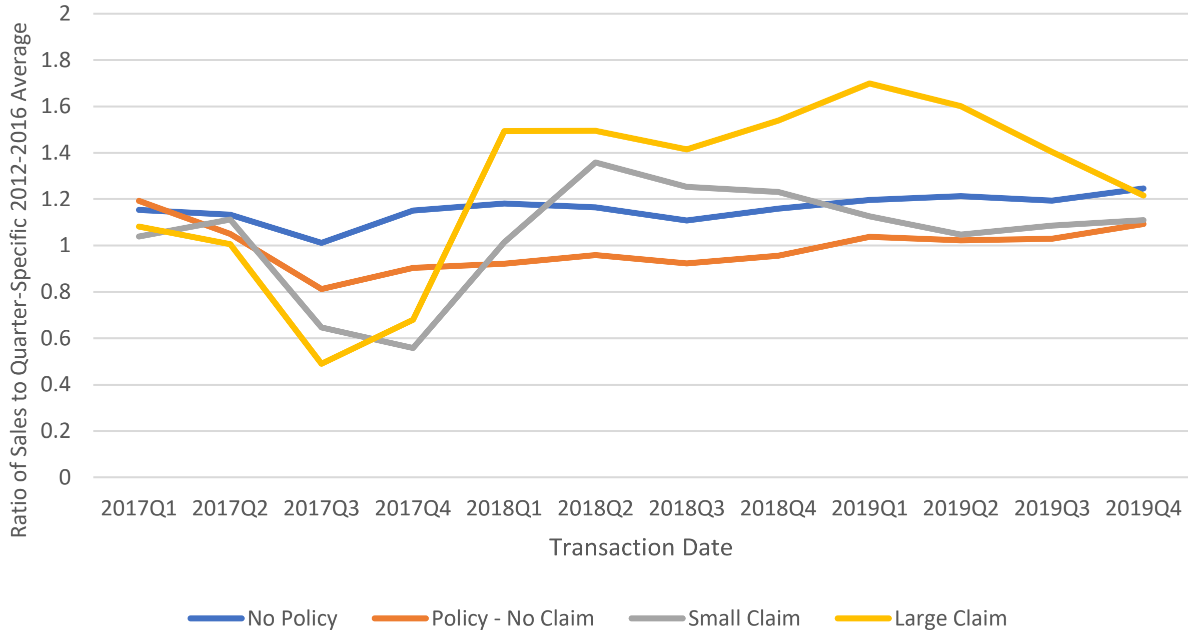


Panel B - prepayment within 24 mths.



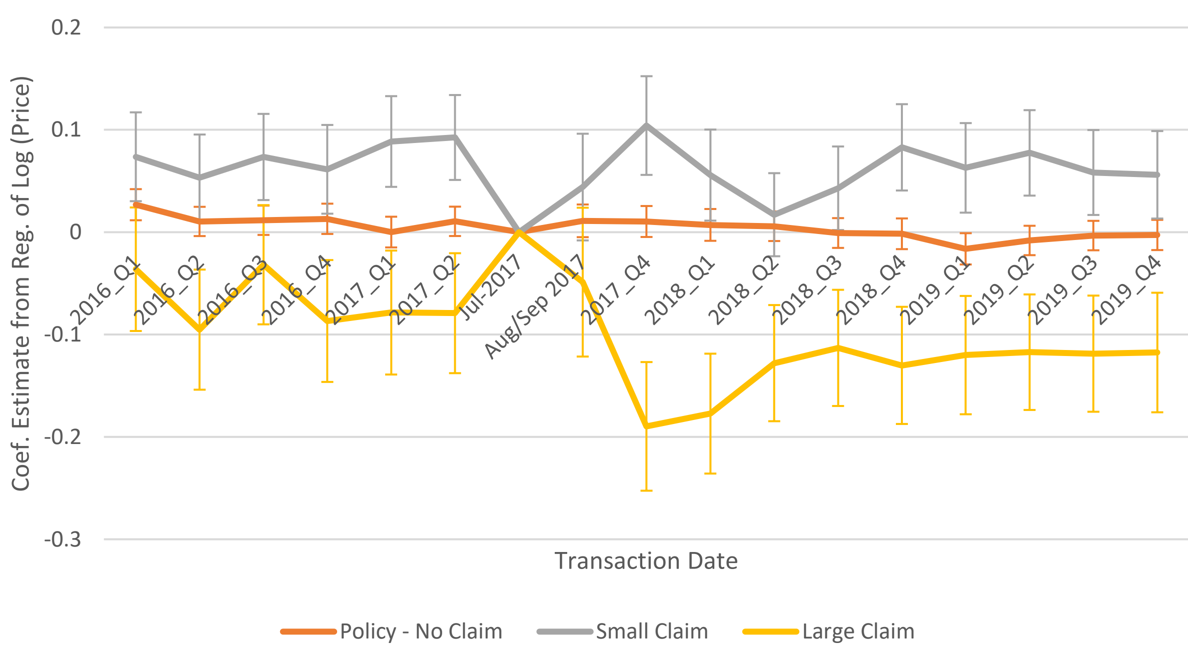
Note: Odds ratios displayed in these figures are obtained from running a logistic regression for the outcome of loan modification and a multinomial logistic regression for the outcomes of prepayment or default (default results not displayed) with the full set of controls detailed in Table 1A. Error bars denote the 95% confidence bands around the estimated odds ratios.

