Natural Disasters and Housing Markets. The Tenure Choice Channel.*

Robin L. Dillon-Merrill†, Lei Ge‡ and Pedro Gete§

August 2020 (work in progress)

Abstract

We analyze the impact of natural disasters on U.S. real estate and mortgage markets. We show: 1) Natural disasters permanently increase housing rents. The effects on housing prices are ambiguous. 2) Conforming mortgage applications for low-mid size homes fall. However, jumbo applications slightly increase. Lending standards do not change; 3) Homeownership rates decline; 4) The results are especially strong for flooding disasters, which are usually not covered by insurance companies. The previous facts suggest a tenure choice channel in which low and mid income households hedge disaster risk by moving from the ownership to the rental market. Wealthy households expand their housing holdings.

Keywords: Credit, Inequality, Natural Disasters, Rentals, Housing, Tenure Choice.

JEL Classification: R3, Q54

*We appreciate the comments of Sandeep Dahiya, Behzad Diba, Jeremy Gabe, Andre Gao, Laura Liu, Lily Liu, Michael LaCour-Little, Doug McManus, Spenser Robinson, Drew Sanderford, Brigitte Roth Tran, Jiro Yoshida, Anthony Yezer, Fan Zhang and seminar participants at 2018 American Real Estate and Urban Economics Association conference, 2018 American Real Estate Society conference and George Washington University. We thank Georgetown's Environment Initiative for financial support. We thank Afras Sial and Austin Parenteau for their research assistance.

†Email: rld9@georgetown.edu. McDonough School of Business at Georgetown University. Phone: (+1) 703-292-4921. Address: 37th and O Sts., NW. Washington DC, 20057, USA.

‡Email: lei.ge@live.com. Fannie Mae. 1100 15th Street, NW Washington, DC 20005, USA.

§Email: pedro.gete@ie.edu. IE Business School. Maria de Molina 12, 28006 Madrid, Spain. (+34) 915689727.

1 Introduction

There is consensus among climate scientists that natural disaster risk will increase in the future. For example, Dahl et al. (2017) claim that over the next two decades the number of locations exposed to the risk of high flooding will double. Thus, an important policy question is to understand how natural disasters affect real estate and mortgage markets. This paper gathers and analyze a new database to answer that question. Our data allow to compare more than one location and different types of disasters. We uncover aggregate and distributional facts.

Our database merges annual data on natural disasters from StormEvent, with housing data from Zillow and mortgage data from HMDA. We are able to compare different kinds of disasters in different locations by focusing on the property damage of each disaster. We document the following facts: (1) Housing rents permanently increase following a disaster. The effects on housing prices are ambiguous; (2) Conforming mortgage applications for low-mid size homes fall while jumbo applications increase. Approval standards do not change; (3) Homeownership rates decline; (4) The results are especially strong for flooding disasters, which are usually not covered by insurance companies.

Facts (1)-(3) highlight a tenure choice channel such that, following natural disasters, low and mid income households move from the ownership to the rental market. Thus, housing rents increase and homeownership falls. Wealthy households expand their housing holdings. The changes are demand driven as illustrated by the drop in mortgage applications and the lack of change in lending standards.

Two theories can drive the previous results: a) A wealth effect: low and mid income households suffer more from natural disasters. Once they have lower wealth, they cannot afford ownership; b) A risk channel: low and mid income households learn about disaster risk, they have lower willingness to take risks, and they reduce their exposure to homeownership to minimize exposure to natural disaster risk. Fact (4) suggests the presence of this second theory. Natural disaster risk becomes then concentrated on the high wealth households who can cope better with it.

The existing literature has so far mostly focused on event studies that analyze individual housing prices following one disaster in one location. For example, Harrison et al. (2001), Bin and Polasky (2004), Bin and Landry (2013), Hallstrom and Smith (2005), Morgan (2007), Bin et al. (2008) and Daniel et al. (2009) show pricing differences between areas with low or high risk of natural disasters. Gibson, Mullins and Hills (2018) study the housing prices and insurance premiums in New York under the recent flood insurance reform and the hurricane Sandy. Boustan et al. (2017) is the only paper we know studying a database with national coverage. They use the American Red Cross and the Federal Emergency Management Agency datasets to study large natural disasters every 10 years. We are also related to Cortes and Strahan (2017). They use a similar database (the SHELDUS dataset) to study how financially integrated banks respond to natural disasters. Notably, Bernstein, Gustafson and Lewis (2018) study the properties in the coastal areas exposed to the risk of the rise of the sea level. There results also witness the departure between the housing prices and rent prices in the coastal properties exposed to submergence risk. Our results coincident this growing gap between the housing prices and housing rents and, further, expand this result to the shocks of varieties of natural disasters in the MSA market level. Our also further results on the tenure choice and mortgage convince this channel.

The tenure choice channel that we uncover is related to Gete and Reher (2018), who show that at the MSA level, tighter credit standards have increased demand for rental housing, leading to higher rents.

