Natural Disasters and Mortgage Risk in the Federal Housing Administration

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Abstract

Climate change poses significant risk to the US housing and mortgage finance ecosystem, with many effects shown or predicted to disproportionately affect economically vulnerable populations. Households exposed to natural disasters face risks of damaged homes, loss of residence and income disruptions, among others. For mortgage borrowers, disaster related financial shocks could lead to significant financial distress resulting in mortgage default. Focusing on the Federal Housing Administration's (FHA) single family mortgage insurance (MI) program, this study characterizes past disaster exposure on a sample of 897,000 FHA insured mortgages from 2004-2017 and estimates a relationship between past exposure and homebuyer outcomes. Additionally, this study estimates risks to the FHA Mutual Mortgage Insurance Fund (MMI Fund) through a two-stage process. Despite FHA safeguards against disaster-related costs through requirements for casualty insurance and "preservation and protection" requirements, results indicate a positive correlation. Using a standard claims-probability logit model with zip-code level disaster exposure data from FEMA and an 18-year loan level panel of FHA borrower and mortgage characteristics, we find disaster exposure correlates with an approximately 20% increase in the probability of mortgage foreclosure with an MI claim. A second stage simulation using estimated coefficients finds that disaster exposure caused an $1.7 billion in additional FHA paid MI claims costs from 2004 to 2019. Additional analysis finds that these effects are heterogeneous across race, disaster type and credit groups, providing evidence that economically vulnerable groups are more susceptible to adverse outcomes within the FHA portfolio.

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Section 1: Introduction

Climate change is increasing both the intensity and frequency of natural disasters, leading to higher economic costs. In an annual report, the National Oceanic and Atmospheric Administration (NOAA) documents the incidence of weather and climate disasters resulting in over $1 billion in damage per event, so called “billion-dollar disasters.” The 2019 report shows that over the last decade there were 119 such events, a stark increase compared to the previous three decades (29, 53 and 62 from the 1980s, 1990s and 2000s, respectively) (NOAA 2019). The changing risk of natural disasters, flooding in particular, is further demonstrated by the increasing frequency of presidential disaster declarations, of which more than 80 percent have been in response to floods and flood related events such as hurricanes (Kousky et al. 2018). While some of the increased costs can be attributed to new and higher value developments in vulnerable areas (Wing et al. 2018), recent research on flood events indicates that historical precipitation changes have contributed to roughly one third of cumulative flood damages from 1988 to 2017 (Davenport et al. 2020). Windstorms, rain events, wildfires, sea level rise and tropical cyclones all pose risk to the United States housing stock, though flooding poses the most widespread threat (NOAA 2020). As such, understanding climate and natural disaster risks to the housing and mortgage finance ecosystem has become an increasingly important topic over the last decade. This study contributes to this literature by focusing on two elements of the housing finance ecosystem: financial outcomes for households with mortgages, and the implications for mortgage credit risk. Specifically, do households with mortgages who live in areas affected by major natural disasters have a higher probability of losing their house to foreclosure compared to those who do not live in affected areas?

Intuitively, household exposure to a large natural disaster can translate into a financial shock, whether through direct damage to homes requiring costly repairs and emergency living expenses, or through economic disruptions that affect household income. Previous research, discussed in more detail below, has found that large natural disasters such as hurricanes and floods increase mortgage default risk (PDR-2M Research, 2020; Kousky, Palin & Pan 2020) and mortgage prepayment risk (Gallegher et al 2017), exposing secondary market participants such as securitizers and mortgage insurance companies to downstream risks.

This study contributes to this body of work by examining the effects of natural disaster exposure, broadly defined, on mortgage performance in the Federal Housing Administration (FHA) single family mortgage guarantee portfolio.

Our approach differs in several meaningful ways from previous work and adds important nuance and support to collective findings. First, our research utilizes FHA administrative data not publicly accessible, offering loan and borrower level details necessary for a loan level analysis. In contrast, many studies use aggregate level measures or anonymized financial data, such as publicly available tax records or credit reports. Second, most previous work focuses on a single disaster event, while we look at a national sample with a 17-year window of originations, including multiple types of disasters across all housing markets. Last, our study sample focuses on the FHA portfolio specifically, rather than conventional markets.

We begin by conducting a descriptive analysis to assess natural hazard exposure in the FHA portfolio, including patterns by borrower race groups as well as by disaster type. After painting a picture of affected borrowers, we then use a multinomial logit model, standard in FHA analysis, and include variables accounting for disaster exposure to estimate the increased probability of *foreclosure with FHA mortgage insurance claim* (henceforth referred to as a *claim*). In our most general specification, we find mortgages that are exposed to a natural disaster are 1.1 to 1.3 times more likely to end in a claim over remaining active in each of the three years following a disaster compared to mortgages with no exposure. We also find evidence that these effects are heterogeneous across race groups and disaster type, suggesting that economically vulnerable groups are more susceptible to adverse outcomes within the FHA portfolio.

In addition to providing insight to the effects of natural disaster exposure on household finances, this study also provides insight to the federal government's climate related financial risk as it pertains to its mortgage lending programs. The Federal government insures mortgage payments on over $2.3 trillion worth of mortgages, over 25% of the $8.9 trillion in value of the US Single Family Mortgage market, approximately half of which is through FHA.[1] To quantify the cost of past materialized risks, we run a second stage simulation using our previously estimated coefficients and calculate an expected value of over $1.7 billion dollars in additional claims correlated to natural disaster exposure from 2004-2019. This is roughly 2% of the $80.6 billion in total claims paid over the same period.