Figure 6. Volume of Sales by Insurance Policy and Claim Status



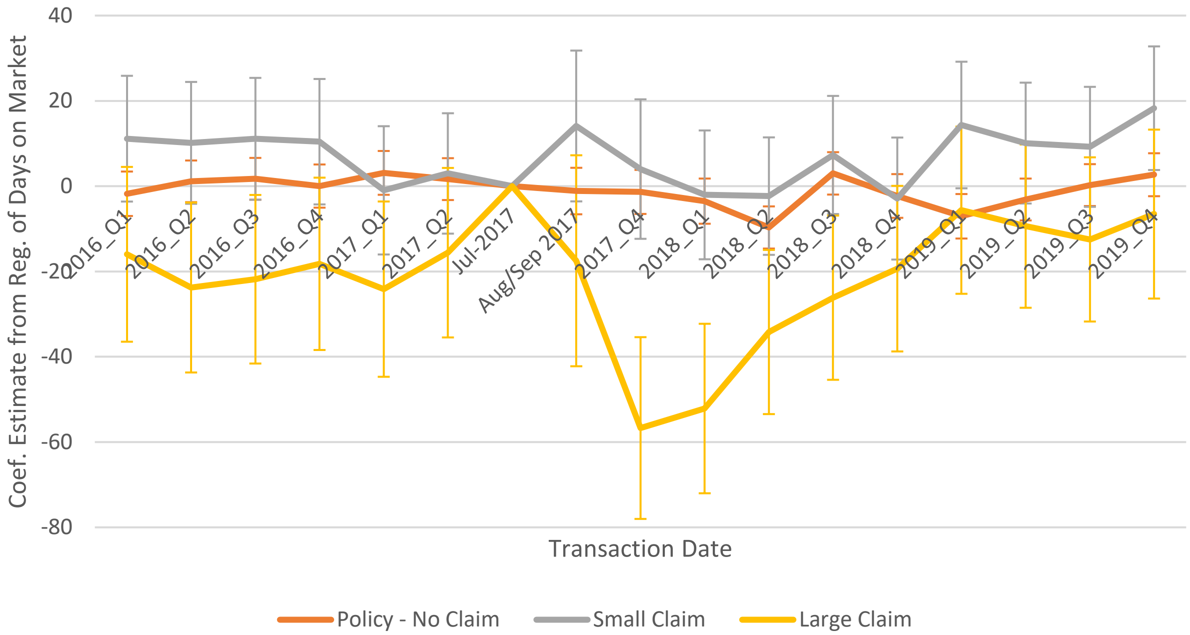
Note: This analysis uses all sales for Harvey affected zip codes matched to NFIP insurance and claim information. Determination of whether a claim is small or large is based off it being above or below 50% of the total insurance coverage (building + contents).