Our income distributional results are related to Smith et al. (2006) and D'Acunto and Rossi (2017). Smith et al. (2006) use household-level data from Dade County (Florida) to show that, following hurricane Katrina, low-income household moved into low-rent housing, mid-income households moved out of the area while wealthy households were insensitive to the shock. They cannot control for local economic and demographic characteristics as we do. D'Acunto and Rossi (2017) show that the increased cost of financial regulation caused redistribution effects through the mortgage market. Mortgage supply increased for the wealthy households, contracted for the mid-income households and did not change much for the low-income households.

The rest of the paper is structured as follows: Section 2 introduces our data sources and variables. Section 3 studies the aggregate variables. Section 4 contains the results across household groups. Section 5 explores the risk aversion channel. Section 6 has the sensitivity tests. Section 7 concludes.

2 Data

We measure natural disasters in terms of property damage. The advantage of using property damage to measure natural disasters is that we can compare different disasters in different locations. For example, we can compare the wildfires in California with the hurricanes in Florida. The data come from the StormEvent database compiled by NOAA's National Weather Service. We focus on 25 types of disasters (flood related disasters, tornados, hail, wildfires etc) that can affect real estate markets.[1] These disasters account for around 98% of all the property

[1] We excluded small natural disasters such as heat or funnel cloud.

damage from all types of natural disasters[2].

Table 1 summarizes the natural disasters in the database. We rank them by total property damage in the first column. The second column is the number of disasters at the MSA level.

Insert Table 1 around here

Table 2 reports the statistics of the variables used in the paper. We have 242 MSAs for the 5 years period from 2010 to 2014.

Insert Table 2 around here

The variables that we use are: a) the logarithm of the disaster damage; b) Real estate variables, like the growth rates of the rent-to-price ratio, housing rents, housing prices, the number of housing units and the number of owner-occupied units; c) Credit variables like growth rates of the number of mortgage applications, the number of mortgage originations, growth rates for the jumbo loans and conforming loans and the number of mortgage denials. We also study these data for households with different wealth levels; d) MSA level control variables, like income, population, age, and the market share of Big-4 banks in terms of the deposits and bank branches in 2008. This last variable controls for the supply of the mortgage credit, like in Gete and Reher (2018).

3 Aggregate Effects

3.1 Housing Markets

We first study the dynamics effects from natural disasters where the dependent variables $Y_{i,t}$ are either the growth of the rent to price ratio, $\Delta log(Rent/Price_{i,t})$; or the growth of the housing rent index, $\Delta log(Rent_{i,t})$; or the growth of the housing price index, $\Delta log(Price_{i,t})$; or the growth rate of the number of mortgage applications $\Delta log(Application_{i,t})$; or the growth rate of the number of the mortgage originations $\Delta log(Origination_{i,t})$; or the mortgage denial rate, $Denial\,Rate_{i,t}$. That is,

$$\begin{aligned}\Delta log(Y_{i,t}) = \beta_0 + \sum_{k=1}^{6} \beta_k Disaster\,Damage_{i,t+1-k} + \gamma\,Control_{i,t-1} + \\ + \eta_i + \eta_t + \mu_{i,t}, \qquad (1)\end{aligned}$$

[2]All our results are robust when we include all 51 types of the natural disasters reported in StormEvent.

where i denotes the MSA and t denotes the year. $Disaster\,Damage_{i,t-1}$ is the logarithmic dollar value of the property damage caused by the natural disasters. $Control_{i,t-1}$ are the MSA level controls: growth of MSA average income, number of housing units, unemployment rate, population, age, lagged level of the Gini index, logarithm of median income and logarithm of population. We also control for the Big-4 bank deposit share and branch share. The η_i and η_t are MSA fixed effects and year fixed effects. Finally, the standard errors are clustered by MSA.

Insert Figures 1 and 2 around here

Figures 1 and 2 plot the coefficients that measure the impact of the natural disasters. $t = 0$ is the year when the disaster hits. The effects of natural disasters on housing markets take one year to arrive. Natural disasters increase rent-to-price growth. This effect seems permanent since there are no reversal effects. Thus, it seems the effect on housing markets comes from changes in demand, not from housing destruction or misallocations. This demand effect is confirmed when we see the large drop in mortgage applications and originations. Lending standards do not change.

Next, we study MSA dynamics following Gete and Reher (2018). We estimate:

$$\Delta log(Rent/Price_{i,t}) = \beta_0 + \beta_1 Disaster\,Damage_{i,t-1} + \gamma\,Control_{i,t-1} + \eta_i + \eta_t + \mu_{i,t}, \quad (2)$$

$$\Delta log(Rent_{i,t}) = \beta_0 + \beta_1 Disaster\,Damage_{i,t-1} + \gamma\,Control_{i,t-1} + \eta_i + \eta_t + \mu_{i,t}, \quad (3)$$

$$\Delta log(Price_{i,t}) = \beta_0 + \beta_1 Disaster\,Damage_{i,t-1} + \gamma\,Control_{i,t-1} + \eta_i + \eta_t + \mu_{i,t}, \quad (4)$$

and

$$\Delta log(Owner\,Occupied\,Units_{i,t}) = \beta_0 + \beta_1 Disaster\,Damage_{i,t-1} + \gamma\,Control_{i,t-1} + \eta_i + \eta_t + \mu_{i,t}, \quad (5)$$

where $\Delta log(Owner\,Occupied\,Units_{i,t})$ is the growth rate of owner-occupied units in MSA i and in year t. Standard errors are clustered by MSA. The results are in Table 3