The rest of the paper is as organized as follows: Section 2 discusses previous research and while Section 3 provides relevant background on the FHA single family guarantee program. Section 4 discusses data sources and Section 5 provides the descriptive analysis of the sample's disaster exposure. Section 5 discusses methodology and section 6 gives the results. Section 7 concludes.

Section 2: Literature Review

A growing literature investigates the effects of climate and natural disaster risk in housing, credit, and insurance markets.[2] This study focuses on household financial outcomes post-disaster, but offers meaningful differences from existing work. For instance, Duryinga et al. (2018) use tax return data to examine household mobility, labor and income outcomes post hurricane Katrina. While finding no statistically significant effects in the long-term, they do find transitory income shocks. This is relevant to our study in that it supports the intuition that

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[1] https://www.urban.org/sites/default/files/2023-09/Housing%20Finance%20At%20A%20Glance%20Monthly%20Chartbook%20September%202023.pdf

[2] Craig (2021) provides an in-depth survey of the literature examining climate risk to the mortgage finance ecosystem.

income disruptions may occur, which could affect a household's ability to maintain mortgage payments. However, they did not specifically study mortgage outcomes.

In another study focused on Hurricane Katrina, Gallagher and Hartley (2017) look for a causal effect of the storm on key household finance distress indicators, including mortgage performance. They find modest evidence of credit card usage for consumption smoothing, increasing balances approximately $500 (15%) for the *most-flooded* group compared to *non-flooded*, though such effects are short lived. They also find that the *most-flooded* residents have general debt delinquency rates 10% higher than *non-flooded* residents on credit reports, though two years later credit scores are only .06 standard deviations lower. Both findings corroborate the transitory nature of shocks found in Deryugina et al. (2018). Contrary to expected negative impacts on financial stability, the authors find that total debt decreases for the *most-flooded* residents. They conclude the relatively larger reductions in total debt for the *most-flooded* residents are driven by homeowners using flood insurance to prepay their mortgages rather than rebuild, with two key determinants behind the prepay decision. First, this was most commonly seen in areas where reconstruction costs exceeded pre-storm home values. Second, mortgages that were originated by non-local lenders were more likely to prepay than rebuild.

To examine the role of local vs non-local mortgage lenders in borrowers' post flood outcomes, they categorize local lenders as those whose share of New Orleans based loans exceed that of the median lender. They find borrowers from non-local lenders are more likely to pay down mortgage with insurance claim proceeds compared to borrowers with local lenders. Furthermore, they find that local lenders returned to pre-Katrina lending levels 2 years later, while non-local lenders largely exited the market. This finding on the role of non-local lending institutions in the decision to rebuild adds important context to the discussion on flood damaged induced pre-payment risk, as well as the discussion on community resiliency.

While these studies offer important context, our study is most similar to recent work by Kousky, Palin and Pan (2020) who use administrative data from Fannie Mae's single-family book of business after Hurricane Harvey. Like ours, their study investigates both household level outcomes as well as climate risks from the perspective of a large mortgage credit holder. When first examining the link between flood damage and mortgage performance, they find moderately to severely damaged homes are three times more likely to become delinquent after the storm compared to undamaged homes and conclude that flood insurance has no short-term effect. Longer term performance (180 days delinquent/default) depends on insurance coverage. Assuming that property location within an SFHA implies having a flood insurance policy (100% compliance) and location outside an SFHA implies no coverage, they compare outcomes for houses inside SFHAs to those outside.[3] They find for homes inside SFHAs with

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[3] It should be noted that this is a strong assumption given most insurance studies find take-up rates closer to 50% (Kousky and Lingle 2018). However, this over estimation of insurance coverage is likely to bias the estimated effect of coverage on post flood outcomes downward. Likewise, the assumption of being outside SFHA implying non-coverage is also strong for the Houston area, as Kousky and Lingle 2018 find Texas has higher than normal non-

flood insurance, prepayment rises with property damage by a factor of 2.1 compared to undamaged homes. There is no difference in prepayment for damaged homes outside SFHAs (i.e., uninsured homes) compared to undamaged homes, corroborating the results suggesting insurance coverage leads to prepayment discussed in Gallagher and Hartley (2017). Outside of SFHAs, increasing damage increases the need for loan modification and the likelihood of the mortgage becoming 180 days delinquent or in default two years post storm. However, our study differs in several meaningful ways. The most significant difference is definition of exposure. While Kousky, Palin and Pan (2020) are able to rely on property level damage reports, our study relies on zip code level exposure indicators determined by FEMA disaster aid applications. As we will elaborate in the methodology section, this changes the interpretation of our results.

Additionally, this work builds on previous HUD research examining several relationships between NFIP claims, insurance premiums and loan performance within the FHA portfolio (HUD-2M Research 2020). Relevant to this discussion, the study team analyzed the effect of a flood insurance claim on loan performance of an FHA insured mortgage for the subset of loans with active flood insurance policies. Using a logistic regression where the dependent variable is a binary indicator for the first time a loan was in default, they consider the effects of a flood claim one year prior and two years prior, for the subsample of mortgages with flood insurance for each state. In summary, for both North Carolina and Florida, the relative likelihood of defaulting in the next year is larger when an FHA-insured property has at least one flood insurance claim in the current year than when the FHA-insured property has no flood insurance claims in the current year. In all three specifications considered, a property with at least one home owners insurance claim in the previous year is 1.6-1.8 more likely to be in default during the current year, significant at the 95% confidence level. Only in the specification including controls for monthly payment and monthly effective income does a flood claim two years prior have a statistically significant effect of being more than twice as likely to default (at the 95% confidence level). This analysis does not include properties without flood insurance, however, so there is no insight to the effect flood insurance has on mortgage outcomes compared to uninsured mortgages.