Figure 7. Transaction Price by Policy and Claim Status Relative to Group with No Insurance Policy



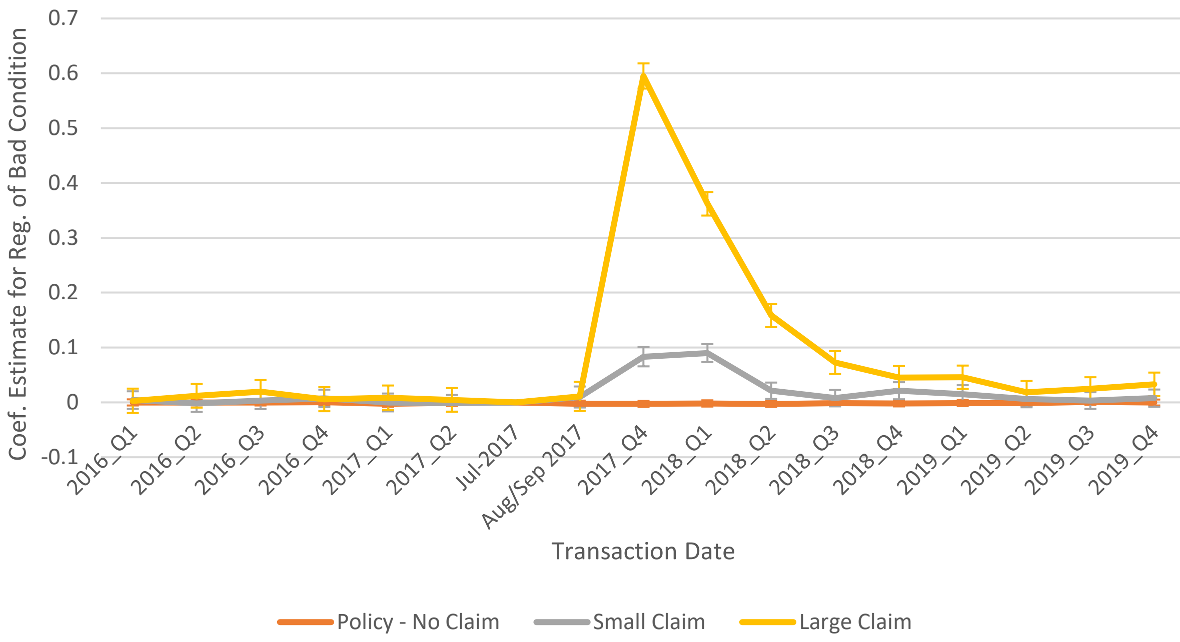
Note: This analysis uses all sales for Harvey affected zip codes matched to NFIP insurance and claim information. Determination of whether claim is small or large is based off it being above or below 50% of the total insurance coverage (building + contents). Hedonic regression of log transaction price controlling for full set of property and location characteristics visible in Table 1B and zip code fixed effects. Error bars denote the 95% confidence bands around the estimated coefficients.

Figure 8. Days on Market by Policy and Claim Status Relative to Group with No Insurance Policy



Note: This analysis uses all sales for Harvey affected zip codes matched to NFIP insurance and claim information. Determination of whether claim is small or large is based off it being above or below 50% of the total insurance coverage (building + contents). OLS regression of days on market controlling for full set of property and location characteristics visible in Table 1B and zip code fixed effects. Error bars denote the 95% confidence bands around the estimated coefficients.

Figure 9. Likelihood Property has a Bad Condition Rating (C5 or C6) Relative to Group with No Insurance Policy



Note: This analysis uses all sales for Harvey affected zip codes matched to NFIP insurance and claim information. Determination of whether claim is small or large is based off it being above or below 50% of the total insurance coverage (building + contents). OLS regression of indicator that the property condition rating is either 5 or 6, denoting a bad property condition. Full set of property (excluding condition rating) and location characteristics visible in Table 1B and zip code fixed effects included in the regression. Error bars denote the 95% confidence bands around the estimated coefficients.

Table 1A. Summary Statistics for Variables Used in Loan Performance Analysis by NFIP Flood Insurance Policy Status