Insert Table 3 around here

Column (1) of Table 3 confirms that natural disasters increase housing rent-to-price ratios. Column (2) estimates the impact of disasters on housing rents growth. The estimate of $Disaster\,Damage_{i,t-1}$ (β_1) is 0.24% and is significant at the 1% level. Thus, a one standard deviation change in disaster damage (2.6) cause a 0.62% increase in rent growth. To put this estimate into perspective, the average rent growth in our sample is 2.5%. Thus, a one standard deviation disaster can explain 25% of the average annual rent growth.

Column (3) of Table 3 has the estimates of equation (4). Natural disasters have negative impacts on housing prices. However, none of the specifications are significant. Our results may be due to the positive effect on prices from higher rents compensating the negative effect from lower demand for ownership housing.

Column (4) studies homeownership. It shows a drop in the growth rate of owner-occupied units. The estimated β_1 is -0.152% and significant at the 5% level. Back-of-the-envelope calculations show that one standard deviation natural disaster can decrease around 18% ($-0.152\% \times 2.6 \div 2.2\%$) in the average growth rate of the owner occupied housing units.

3.2 Mortgage Markets

Next, we study the mortgage market. We study the growth rate of the number of mortgage applications, $\Delta log(Application_{i,t})$, of originations, $\Delta log(Origination_{i,t})$, and the denial rate:

$$\Delta log(Application_{i,t}) = \beta_0 + \beta_1 Disaster\, Damage_{i,t-1} + \gamma\, Control_{i,t-1} + \eta_i + \eta_t + \mu_{i,t}, \quad (6)$$

$$\Delta log(Origination_{i,t}) = \beta_0 + \beta_1 Disaster\, Damage_{i,t-1} + \gamma\, Control_{i,t-1} + \eta_i + \eta_t + \mu_{i,t}, \quad (7)$$

$$Denial\, Rate_{i,t} = \beta_0 + \beta_1 Disaster\, Damage_{i,t-1} + \gamma\, Control_{i,t-1} + \eta_i + \eta_t + \mu_{i,t}, \quad (8)$$

where i denotes the MSA and t denotes the year. Disaster damage, MSA level controls and fixed effects are defined as before. Standard errors are clustered by MSA. Table 4 reports the results

Insert Table 4 around here

Column (1) of Table 4 shows a fall in aggregate mortgage applications after the natural disasters. The coefficient of the $Disaster\, Damage_{i,t-1}$ (β_1) is -0.339%, which is significant at 5% level. One standard deviation of the property damage causes the applications to drop by 0.9%. This value is around 18% the average mortgage application growth rate.

Column (2) of Table 4 shows that mortgage originations follow applications. That is, demand dominates. The β_1 in column (2) is -0.331%, and significant at the 5% level. This estimate implies a change of around 18% of the average growth rate of origination for a one standard deviation disaster damage.

Column (3) of Table 4 shows that natural disasters do not have significant impact on credit supply, as measured by mortgage denials. Next we dig deeper in the demand drivers by studying different groups of households.

4 Results Across Household Groups

Here, we study credit demand for different levels of household wealth. First we study applications and originations like in $(6)-(7)$ but now only for conforming loans. The top panel of Table 5 has the results. Then we redo the exercise for jumbo loans. The bottom panel of Table 5 has the results.

Insert Table 5 around here

Applications and originations for conforming loans are seriously affected by the natural disasters. However, jumbo loans do not drop after the natural disaster. In fact, jumbo loans slightly increase.

Next we follow D'Acunto and Rossi (2017) and study applications and originations per loan size. The first group is the loan size smaller than 100 thousand USD. These applications usually come from low wealth households. The second group is the loan size larger than 100 thousand USD but smaller than 417 thousand USD. These applications usually come from mid-wealth households. The third group is the loan size larger than 417 thousands USD. These applications usually come from wealthy households. Table 6 reports our results.

Insert Table 6 around here

The panel (a) reports the percentage change of the loan applications and panel (b) reports the percentage change of the loan originations. On both panels, the column (1) is for the smallest loan sized group ($0-100K) . The natural disasters slightly decrease the mortgage applications and mortgage originations. However, the impacts are not significant. Column (2) is for mid-sized loans ($100K-417K). Here the impact of the natural disaster is significant for both loan applications and originations. For a one standard deviation shock to the property damage from natural disasters, there is a 1.2% decrease in mid-sized loans applications and 1.1% decrease in originations. These effects are large because the average annual growth rate of mid-sized loans applications is 5% and originations around 5.4%.