The 2011 HUD study used a survey of individuals who owned properties in 2005 that were destroyed by hurricanes Katrina and Rita to examine how Disaster Recovery-Community Development Block Grants (CDBG-DR) were used in rebuilding in Louisiana, Mississippi and Texas. Employing a multivariate analysis of factors that influenced likelihood of rebuilding, the authors found households covered by flood insurance were 37% more likely to rebuild after Hurricanes Katrina and Rita compared to households without insurance (Turnham et al. 2011). Homeowners with an active mortgage, however, were 13% less likely to rebuild, all other things being equal. The authors further investigate the interaction between these two variables by estimating the effect of having an active mortgage on the decision to rebuild among the fully

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SFHA. This too may bias the estimates of the effect of insurance downward. With two potential downward biases, the true effect may be larger than reported.

insured sample and find that those with a mortgage were more than 11% less likely to rebuild, indicating that homeowners may use insurance proceeds to pay off a mortgage and move rather than rebuild, although the study does not draw this conclusion.[4]

The relative scarcity of studies examining this issue demonstrates the data limitations relating to matching insurance policies directly to mortgage information, which make this problem particularly difficult to study. This further highlights the need for an automated data set linking mortgages to flood insurance policies.

Section 3: Background on FHA Single Family Mortgage Insurance Program

FHA's single family mortgage insurance program exists to expand homeownership opportunities to potential borrowers who may be unable to afford or obtain a conventional mortgage. The program operates by providing insurance to the lender/servicer of the mortgages on monthly payments for principal and interest of the loan, effectively reducing the risk of lender losses should a mortgage default. In the event of mortgage default or losses related to missed payments, mortgage servicers may file an insurance claim for the remainder of the principal balance. FHA maintains the Mutual Mortgage Insurance Fund (MMIF) which funds payments to mortgage insurance claims. The MMIF is funded by collecting mortgage insurance premiums, either through up-front premiums at the time of endorsement, or through monthly insurance premiums that lenders/servicers collect from borrowers and forward to FHA. As a wholly owned federal entity, climate related financial risks to the MMIF and the FHA represent risks to both the operation of the program as well as the public. Therefore, understanding the extent to which climate risks affect the MMIF is an important area of inquiry.

FHA guards against disaster-related costs through requirements for casualty insurance (transfer of risk to counter-parties) and "preservation and protection" (maintenance and repair). This means that in the event of a disaster related mortgage default where the home was damaged, FHA is not liable for insurance payouts if the property is badly damaged. There are other program features to protect FHA from disaster related losses or claims costs more generally that can be applied in the event of a disaster. FHA offers a loss-mitigation waterfall – a series of steps that households and lenders can take together to prevent foreclosure once a mortgage is in default that may allow borrower to get back on track with their mortgage payments. In this case, losses to the MMI Fund could be minimized and households remain in their homes. There are also disaster related mortgage foreclosure moratoria that accompany presidential disaster declarations. This study focuses on costs resulting from foreclosures leading to full MI claims and therefore does not include the costs of the loss mitigation programs and foreclosure moratorium protocols should households return to payments.

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[4] All results discussed from this study were statistically significant at least at the 90% confidence level.

Section 4: Data and Descriptive Analysis

Data

We use FHA administrative data to build an annual panel of individual FHA mortgage endorsements from 2004-2017. We extract a 10% sample stratified by year of all FHA endorsements in the single-family program.

Table 4.1: Sample Endorsements by year

year	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
N	24,515	29,922	27,188	28,379	76,509	103,662	91,324	72,340	70,692	64,135	58,039	78,745	86,784	83,146

The data contains borrower income and credit characteristics, borrower demographics, loan details and loan status. If a loan has been paid off in full, either through completion of term or prepayment, a status of T is recorded with the termination date. Prepayment or paid in full are not specifically differentiated, however this information can be identified by the termination date, which is included. If a mortgage ends in foreclosure with a mortgage insurance claim, a status of C is recorded, along with termination dates and the date of the default event that leads to the foreclosure. It is possible that termination dates and default dates do not align if a mortgage goes through the loss mitigation waterfall, extending the time between default and termination. Table 2 provides summary statistics.

Table 4.2: Sample Summary Statistics

Variable	Mean
Interest rate	4.72
	(1.01)
Original mortgage amount	$174,867
	(94391)
Loan-to-Value Ratio	95.49
	(4.61)
term (months)	358.09
	(18.12)
front end DTI	26.67%
	(8.74)
FICO	680.19
	(56.29)
N	895,380
Loan Outcome	
Active	210,986
Terminate (without claim)	623,293
Claim	61,101

To identify disaster exposure and zip-code level disaster intensity measures, we use two datasets from FEMA's open data platform. The first provides disaster declaration data, including FEMA disaster aid program eligibility, disaster start and end date, and information on the type of disaster. The second provides housing assistance program statistics aggregated to the zip code level, by disaster declaration number. As a quick note, disaster declarations are enacted on a state-by-state basis, requested by the governor of each affected state. Therefore, large disasters such as hurricanes that can span multiple states will have different declaration numbers. The two datasets are linked by FEMA's disaster declaration number to create a set of housing assistance information at the zip code level for individual disasters.