Variable	Has NFIP Policy			No NFIP Policy		
	N	Mean	Std. Dev.	N	Mean	Std. Dev.
90-day Delinquency	17,001	0.021	0.310	54,692	0.033	0.361
Forbearance	17,001	0.035	0.394	54,692	0.047	0.428
Modification	17,001	0.012	0.229	54,692	0.020	0.283
180 Or More Days Delinquency or Default	17,001	0.002	0.088	54,692	0.002	0.093
Prepayment	17,001	0.247	0.923	54,692	0.215	0.828
SFHA	17,001	0.204	0.863	54,692	0.010	0.202
Policy	17,001	1.000	0.000	54,692	0.000	0.000
Claim Size	3,823	$119,099	$188,665	-	.	.
IHP ratio	17,001	0.465	1.197	54,692	0.348	0.775
Loan Age (month)	17,001	60.622	103.811	54,692	60.988	109.701
MTMCLTV < 30 (as of July 2017)	17,001	0.218	0.884	54,692	0.149	0.719
MTMCLTV between 30 and 80 (as of July 2017)	17,001	0.708	0.974	54,692	0.744	0.881
MTMCLTV > 80 (as of July 2017)	17,001	0.074	0.560	54,692	0.106	0.622
FICO < 620	17,001	0.016	0.268	54,692	0.035	0.371
FICO between 620 and 820	17,001	0.971	0.359	54,692	0.950	0.439
FICO > 820	17,001	0.006	0.163	54,692	0.002	0.092
DTI < 36%	17,001	0.644	1.025	54,692	0.536	1.006
DTI - between 36% and 45%	17,001	0.266	0.946	54,692	0.342	0.957
DTI > 45%	17,001	0.080	0.581	54,692	0.105	0.619
Single Borrower Indicator	17,001	0.452	1.065	54,692	0.558	1.001
Loan Purpose - Cash out Refinance	17,001	0.175	0.813	54,692	0.147	0.714
Loan Purpose - Rate and term refinance	17,001	0.421	1.057	54,692	0.370	0.974
Loan Purpose - Purchase Money	17,001	0.404	1.050	54,692	0.483	1.008
Product Type - 25, 30 and 40 year fixed-rate mortgage	17,001	0.558	1.063	54,692	0.625	0.976
Product Type - 15 and 20 year fixed-rate mortgage	17,001	0.423	1.057	54,692	0.357	0.966
Product Type - adjustable-rate mortgage	17,001	0.019	0.290	54,692	0.018	0.269
Third Party Origination	17,001	0.393	1.046	54,692	0.414	0.993
Reserves < 6m	17,001	0.560	1.062	54,692	0.623	0.977
Reserves 6-11m	17,001	0.114	0.680	54,692	0.113	0.638
Reserves >= 12m	17,001	0.326	1.003	54,692	0.264	0.889
MTM Home Value (as of July 2017)	16,994	$344,456	$474,590	54,638	$288,142	$528,438
Borrower Income	16,901	$124,263	$208,279	54,061	$101,864	$157,806
Inspected Damage Level - No Damage	6,535	0.911	0.284	20,415	0.937	0.243
Inspected Damage Level - Minor Damage	6,535	0.036	0.185	20,415	0.043	0.202
Inspected Damage Level - Moderate/Severe Damage	6,535	0.053	0.224	20,415	0.021	0.142

Table 1B. Summary Statistics for Variables Used in Sales Analysis by NFIP Flood Insurance Policy Status

Variable	Has NFIP Policy			No NFIP Policy		
	N	Mean	Std. Dev.	N	Mean	Std. Dev.
Transaction Price	71,994	$353,572	$312,246	320,381	$283,320	$241,643
Days on Market	71,389	61.0	81.4	313,842	60.7	80.4
SFHA	71,994	0.274	0.446	320,381	0.045	0.208
Policy	71,994	1	0	320,381	0	0
Claim Amount	13,435	$101,520	$108,088	.	.	.
Property Age	71,994	27.2	20.9	320,381	21.6	21.3
GLA	71,994	2,421	1,050	320,381	2,292	943
Num. Bathrooms	71,994	2.6	0.756	320,381	2.5	0.7
Num. Bedrooms	71,994	3.4	0.825	320,381	3.4	0.8
condition_C1	71,994	0.086	0.280	320,381	0.226	0.418
condition_C2	71,994	0.062	0.241	320,381	0.053	0.225
condition_C3	71,994	0.733	0.442	320,381	0.594	0.491
condition_C4	71,994	0.111	0.314	320,381	0.120	0.325
condition_C5	71,994	0.006	0.079	320,381	0.006	0.075
condition_C6	71,994	0.002	0.046	320,381	0.001	0.030
quality_Q1	71,994	0.002	0.044	320,381	0.001	0.036
quality_Q2	71,994	0.028	0.164	320,381	0.016	0.125
quality_Q3	71,994	0.531	0.499	320,381	0.483	0.500
quality_Q4	71,994	0.434	0.496	320,381	0.491	0.500
quality_Q5	71,994	0.005	0.071	320,381	0.009	0.096
quality_Q6	71,994	0.000	0.009	320,381	0.000	0.011
Location Beneficial	71,994	0.054	0.226	320,381	0.023	0.151
Location Neutral	71,994	0.936	0.245	320,381	0.966	0.181
Location Adverse	71,994	0.010	0.100	320,381	0.011	0.102
View Beneficial	71,994	0.098	0.298	320,381	0.048	0.214
View Neutral	71,994	0.896	0.305	320,381	0.945	0.228
View Adverse	71,994	0.006	0.075	320,381	0.007	0.083