Finally, the estimates for the largest loan size group ($417K and above) are in column (3). The results show that large sized loans increase after the natural disasters. That is, wealthy households increase their mortgage applications.

5 Risk Taking Channel

In this section, we focus on flood related disasters. Most insurance policies do not cover the damage from flooding. Thus, flood disasters cause an increase in risk exposure that households can only hedge by reducing their housing exposure.

Flood related disasters include coastal flood, flood, flash flood, thunderstorm wind, storm surge tide, hurricane, winter storm, tropical storm, debris flow, tsunami and heavy rain. We classify other types of natural disasters as non-flooding related. Then we estimate the equivalent of equations (2), (3) and (4). The results are in Table 7.

Insert Table 7 around here

Table (7) shows that flood disasters have larger effects on rent-to-price ratio (column 1) and in housing rents growth (column 2). There are no differences across type of disaster for housing prices.

6 Robustness

In the previous sections, we used property damage to evaluate the severity and intensity of the natural disasters. Now, we revisit the previous results using instead the disasters damage above the historical average, the fatality of the disasters, and their frequency.

6.1 Disasters impact above historical average

The sudden increase of the natural disasters should change household expectation more. In this way, we use the $\mathrm{Disaster\,Damage}_{i,t-1} - \mathrm{Average\,Damage}_{1998-2008}$ that the deviation of the property damage from its average historical damage of the natural disasters (from 1998 to 2008) to re-estimate 2, 3 and 4. Our results show that the disasters impact above the historical average also has same results in our benchmark specification.

6.2 Fatal disasters

Like Boustan et al. (2017), we also test whether measuring disasters by their casualties affects our previous results. We use indicator $Fatal\,Disaster_{i,t-1}$ that measures whether the location has at least one fatal disaster with multiple direct deaths. Thus, we replace $Disaster\,Damage_{i,t-1}$ by $Fatal\,Disaster_{i,t-1}$ to estimate 2, 3 and 4. An Online Appendix contains the results. The results are the same as before with one difference: fatal disasters tend to lower housing prices. Thus, once we focus on life-threatening disasters, the drop in demand for ownership dominates the increase in prices from higher rents.

6.3 Frequencies of the disasters

We also redo equations 2, 3 and 4 replacing $Disaster\, Damage_{i,t-1}$ by the frequency of the natural disasters. To do so we create indicators for the frequency of large disasters and small natural disasters. First indicator equals to 1 if the frequency of the large disasters is above the its year median frequency and the second indicator equals to 1 if the frequency of the small disasters is above its year median frequency[3]. We report our results in the Online Appendix. The results support the previous results with large disasters having larger effects.

7 Conclusions

In this paper we study how households react to natural disasters. We document that housing rents go up but prices do not drop much. Thus, rent-to-price ratios increase. These dynamics are driven by the low and mid-wealth households, who reduce their demand for mortgage credit and ownership housing while increasing their demand for rental housing.

High-wealth households, who are more risk tolerant, increase their housing holdings and receive higher rent revenue from their housing investments. These households increase their mortgage applications. Thus, natural disasters lead to a reallocation of the housing stock and mortgage credit.

References

Bernstein, A., Gustafson, M. and Lewis, R.: 2018, Disaster on the horizon: The price effect of sea level rise.

Bin, O., Kruse, J. B. and Landry, C. E.: 2008, Flood hazards, insurance rates, and amenities: Evidence from the coastal housing market, *Journal of Risk and Insurance* **75**(1), 63–82.

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

Bin, O. and Polasky, S.: 2004, Effects of flood hazards on property values: evidence before and after hurricane floyd, *Land Economics* **80**(4), 490–500.

Boustan, L. P., Kahn, M. E., Rhode, P. W. and Yanguas, M. L.: 2017, The effect of natural disasters on economic activity in us counties: A century of data.

[3]The cutoff of the large and small disasters is 100 thousand USD in our study.

Cortés, K. R. and Strahan, P. E.: 2017, Tracing out capital flows: How financially integrated banks respond to natural disasters, *Journal of Financial Economics* .

D'Acunto, F. and Rossi, A. G.: 2017, Regressive mortgage credit redistribution in the post-crisis era.

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

Gete, P. and Reher, M.: 2018, Mortgage supply and housing rents, *Reiew of Financial Studies* (forthcoming).

Gibson, M., Mullins, J. and Hill, A.: 2018, Climate change and flood beliefs:evidence from new york real estate.

Hallstrom, D. G. and Smith, V. K.: 2005, Market responses to hurricanes, *Journal of Environmental Economics and Management* **50**(3), 541–561.

Harrison, D., T. Smersh, G. and Schwartz, A.: 2001, Environmental determinants of housing prices: the impact of flood zone status, *Journal of Real Estate Research* **21**(1-2), 3–20.

Morgan, A.: 2007, The impact of hurricane ivan on expected flood losses, perceived flood risk, and property values, *Journal of housing research* **16**(1), 47–60.

Smith, V. K., Carbone, J. C., Pope, J. C., Hallstrom, D. G. and Darden, M. E.: 2006, Adjusting to natural disasters, *Journal of Risk and Uncertainty* **33**(1), 37–54.