Section 5: Descriptive Analysis

The first objective of this paper is to characterize disaster exposure in FHA's single family mortgage portfolio. To begin, we map our sample to FEMA's National Risk Index and compute the share of each race group by overall risk rating category (Table 5.1). This provides a high-level measure of expected risk of exposure for the portfolio and within race groups. Additionally, loan counts and sample shares by race are included in the bottom two rows to provide additional context of how each race group's exposure fits in to the sample at large. Notably, Latinx borrowers have the highest risk of exposure overall, with over 60% of borrowers located in *Very High*- or *High*- risk counties, followed by Asian borrowers with 58%. On the other hand, white-non-Hispanic borrowers have the lowest expected exposure with only 31% of borrowers in the highest risk counties.

Table 5.1: Race of Primary Borrower

FEMA NRI Risk Rating	American Indian	Asian	Black	Hawaiian	Latino	Multi-racial	Not Disclosed	White, non Hispanic	Total Count
Very High	16.0%	21.3%	12.0%	16.6%	28.1%	10.9%	13.8%	6.6%	11.5%
High	32.5%	37.1%	28.3%	34.2%	35.2%	28.0%	29.5%	25.6%	28.0%
Moderate	30.2%	31.6%	44.1%	29.7%	26.9%	34.9%	34.6%	35.7%	35.0%
Low	17.9%	9.0%	14.0%	15.8%	8.5%	21.2%	17.6%	25.2%	20.4%
Very Low	3.4%	0.9%	1.6%	3.8%	1.3%	5.0%	4.4%	6.9%	5.1%
Counts	4,840	24,516	96,778	6,259	138,806	4,918	51,747	567,489	895,353
Sample Share	0.5%	2.7%	10.8%	0.7%	15.5%	0.5%	5.8%	63.4%	100.0%

Next, we compare NRI-expected exposure to realized exposure by matching mortgages in our sample to Presidentially Declared Major Disaster Areas that were eligible for household assistance, the treatment criteria for disaster exposure in our empirical strategy (Table 5.2). Panel A illustrates exposure for each race group across all disasters, as well as how each group fits in to our sample's overall exposure. Black and multiracial borrowers have the highest proportions of group of exposure, both at roughly 40%. On the other hand, Asian borrowers have the lowest group exposure at 14%, while the rest of the race groups have about 30% exposure. Recall, that sample exposure was also 30%. Differences in the group share of exposure (row 2) and the group share of sample (row 3) indicate disproportionate exposure to natural disasters. Most race groups are within a single percentage point difference, indicating proportionate exposure. The two exceptions are Black borrowers, who have disproportionately high exposure (14% of sample exposure vs 11% of sample) and White non-Hispanic borrowers with disproportionately low (60% of exposure vs 63% of sample).

Table 5.2: Disaster Exposure by Race Group

Race Group	American Indian	Asian	Black	Hawaiian	Latino	Two or More	Not Disclosed	White, non hispanic
				Panel A				
% Group Exposed	29.8%	24.5%	40.0%	30.2%	31.4%	39.4%	29.6%	29.5%
Group Share of Sample Exposure	0.52%	2.18%	14.02%	0.69%	15.81%	0.70%	5.54%	60.54%
Share of Sample	0.50%	2.70%	10.80%	0.70%	15.50%	0.50%	5.80%	63.40%
				Panel B				
Earthquake	1.1%	0.8%	0.2%	1.0%	0.2%	0.4%	0.5%	0.3%
Wildfire	2.1%	2.2%	0.6%	1.9%	2.5%	1.6%	1.4%	0.8%
Flood	6.9%	7.2%	11.8%	7.4%	9.2%	8.9%	9.1%	8.8%
Hurricane	8.8%	11.4%	19.7%	11.5%	18.2%	15.2%	13.7%	10.5%
Mud Slides	0.1%	0.1%	0.0%	0.1%	0.0%	0.1%	0.1%	0.1%
Severe Storms	17.7%	9.7%	19.6%	15.5%	12.4%	24.9%	13.5%	14.8%
Tornado	1.2%	0.4%	1.2%	0.7%	0.4%	1.2%	0.8%	1.1%

Panel B of Table 5.2 breaks out race-group exposure by disaster type.[5] For all race groups, severe storms and hurricanes represent the two largest sources of exposure in the FHA portfolio.[6] Flooding was the next most prevalent disaster type for all race groups.

Section 6: Methodology

We employ a two-stage methodology, where the first stage estimates the statistical relationship between disaster exposure and a mortgage ending in foreclosure with mortgage claim. The coefficients from the first stage are then applied in the second stage to create a simulation for expected losses throughout the life of the mortgage. Additional specifications examining outcomes by credit group, disaster type or racial groups will be introduced later in the paper.

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[55] Disaster percentages will not total race group percentages as some borrowers will be exposed to multiple types of disasters

[6] Our sample had no typhoon exposure, and less than 20 volcano exposures, so neither were reported in Table 5.2. Volcano exposures are included in empirical estimations in later sections.