Note: total observation count is higher for Table 1B than for Table 1A because for the sales analysis we include all sale transactions visible in Harvey-impacted zip codes, which includes both transactions for properties that are not in our loan sample. By contrast, for the loan performance analysis we make use of the sampling procedure described in section 3, hence a smaller observation count.

Table 2. Short-Term Loan Performance: 90-Day Delinquency

Dependent variable: 90 or more day delinquency within 5 months of Harvey		
	(1)	(2)
SFHA - Yes	1.48***	
SFHA - No	1	
Policy - Yes & Claim - Large	3.50***	
Policy - Yes & Claim - Small	1.47***	
Policy - Yes & Claim - None	0.52***	
Policy - No & Claim - N/A	1	
SFHA Yes - Policy - Yes & Claim - Large		5.02***
SFHA Yes - Policy - Yes & Claim - Small		1.89***
SFHA Yes - Policy - Yes & Claim - None		0.86**
SFHA Yes - Policy - No & Claim - N/A		1.55***
SFHA No - Policy - Yes & Claim - Large		3.63***
SFHA No - Policy - Yes & Claim - Small		1.81***
SFHA No - Policy - Yes & Claim - None		0.50***
SFHA No - Policy - No & Claim - N/A		1
IHP Ratio	1.35***	1.35***
Control Variables	Y	Y
Number of Observations	71,693	71,693
Number of Events	9,040	9,040
Gini	0.467	0.467

The coefficients represent the odds ratio from a logistic regression. The groups with odds ratio 1 indicate the reference groups. A claim is defined as large if it is above the sample median amount of around $125,000, small if it is below the median. Control variables included in the regression are visible in Table 1A (see footnote 10 for details of specification).
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3. Medium-Term Loan Performance: Forbearance

Dependent variable: forbearance within 18 months of Harvey		
	(1)	(2)
SFHA - Yes	1.43***	
SFHA - No	1	
Policy - Yes & Claim - Large	4.28***	
Policy - Yes & Claim - Small	1.89***	
Policy - Yes & Claim - None	0.58***	
Policy - No & Claim - N/A	1	
SFHA Yes - Policy - Yes & Claim - Large		5.83***
SFHA Yes - Policy - Yes & Claim - Small		2.29***
SFHA Yes - Policy - Yes & Claim - None		0.96
SFHA Yes - Policy - No & Claim - N/A		1.50***
SFHA No - Policy - Yes & Claim - Large		4.50***
SFHA No - Policy - Yes & Claim - Small		2.37***
SFHA No - Policy - Yes & Claim - None		0.55***
SFHA No - Policy - No & Claim - N/A		1
IHP Ratio	1.48***	1.48***
Control Variables	Y	Y
Number of Observations	71,693	71,693
Number of Events	12,774	12,774
Gini	0.577	0.578

The coefficients represent the odds ratio from a logistic regression. The groups with odds ratio 1 indicate the reference groups. A claim is defined as large if it is above the sample median amount of around $125,000, small if it is below the median. Control variables included in the regression are visible in Table 1A (see footnote 10 for details of specification).
*** p<0.01, ** p<0.05, * p<0.1