Appendix: Data Sources and Variable Definitions

In general, we merge the housing rents, prices from the Zillow dataset, mortgage applications, originations and denial rate from the HMDA data, the disasters related data from the StormEvent dataset and MSA level control variables from others. After merging, our rent and price data cover 242 out of 382 MSAs from 2009 through 2014. The MSA consists of the counties or equivalent entities associated with at least one core of at least 50,000 population, plus adjacent counties having a high degree of social and economic integration with the core as measured through commuting ties with the counties associated with the core. In this way, we treat the MSA as a separate local housing market.

Zillow

The housing rents and housing prices at each MSA level are from the Zillow dataset. To measure housing rents, we use the Quarterly Historic Metro Zillow Rent Index (ZRI). Zillow imputes this rent based on a proprietary machine learning model taking into account the specific characteristics of each home and recent rent listings for homes with similar characteristics. To measure housing prices, we use the Quarterly Historic Metro Zillow Home Value Index (ZHVI). The ZHVI is computed using a methodology analogous to that of the ZRI.

We merge all datasets based on year and the MSA's 2004 core based statistical area (CBSA) code. For submetro areas of the largest MSAs, we use the CBSA division code. After merging with the MSAs for which we have the mortgage data described below, we have rent data for 242 MSAs. These are the variables that we generated from the Zillow dataset:

$\Delta log(Rent/Price_{i,t})$ is the growth of the rent to price ratio in MSA i and year t.

$\Delta log(Price_{i,t})$ is the growth of the price in MSA i and year t.

$\Delta log(Rent_{i,t})$ is the growth of the rent.

HMDA

We only retain mortgage applications, originations and denials for the purchase of a owner-occupied home for 1 to 4 families. We also exclude the loan flagged for data quality concerns. Then, we aggregate the loan data at the MSA level. These are the variables that we generated from HMDA:

$\Delta log(Application_{i,t})$ is the growth rate of the number of the loan applications.

$\Delta log(Origination_{i,t})$ is the growth rate of the number of the loan originations.

$Denial\,Rate_{i,t}$ is the mortgage denial rate.

We define similarly the loan applications and loan originations for the conforming loans and jumbo loans respectively.

StormEvent

We get the disasters related variables from the StormEvent dataset provided by National Oceanic and Atmospheric Administration (NOAA). It has the location, types, frequency and fatalities of the natural disasters. We aggregate the disasters at the MSA level. These are the disasters variables that we generate from the StormEvent dataset:

$Disaster\,Damage_{i,t-1}$ is the logarithm of aggregate property damage caused by the natural disasters in given time and location. We only include the natural disasters only having significant physical damage to the real-estate and excludes the disasters such as high temperature, dense fog and etc. The disasters we include cover 98% of all the disasters from StormEvent dataset valued by the disasters damage.

$Flood\,Disaster\,Damage_{i,t-1}$ is logarithm of the property damage from the disasters related to the floods. The flood related disasters include coastal flood, flood, flash flood, thunderstorm wind, storm surge tide, hurricane, winter storm, tropical storm, debris flow, tsunami and heavy rain.

$Other\,Disaster\,Damage_{i,t-1}$ is the log of the property damage from the disasters not related to the floods.

$High\,Freq\,Large_{i,t-1}$ (β_1) is the indicator to show that whether the frequency of large disasters (damage $>$ 100 thousand USD) is above the median frequency of the sample.

$High\,Freq\,Small_{i,t-1}$ (β_2) is the indicator to show that whether the frequency of small sized disasters (damage is between 1 thousand to 100 thousand USD) is above the median frequency of the sample.

HMDA-FFIEC Census Report

$\Delta log(Unit_{i,t})$ is the growth rate of the housing units. Number of units is the total number of dwellings in a given MSA that are built to house fewer than 5 families.

$\Delta log(Owner\,Occupied\,Unit_{i,t})$ is the growth rate of the owner-occupied housing units. Number of owner-occupied units is the number of dwellings, including individual condominiums, that are lived in by the owner.

The data about the population and per-capital housing stock are also generated from the FFIEC Census Report.

American Community Survey (ACS) and Bureau of Labor Statistics (BLS)

Age data, unemployment data, and Gini Index at the MSA level are from the American Community Survey 1-Year Estimates, provided by the U.S. Census Bureau.

Data on MSA-level income growth come from the Bureau of Labor Statistics.

FDIC's Summary of Deposits and FHFA

Deposit market shares of the Big-4 banks are generated from the FDIC's Summary of Deposits.

The data on conforming loan limits are from the Federal Housing Finance Agency (FHFA). Together with the HMDA mortgage data, we calculate the quantity of the conforming and the jumbo loans.

Figures and tables

Figure 1. Growth rate of rent-to-price, housing rents and housing prices after the natural disasters. This figure plots the coefficients of the disaster damage (β_1) of the equation (1) to the growth rates of the rent-to-price ratio, housing rents and housing prices as the dependent variables respectively. The vertical bars are the 95% confidence interval of the coefficients. $t = 0$ is the year the damage of the natural disasters occur.