Stage 1

In the first stage, we use a multinomial logit regression to estimate the probabilities of potential loan outcomes relative to a baseline outcome, while controlling for standard borrower credit characteristics, mortgage characteristics, and macroeconomic indicators (Green 2018). In our model, the loan being active the following current period of observation is the baseline case, and the alternate outcomes are *prepayment* and *claim* (i.e. a default leading to a mortgage insurance claim). In both alternate cases, the loan is terminated and no longer observed in the panel. Only terminal default cases that result in a claim are identified as alternate outcomes. Hence, a loan that is in default but will eventually become current again would be considered active, including mortgages in forbearance or other stages of the loss mitigation waterfall. It is possible that a mortgage goes into default and terminates in prepayment before a foreclosure occurs, and these mortgages are not treated differently from mortgages in the prepayment category. The multinomial model estimates a set of coefficients: $\beta^{(1)}$, $\beta^{(2,)}$, $\beta^{(3)}$, for the distinct outcomes described above and given by Equation 1:

$$Probabilty(Y = k) = \frac{e^{X_{j,t}*\beta(k)}}{e^{X_{j,t}*\beta(1)} + e^{X_{j,t}*\beta(2)} + e^{X_{j,t}*\beta(3)}}$$

Where *Equation 1* is the binary outcome logistic equation, *K* = 1 (remains active), 2 (ends in prepayment) or 3 (default ending in claim), *X* is a vector of explanatory variables related to claims outcomes for mortgage observation *j* in policy year *t*, and β is a vector of coefficients. The model is unidentified as stated, as there are multiple solutions that lead to the same probabilities for $Y = 1, Y = 2, Y = 3$. This is addressed by setting a one of the coefficient vectors equal to 0 to set a baseline outcome. As mentioned above, our baseline outcome is *Y* = 1, the loan remains active. Therefore, coefficients and reported Relative Risk Ratios will compare the probability for the remaining two outcomes relative to the baseline case.

Our explanatory variable of interest is disaster exposure, which is defined at the county level by eligibility of federal disaster aid from FEMA's Individuals and Households program (IHP). Regarding the timing of exposure relative to the timing of default, there are numerous reasons why borrowers may experience financial stress related to a disaster along different timelines, most of which we are unable to control for in our model. To account for this, we also include indicators of lagged exposure. There are three disaster exposure indicator variables in the list of explanatory variables, indicating whether the policy year observation was within 0-12 months of the disaster, 13-24 months, or 25-36 months. We also include a specification with a single variable for disaster exposure in the last three years, which we will use for simplicity in our additional analysis on disaster type, race group effects, and credit group effects. The model controls for borrower, loan, mortgage market, and local economic characteristics, standard in the mortgage finance literature.

These lagged exposure variables may also give insight into the direct vs indirect discussion in the Data section. Our intention in using local unemployment rates is to capture effects of economic distress both in non-disaster and disaster periods with the latter intended to control for direct effects of disasters and allow the disaster exposure variables to estimate additive claim risk created by disasters. Such additive risk could include damage to general (non-economic) community health caused by disasters.

All explanatory variables used in the analysis are listed and explained in Table 1A in the appendix. Results from the logit regressions will be reported as Odds Ratios and discussed in detail in the next section.

Stage 2

After the stage 1 regression, we use estimated coefficients to predict the probability of each alternate outcome, prepayment and default resulting in mortgage claim, for each (mortgage case)-(policy year) observation. The predicted probabilities for claims and prepayment are used to simulate the expected life of the mortgage. Starting with the initial mortgage amount as the first period beginning unpaid balance (UPBbegin), the simulation calculates and updates expected principal and interest payments, claims costs, and prepayment costs to calculate the end of period unpaid balance (UPBend). The UPB end is then updated as the UPBbegin in the following period, and this process continues until either the UPB value is 0 or the end of the simulation time frame, which is the year 2019.

The simulation is run for two separate scenarios. First the simulation is run with the effects of disaster exposure included, and then again with the coefficients for disaster exposure set equal to 0. The difference in expected claims costs with and without disasters are interpreted as the additional claims associated with disaster exposure, given by Equation 2 below. A full equation list is included in the Appendix in Table A.2

$$\begin{aligned} &\mathrm{E}\,[Disaster\ Related\ Claims\ Costs] \\ &\qquad = \mathrm{E}[Claims\ Costs \mid Disasters\ ] - \mathrm{E}\,[Claims\ Costs \mid no\ Disasters] \end{aligned}$$

Section 6: Results and Discussion

Results are first presented for our primary analysis focusing on losses to the MMI fund. Analysis on household effects by subgroups and disaster types will follow.

Table 6.1 reports the relative risk ratios from the Stage 1 multinomial logit estimations. RRRs greater than one indicate that the mortgage is more likely to end in the corresponding alternate outcome than to continue to remain active in the portfolio the following period. RRRs less than one mean the alternate outcome is less likely. We consider two specifications of disaster exposure. First, as reported in columns (1) and (2), are the individual year exposure lag variables. Second, as reported in columns (3) and (4), is the single exposure within the last three years specification. Given the effects of the Great Recession on mortgage performance as well as the tightening of lending standards in the immediate aftermath, we run both specifications on the full sample of originations, years 2004-2017, as well as the post-recession sample, which we define as 2010-2017.