Table 4. Medium-Term Loan Performance: Loan Modification

Dependent variable: loan modification within 18 months of Harvey		
	(1)	(2)
SFHA - Yes	1.28***	
SFHA - No	1	
Policy - Yes & Claim - Large	2.12***	
Policy - Yes & Claim - Small	1.52***	
Policy - Yes & Claim - None	0.54***	
Policy - No & Claim - N/A	1	
SFHA Yes - Policy - Yes & Claim - Large		2.63***
SFHA Yes - Policy - Yes & Claim - Small		1.90***
SFHA Yes - Policy - Yes & Claim - None		0.78***
SFHA Yes - Policy - No & Claim - N/A		1.01
SFHA No - Policy - Yes & Claim - Large		2.17***
SFHA No - Policy - Yes & Claim - Small		1.56***
SFHA No - Policy - Yes & Claim - None		0.51***
SFHA No - Policy - No & Claim - N/A		1
IHP Ratio	1.32***	1.32***
Control Variables	Y	Y
Number of Observations	71,693	71,693
Number of Events	5,267	5,267
Gini	0.580	0.566

The coefficients represent the odds ratio from a logistic regression. The groups with odds ratio 1 indicate the reference groups. A claim is defined as large if it is above the sample median amount of around $125,000, small if it is below the median. Control variables included in the regression are visible in Table 1A (see footnote 10 for details of specification).
*** p<0.01, ** p<0.05, * p<0.1

Table 5. Long-Term Loan Performance: Default

Dependent variable: default (180 or more days delinquent) within 24 months of Harvey		
	(1)	(2)
SFHA - Yes	1.73***	
SFHA - No	1	
Policy - Yes & Claim - Large	0.61	
Policy - Yes & Claim - Small	0.86	
Policy - Yes & Claim - None	1.04	
Policy - No & Claim - N/A	1	
SFHA Yes - Policy - Yes & Claim - Large		0.91
SFHA Yes - Policy - Yes & Claim - Small		1.22
SFHA Yes - Policy - Yes & Claim - None		2.09***
SFHA Yes - Policy - No & Claim - N/A		1.49
SFHA No - Policy - Yes & Claim - Large		0.78
SFHA No - Policy - Yes & Claim - Small		1.23
SFHA No - Policy - Yes & Claim - None		0.94
SFHA No - Policy - No & Claim - N/A		1
IHP Ratio	1.15**	1.15**
Forbearance	13.73***	13.67***
Modification	0.20***	0.20***
Control Variables	Y	Y
Number of Observations	71,693	71,693
Number of Events	438	438
-2 Log L	315,091	315,045

The coefficients represent the odds ratio from a multinomial logistic regression where the outcomes are default (180 or more days delinquent), prepayment, or neither. The groups with odds ratio 1 indicate the reference groups. A claim is defined as large if it is above the sample median amount of around $125,000, small if it is below the median. Control variables included in the regression are visible in Table 1A (see footnote 10 for details of specification).
*** p<0.01, ** p<0.05, * p<0.1

Table 6. Long-Term Loan Performance: Prepayment

Dependent variable: prepayment within 24 months of Harvey		
	(1)	(2)
SFHA - Yes	1.16***	
SFHA - No	1	
Policy - Yes & Claim - Large	1.97***	
Policy - Yes & Claim - Small	1.37***	
Policy - Yes & Claim - None	1.01	
Policy - No & Claim - N/A	1	
SFHA Yes - Policy - Yes & Claim - Large		2.45***
SFHA Yes - Policy - Yes & Claim - Small		1.81***
SFHA Yes - Policy - Yes & Claim - None		1.08***
SFHA Yes - Policy - No & Claim - N/A		1.24***
SFHA No - Policy - Yes & Claim - Large		1.86***
SFHA No - Policy - Yes & Claim - Small		1.18***
SFHA No - Policy - Yes & Claim - None		1.02*
SFHA No - Policy - No & Claim - N/A		1
IHP Ratio	0.96***	0.95***
Forbearance	1.08***	1.08***
Modification	0.44***	0.44***
Control Variables	Y	Y
Number of Observations	71,693	71,693
Number of Events	15,579	15,579
-2 Log L	315,091	315,045

The coefficients represent the odds ratio from a multinomial logistic regression where the outcomes are 180 or more days delinquent, prepayment, or neither. The groups with odds ratio 1 indicate the reference groups. A claim is defined as large if it is above the sample median amount of around $125,000, small if it is below the median. Control variables included in the regression are visible in Table 1A (see footnote 10 for details of specification).