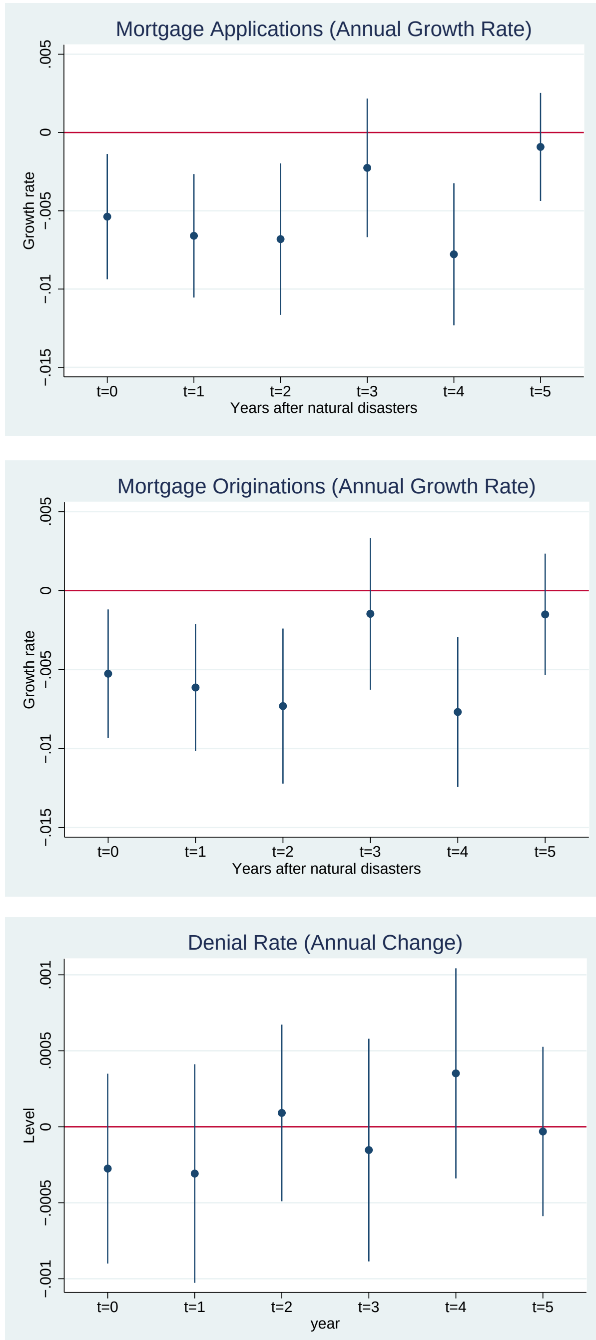

Figure 2. The growth of the loan applications, originations and denials after the natural disasters. This figure plots the coefficients of the disaster damage (β_1) of the equation (1) to the growth rates of the mortgage applications, originations and denials as the dependent variables respectively. The vertical bars are the 95% confidence interval of the coefficients.

Table 1. Natural Disasters, 2010 to 2014

Disaster Type	Aggregate property damage	# Events (MSA level)
Coastal Flood	21,112	135
Tornado	16,734	2,237
Flood	11,199	2,588
Hail	8,926	2,398
Flash Flood	6,003	4,213
High Wind	4,324	1,541
Wildfire	3,052	544
Thunderstorm Wind	1,762	19,017
Storm Surge/Tide	797	41
Winter Storm	587	694
Tropical Storm	279	145
Blizzard	248	121
Hurricane	235	18
Lightning	219	2,174
Ice Storm	192	185
Heavy Snow	145	246
Strong Wind	82	2,383
Debris Flow	71	64
Tsunami	58	8
Landslide	41	46
Heavy Rain	26	280
Dust Storm	6	43
Avalanche	0.6	11
Dust Devil	0.5	39
Total	76,097	39,171

This table summarizes the natural disasters in the database. The sample covers 2010 to 2014. Aggregate property damage is in millions of US dollars.