In the individual year lags in the full sample, we find that disaster exposed mortgages are more likely to default and go to claim in each of the first three years following disaster exposure compared to the baseline outcome of remaining active in the portfolio in both the full sample and the post-recession sample. RRRs are similar for the first two years, but the post-recession year 3 RRR is slightly larger at 1.4 compared to 1.3 in the full sample. RRRs are equivalent for the single three-year exposure window specification in both samples. These results match our expectations that disaster exposure affects borrowers' ability to repay their mortgage.

Table 6.1: First Stage Multinomial Results

	(1)	(2)	(3)	(4)
	Individual Year Lags		Three Year Window	
	2004-2017	2010-2017	2004-2017	2010-2017
Prepayment				
exposurelag_last3yrs			.94***	.91***
			(.0035)	(.0044)
exposure1_12m	.9***	.85***		
	(.0044)	(.0053)		
exposure13_24	1***	1.1***		
	(.0058)	(.0078)		
exposure25_36	.97***	.95***		
	(.0063)	(.0086)		
Claim				
exposurelag_last3yrs			1.2***	1.2***
			(.014)	(.034)
exposure1_12m	1.1***	1.1**		
	(.017)	(.038)		
exposure13_24	1.2***	1.2***		
	(.021)	(.055)		
exposure25_36	1.3***	1.4***		
	(.026)	(.078)		
N	4304306	2572045	4304306	2572045

Exponentiated coefficients;
Standard errors in parentheses

="* p<.1 ** p<.05 *** p<.01"

On the other hand, we find that disaster exposed mortgages are less likely to prepay compared to non-exposed mortgages in the first-year post disaster, but effects are close to zero in years two and three. Looking at the post-recession sample results in column (2), we see the effects are similar directionally in the first and third years with slightly larger magnitudes, but interestingly the second year shows a slight increase in probability of prepayment relative to the base outcome. Therefore we do not find evidence in the FHA sample of disaster exposure increasing prepayment rates driven by homeowners taking the insurance proceeds to payoff their mortgages and sell their homes. While previous research has found evidence of this, we think there differences in study design could explain this non-finding. The broader definition of disaster exposure to include local area economic affects we use means that we are also including households who did not face physical damage to their homes. If the mechanism behind increased prepayment rates is driven by insurance payouts based on disaster damage, then it is possible that these effects are drowned out by the non-damaged segments of the treatment groups.

The second stage simulation generates the life of the mortgage in expectation. This process is completed separately for two scenarios. First, expected claims are simulated with disaster effects. Second, the disaster exposure coefficients are set equal to 0, nulling the effect disaster exposure has on mortgage performance. The differences in expected claims payments with disasters and without disasters are reported for each cohort-performance year in Table A3. The sum of all cohort-performance year claims differentials is approximately $177 million and is interpreted as the total additional expected claims related to disaster exposure for the sample. Scaling this total from our 10% portfolio sample, we estimate that disaster exposure caused an additional $1.77 billion dollars on mortgage insurance claims from 2004-2017, or just over 2% of the $80 billion in total claims payments for the same period.

The following subsections break down disaster effects by race, disaster type and credit score. For each of these specifications, exposure is simplified to a simple three-year window rather than individual year lags, as exposure will be interacted with other variables.

Effects by Racial Groups

To understand how disaster exposure affects borrowers by primary racial group, we add a vector of race-exposure interaction terms to disaster exposure to Equation 1 in place of the three-year exposure window treatment term. The RRRs reported in Table 6.2 are interpreted as race specific effects compared to the non-disaster affected sample. Recall from Table 6.1 that the overall affect on prepayment was close to 0, but slightly decreases prepayment risk, while the relative probability of default with claim was 1.1-1.3 times higher. As shown in column (2), we find very different effects on the relative probability of claim given disaster exposure across race groups. American Indian, white and multiracial borrowers are affected to the greatest extent by exposure, with RRRs of 1.4. Black borrowers also have increased odds of claim, though at a much smaller magnitude. Disaster exposure has no effect on relative claim probability for Hawaiian and Latino borrowers. Asian borrowers are the only group that are less likely to default with claim post disaster.

We see that across the board, most race groups have decreased relative odds of prepayment, with black borrowers having the largest effect. Asian borrowers have no effect, but white non-Hispanic borrowers have increased probability of prepayment. Given the weight of white borrowers in the FHA population, this modest increase in prepayment odds may counteract the larger reductions in prepayment probability seen in most other race groups, which explains why prepayment does not have a large effect in the specification without race-specific exposure terms.

Table 6.2 Race-Exposure Interactions

	(1) Prepay	(2) Claim
American Indian	.73***	1.4**
	(.036)	(.17)
Asian	1	.82**
	(.022)	(.08)
Black	.58***	1.1***
	(.0061)	(.026)

Hawaiian	.92**	1.2
	(.037)	(.13)
Latino	.81***	1
	(.007)	(.03)
Not Disclosed	.96***	1.1**
	(.013)	(.051)
White non-Hispanic	1.1***	1.4***
	(.0048)	(.019)
Multiracial	.68***	1.4***
	(.029)	(.12)
N	4304306	

Standard errors in parentheses * p<.1 ** p<.05 ***p<.01

Effects by Disaster Type

Next, we investigate exposure by disaster type, creating individual exposure variables for each type of disaster as recorded by FEMA. Again, relative risk ratios are presented and interpreted as the relative likelihood of the alternate outcome to remaining active. The results that are most different are the RRRs for prepayment. Recall from Table 6.1 that disaster exposure either slightly decreased prepayment or had an effect close to 0. When broken out by disaster type, we see that Earthquakes, wildfires and hurricanes increase the relative odds of prepayment for exposed borrowers, with wildfire victims being twice as likely to prepay. These results could be explained by the severity of damage these event types are known for. Additionally, these events are relatively rare compared to riverine and inland flooding, severe storms and tornadoes which all reduce the likelihood of prepayment. Given the frequency of these types of events in the sample, these prepayment reductions should outweigh the increases. For the alternative outcome of default ending with claim, we also see mixed results across disaster type. Mudslide, earthquakes and hurricanes have little effect on the relatively likelihood of claim, while floods actually decrease probability. Wildfires, severe storms and tornados all have the strongest effects on increasing probability of claims, at 1.1 to 1.3 times the odds for mortgages ending in claim for exposed homes.