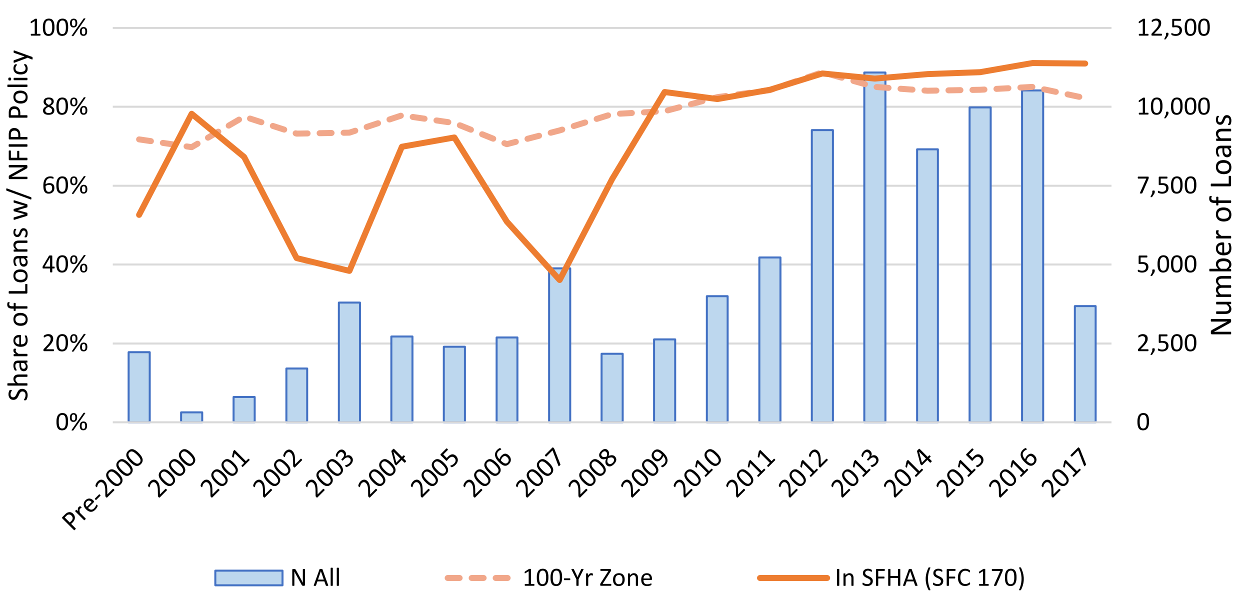
*** p<0.01, ** p<0.05, * p<0.1

Appendix 1. NFIP Match Quality

We match NFIP flood insurance data with Fannie Mae sample loans based on standardized street addresses and zip codes. If we do not find an exact match, we rely on two measures: physical distance and spelling distance between two addresses. If there are multiple candidates, we choose the physically closest match within the set of matches with a low spelling distance. To assess our matching quality, we examine the match rate inside SFHAs. Since for properties inside SFHAs loans in our book are required to have flood insurance, the match rate between the NFIP data and our data should be close to 100 percent. However, our Special Feature Code (SFC)-based designations of properties being in SFHAs are potentially outdated because they are the records from the time of loan origination. We, therefore, update this information based on our internal system which contains LOMC (Letter of Map Change) address and FEMA flood zone information from 2017 onwards, allowing us to estimate SFHA status at the time when Hurricane Harvey occurred.

Figure A1 shows the match rate of properties inside SFHAs by loan origination year. The left vertical axis represents the match rate, i.e., share of loans with an NFIP policy match. The right vertical axis represents the total number of loans originated in a given year. The match rate using SFC is generally high for recent loans, whereas the updated FEMA map designation (labeled "100-Yr Zone" in Figure A1) yields higher match rates for loans originated prior to 2013. Yearly match rate fluctuations are likely a function of difference in geographic composition, with potentially greater prevalence of areas with subsequent map changes, or fluctuations in data quality. Therefore, we construct a new measure of SFHA status, using the updated FEMA map designation for loans originated in 2012 or earlier, and SFC-based designation for loans originated in 2013 or later, which results in a final match rate of 87 percent for properties inside SFHAs.

Figure A1. NFIP Policy Match Rate by Measure of Location in SFHAs and Loan Origination Year



Appendix 2. Loan Performance Measures

Figure A2. Timeline of Loan Performance