Table 2. Data Description, 2010 to 2014

Variable	N	MSAs	Mean	SD	P25	Median	P75	Min	Max
a. Natural Disasters									
Disaster Damage	1079	242	13.359	2.586	11.695	13.313	14.958	6.215	21.826
b. Real Estate Variables									
Δlog(Rent/Price)	1079	242	0.023	0.081	-0.023	0.023	0.072	-0.283	0.588
Δlog(Rent)	1079	242	0.025	0.060	-0.003	0.027	0.054	-0.292	0.570
Δlog(Price)	1079	242	0.001	0.060	-0.035	0.000	0.035	-0.259	0.280
Δlog(Owner Occupied Units)	1079	242	0.022	0.078	0.000	0.000	0.005	-0.552	1.301
Δlog(For Sale Inventory)	793	220	-0.073	0.195	-0.174	-0.051	0.034	-1.062	0.576
c. Credit Variables									
Δlog(Applications)	1079	242	0.050	0.139	-0.047	0.040	0.145	-0.621	1.610
Δlog(Originations)	1079	242	0.054	0.145	-0.044	0.045	0.150	-0.570	1.596
Denial Rate	1079	242	0.112	0.034	0.089	0.109	0.132	0.031	0.426
Δlog(Applications Conforming)	1079	242	0.047	0.139	-0.050	0.036	0.143	-0.629	1.586
Δlog(Originations Conforming)	1079	242	0.051	0.145	-0.048	0.042	0.148	-0.582	1.577
Δlog(Applications Jumbo)	1033	241	0.213	0.502	0.000	0.223	0.457	-1.946	2.944
Δlog(Originations Jumbo)	1004	239	0.231	0.509	0.000	0.251	0.483	-1.946	2.552
d. MSA Controls									
Δlog(Income)	1079	242	0.010	0.034	0.000	0.013	0.026	-0.148	0.141
Δlog(Population)	1079	242	0.020	0.062	-0.002	0.000	0.010	-0.147	0.435
Δlog(Unemployment)	1079	242	0.005	0.023	-0.011	0.001	0.019	-0.065	0.088
Δlog(Age)	1079	242	0.005	0.022	-0.003	0.005	0.013	-0.117	0.170
Δlog(Units)	1079	242	0.027	0.087	-0.001	0.000	0.015	-0.556	1.433
Per Capita Housing Stock	1079	242	0.365	0.049	0.342	0.365	0.383	0.242	0.887
Gini Index	1079	242	0.451	0.025	0.436	0.451	0.466	0.383	0.538
log(Income)	1079	242	11.022	0.145	10.917	11.020	11.118	10.527	11.469
log(Population)	1079	242	12.758	0.976	11.926	12.629	13.392	10.961	15.580

This table presents summary statistics of the key variables in our sample. All variables are at the MSA level. *Disaster Damage* is the logarithmic dollar value of the property damage caused by the natural disasters. Δlog(Rent/Price), Δlog(Rent) and Δlog(Price) denote growth rates of the rent-to-price ratio, rent and housing price. based on HMDA data. $Big\,4\,Share_{2008}$ and $Big\,4\,Branch_{2008}$ are, respectively the branch deposit share of the Big-4 banks in 2008 and the branch numbers share of the Big-4 banks. Wages are the median hourly wage in the MSA. Age and Income refer to the median in the MSA. All the variables are from 2010 to 2014. The *Disaster Damage* and MSA controls are one period lag variables, so they are from 2009 to 2013. The Data Appendix has more details.

Table 3. Rent-to-Price Ratio, Rents and Housing Prices

	Δlog(Rent-to-Price) (1)	Δlog(Rents) (2)	Δlog(Prices) (3)	Δlog(Owner Occupied Units) (4)
Disaster Damage$_{i,t-1}$	0.00358***	0.00240***	-0.00118	-0.00152**
	(0.001)	(0.006)	(0.138)	(0.040)
MSA Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes
R^2	0.265	0.035	0.490	0.367
Observations	1079	1079	1079	1079

The dependent variables Δlog(Rent-to-Price), $\Delta log(Rents)$, $\Delta log(Prices)$ and $\Delta log(Owner\,Occupied\,Units)$ are the growth rates of the rent-to-price ratio, rents, housing prices and the number of the owner-occupied housing units are respectively. MSA controls are those from Table 2. The p-values are in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level. Each observation is an MSA. The standard errors are clustered at the MSA level. The Data Appendix discusses these variables.

Table 4. Mortgages Applications, Originations and Denials for all Home Purchase Mortgage

	Δlog(Applications) (1)	Δlog(Originations) (2)	Denial Rate (3)
Disaster Damage$_{i,t-1}$	-0.00339**	-0.00331**	-0.000224
	(0.022)	(0.044)	(0.368)
MSA Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes
R^2	0.409	0.400	0.152
Observations	1079	1079	1079

The dependent variable $\Delta log(Applications)$, $\Delta log(Originations)$ and *Denial Rate* are respectively, the growth rates of the number of mortgages applications, number of mortgages originations and mortgage denial rate at the MSA level. MSA controls are those from Table 2. The p-values are in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level. Each observation is an MSA. The standard errors are clustered at the MSA level. The Data Appendix discusses these variables.

Table 5. Conforming and Jumbo Mortgages

(a) Conforming Mortgages

	Δlog(Applications) (1)	Δlog(Originations) (2)
Disaster Damage$_{i,t-1}$	-0.00350**	-0.00340**
	(0.019)	(0.041)
MSA Controls	Yes	Yes
Year FE	Yes	Yes
MSA FE	Yes	Yes
R^2	0.407	0.399
Observations	1079	1079

(b) Jumbo Mortgages

	Δlog(Applications) (2)	Δlog(Originations) (4)
Disaster Damage$_{i,t-1}$	0.0153*	0.00950
	(0.053)	(0.278)
MSA Controls	Yes	Yes
Year FE	Yes	Yes
MSA FE	Yes	Yes
R^2	0.077	0.081
Observations	1033	1004

The dependent variable $\Delta log(Applications)$ and $\Delta log(Originations)$ are respectively, the growth rates of the number of applications and number of originations at upper panel and for the jumbo mortgages at the lower panel. MSA controls are those from Table 2. The p-values are in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level. Each observation is an MSA. The standard errors are clustered at the MSA level. The Data Appendix discusses these variables.