Table 6.3 Disaster Type Specific Exposure

	(1) Prepayment	(2) Claim
Earthquake	1.2***	.87
	(.044)	(.18)
Wildfire	2***	1.2***
	(.035)	(.086)
Flood	.94***	.95*
	(.0063)	(.03)
Hurricane	1.1***	1**

	(.0062)	(.022)
Mud/Land slides	1.1	9.2e-09***
	(.072)	(3.5e-10)
Severe Storms	.77***	1.3***
	(.0044)	(.018)
Tornados	.7***	1.6***
	(.018)	(.13)
N	4304306	

Exponentiated coefficients; Standard errors in parentheses
="* p<.1 ** p<.05 *** p<.01"

Effects by Credit Groups

In this subsection, we explore how borrowers in different credit groups respond to disaster exposure. Using credit score groupings as defined in the Consumer Financial Protection Bureau's Home Mortgage Disclosure Act database, we interact binary group indicators with the disaster exposure in previous three-year term to estimate separate effects for each group. In addition to adding the credit group-exposure interaction terms, we also change the regression equation by replacing the FICO score with credit group indicators. We omit the Good credit group to prevent collinearity, and to force interpretation of our results to be relative to the average credit group. Relative Risk Ratios are presented below in Table 6.4.

Table 6.4: Credit Score-Exposure Interactions

	(1)	(2)
Credit Group x Exposure	Prepay	Claim
Poor (300 to 579)	.79***	1.1**
	(.017)	(.031)
Fair (580 to 669)	.91***	1.2***
	(.0052)	(.018)
Good (670 to 739)	.96***	1.3***
	(.0058)	(.034)
Very Good (740 to 799)	.98**	1.6***
	(.0089)	(.078)
Excellent (670 to 739)	.91***	1.3
	(.029)	(.23)
N	4304306	

Standard errors in parentheses * p<.1 ** p<.05 *** p<.01

Intuitively, we would expect the lower credit score groups would be more vulnerable to adverse outcomes than higher credit score groups. However, we find the exact opposite. While all credit groups have increased odds of default with claim, the effect is stronger the higher the credit group. One possible explanation is a geospatial correlation between credit groups and the greatest loss types of risks. Wildfire areas, particularly in the west, have high amenity value and often above average home values. This also applies to high-risk coastal areas. This would correlate with a higher credit score necessary for loan qualification, but also increase the risk of disaster exposure. Based on our results for disaster specific effects, wildfire exposure increases risk of claims. However, this is only an intuitive explanation at this time and additional analysis is needed for confirmation.

Section 8: Conclusion

Natural disasters have become more frequent and more destructive over the last two decades. Additionally, shifting development patterns continue to put more homes in disaster prone areas. This means more households are facing increasing financial risk, increasing the potential for this risk to spread into other components of the mortgage finance ecosystem. In this paper, we explore this risk for borrowers in FHA's single family mortgage portfolio to understand both household risk and how this risk may affect mortgage insurers. Using administrative data to get an in-depth look at mortgage level outcomes not commonly utilized in the literature, we find that mortgage exposure increases the probability of mortgage default leading to MI claims in the FHA portfolio, confirming results from previous research that find adverse financial and household outcomes after disasters. We then use estimated coefficients from our mortgage performance analysis to simulate expected claims losses to the FHA to assess the downstream impacts of climate risk in the mortgage insurance market, to our knowledge a strategy not yet applied in this line of research. While this analysis finds that natural disaster exposure caused $1.7 billion in additional FHA paid MI claims from 2004 to 2017, this only 2% of the $80.6 billion in total claims paid over the same period suggesting climate change related losses are not yet a threat to the viability of the FHA insurance program.

We also explore how different groups of borrowers based on race of the primary borrower or credit score are affected by exposure. American Indian, white, black, and multiracial borrowers are more likely to go to claim post disaster, while Latino, Asian, and Hawaiian borrowers are not. Perhaps the most surprising result is that higher credit score groups are more likely to go to claim than lower credit score groups post disaster, contrary to the well documented association between credit score and mortgage performance. We provide an intuitive explanation for this result, but further analysis is needed. We also find very different effects based on disaster type, with some disaster having much stronger effects on prepayment and claim than others, wildfires, tornados and severe storms in particular.

A missing component of this analysis however is the role of hazard insurance. While results from previous research provide some intuitive linkages between insurance coverage and these relatively small losses to the program, the home insurance market is in the midst of a very dynamic period in the last five years since our study window. As the availability of insurance to homeowners in the highest risk areas changes, this layer of financial protection between household risk and downstream sectors of the housing finance ecosystem may prove insufficient to protect other participants in the mortgage market. This highlights both the necessity to fully understand the protective role of hazard insurance as well as the need to maintain the stability of the insurance market.

Appendix

Table A.1: Variables used in logistic regressions

Variable	Description	Rationale
defBoolPY	Dependent variable: year of observation in which a loan defaulted and subsequently became an insurance claim.	
frontDTI	Front-end mortgage debt payment-to-income ratio at origination.	Indicator of payment. Prior: positive.
fico	Borrower credit score at origination.	Measure of borrower credit quality. Prior: negative.
giftGovtPrc	Downpayment assistance from government sources as a percentage of sales price.	Literature finds association of borrower financial assistance at origination with claims. Prior: positive.
giftFamilyPrc	Downpayment assistance from family sources as a percentage of sales price.	
sellerPrc	Seller contribution to closing costs as a percentage of sales price.	
scndFincPrc	Downpayment assistance from secondary (sofr) finance as a percentage of sales price.	
mtmLTV	Loan to property value (sales price adjusted by FHFA House Price Index) at policy year of observation.	Inverse measure of borrower equity. Prior: positive.
unempRate	Unemployment rate at policy year of observation.	Measure of economic stress. Prior: positive.
ratePMMS	Freddie Mac survery of 30-year fixed mortgage rates at policy year of observation.	Measure of cost of default exit options (loan modifcation, re-finance). Prior: positive.
py1	Boolean variable for first policy year obersvation.	Outside of manufacturing defects, first year defaults are rare.
Exposure1	Boolean variable for property in a zip code that experienced a disaster in the last 12 months.	
Exposre2	Boolean variable for property in a zip code that experienced a disaster in the last 13 to 24 months.	
Exposure3	Boolean variable for property in a zip code that experienced a disaster in the last 25 to 36 months.	

Table A.2 List of Simulation Equations

Note: for all simulation equations, subscript *j,t* refers to on observation of mortgage *j* in policy year *t*

Equation A.1: Begin period unpaid balance ($UPBbegin_{j,t}$)

$UPBbegin_{j,t}$ = *Original Mortgage Amount* for t= 0,

$UPBbegin_{j,t} = UPBend_{j,t-1}$ for $t > 0$ and is given by Equation A.2

Equation A.2: Expected End of period unpaid balance ($UPBend_{j,t}$)

$$E[UPBend_{j,t}] = \mathrm{E}[UPBbegin_{j,t}] + \mathrm{E}\left[interest_{j,t}\right] - \mathrm{E}\left[payment_{j,t}\right] - \mathrm{E}\left[claimamount_{j,t}\right] - \mathrm{E}[prepayamount_{j,t}]$$

Equation A.3: Expected interest charges

$$\mathrm{E}\left[interest_{j,t}\right] = r * \mathrm{E}[UPBbegin_{j,t}]$$

Equation A.4: Expected annual mortgage payments on P&I

$$\mathrm{E}\left[payment_{j,t}\right] = insert\ amortization\ formula$$

Equation A.5: Expected Claim Costs for observation *j*

$$\mathrm{E}\left[Claim\ Costs_{j,t}\right] = (py1_{j,t} * Exposure1_{j,t} + py2_{j,t} * Exposure2_{j,t} + py3_{j,t} * Exposure3_{j,t}) * UPBbegin_{j,t}$$

Equation A.6: Expected Claim Costs for observation *j*

$$\mathrm{E}\left[prepayamount_{j,t}\right] = cohort\_year * \mathrm{E}[UPBbegin_{j,t}]$$

Table A.3 Simulation Output

Differences in Claim Costs by Cohort-Policy Year (millions of dollars) with and without disaster exposure

	Policy Year																
Cohort Year	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	Total
2004	0.3	2.07	2.08	2.76	1.55	1.34	1.1	0.43	0.22	0.16	0.06	0.03	0	0	0	0	$12.14
2005	0.13	1.59	3.01	4.03	3.19	2.67	1.23	0.59	0.44	0.16	0.08	0.04	0.03	0	0		$17.21
2006	0.09	2.74	4.38	4.93	3.57	1.55	0.78	0.67	0.25	0.1	0.04	0.03	0.03	0			$19.15
2007	0.36	4.42	5.41	6	2.53	1.35	1.15	0.41	0.15	0.07	0.07	0.05	0				$21.96
2008	0.8	6.19	8.77	7.99	3.82	3.3	1.22	0.47	0.2	0.17	0.13	0					$33.07
2009	0.15	4.85	6.02	6.15	5.49	2.17	0.91	0.38	0.3	0.21	0						$26.66
2010	0.24	2.86	3.69	6.09	2.66	1.16	0.45	0.32	0.25	0.01							$17.72
2011	0.22	1.4	2.72	1.93	0.83	0.34	0.25	0.19	0								$7.88
2012	0.09	1.47	1.11	1.11	0.48	0.38	0.28	0									$4.92
2013	0.05	0.32	0.48	0.6	0.49	0.38	0										$2.33
2014	0.02	0.5	0.74	0.82	0.58	0.02											$2.67
2015	0.12	1.06	1.64	1.76	0.05												$4.63
2016	0.16	1.77	2.5	0.12													$4.55
2017	0.29	2.32	0.16														$2.77
Total	$3.01	$33.57	$42.70	$44.29	$25.24	$14.66	$7.38	$3.47	$1.81	$0.88	$0.38	$0.16	$0.08	$0.04	$0.01	$0.00	$177.66

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