Table 6. Mortgage Applications and Originations per Loan Size

(a) Mortgage Applications per Loan Size

Δlog(Applications) in	\$ 0-100k (1)	\$ 100k-417k (2)	\$ 417k+ (3)
Disaster Damage$_{i,t-1}$	-0.00203	-0.00401**	0.0136*
	(0.454)	(0.012)	(0.089)
MSA Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes
R^2	0.085	0.472	0.077
Observations	1079	1079	1033

(b) Mortgage Originations per Loan Size

Δlog(Originations) in	\$ 0-100k (1)	\$ 100k-417k (2)	\$ 417k+ (3)
Disaster Damage$_{i,t-1}$	-0.00222	-0.00398**	0.00746
	(0.465)	(0.017)	(0.397)
MSA Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes
R^2	0.077	0.456	0.076
Observations	1079	1079	1005

The dependent variables $\Delta log(Applications)$ and $\Delta log(Originations)$ are the growth rates of the number of mortgage applications and originations for the three loan size groups from 0 to \$100 thousands, from \$100 thousand to \$417 thousand, above \$417 thousand. MSA controls are those from Table 2. The p-values are in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level. Each observation is an MSA. The standard errors are clustered at the MSA level. The Data Appendix discusses these variables.

Table 7. Flooding Related Disasters

	Δlog(Rent-to-Price) (1)	Δlog(Rents) (2)	Δlog(Prices) (3)
Flooding Damage$_{i,t-1}$	0.00135***	0.00136***	0.0000132
	(0.001)	(0.001)	(0.961)
Other Disaster Damage$_{i,t-1}$	0.00156	0.00101	-0.000552
	(0.107)	(0.150)	(0.411)
MSA Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes
R^2	0.267	0.044	0.489
Observations	1079	1079	1079

The dependent variable Δlog(Rent-to-Price), $\Delta log(Rents)$ and $\Delta log(Prices)$ are respectively, the growth rates of the rent-to-price ratio, rents and housing prices. The $Flood\,Disaster\,Damage_{i,t-1}$ is logarithm of the property damage from the disasters related to the floods plus 1. The $Other\,Disaster\,Damage_{i,t-1}$ is logarithm of the property damage from the disasters not related to the floods plus 1. The flood related disasters include coastal flood, flood, flash flood, thunderstorm wind, storm surge tide, hurricane, winter storm, tropical storm, debris flow, tsunami and heavy rain. We classify other types of the natural disasters as non-flooding related. MSA controls are those from Table 2. The p-values are in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level. Each observation is an MSA. The standard errors are clustered at the MSA level. The Data Appendix discusses these variables.

Extra Table

Table A1. Rent-to-Price Ratio, Rents and Housing Prices

	Δlog(Rent-to-Price) (1)		Δlog(Rents) (2)		Δlog(Prices) (3)	
Disaster Damage$_{i,t-1}$	0.00278*** (0.004)		0.00233*** (0.003)		-0.00045 (0.511)	
Disaster Damage$_{i,t-1}-$ $-$Average Damage$_{1998-2008}$		0.00242*** (0.007)		0.00173*** (0.006)		-0.00069 (0.291)
MSA Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
MSA FE	No	No	No	No	No	No
R^2	0.282	0.281	0.08	0.077	0.483	0.484
Observations	1079	1079	1079	1079	1079	1079

The dependent variables Δlog(Rent-to-Price), $\Delta log(Rents)$, $\Delta log(Prices)$ and $\Delta log(Owner\,Occupied\,Units)$ are the growth rates of the rent-to-price ratio, rents, housing prices and the number of the owner-occupied housing units are respectively. $Average\,Damage_{1998-2008}$ is the historical average disasters property damage from 1998 to 2008 at MSA i. Because, the historical average is fixed at the MSA level, we remove the MSA fixed effects for our estimation. MSA controls are those from Table 2. The p-values are in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level. Each observation is an MSA. The standard errors are clustered at the MSA level. The Data Appendix discusses these variables.

Table A2. Impacts of the Fatal Disasters

	Δlog(Rent-to-Price) (2)	Δlog(Rents) (4)	Δlog(Prices) (6)
Fatal Disaster$_{i,t-1}$	0.0230**	0.00856	-0.0145**
	(0.011)	(0.261)	(0.011)
MSA Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes
R^2	0.260	0.033	0.494
Observations	1079	1079	1079

The dependent variables Δlog(Rent-to-Price) and $\Delta log(Rents)$, $\Delta log(Prices)$ are the growth rates of the rent-to-price ratio, rents and housing prices are respectively. Indicator Fatal Disaster$_{i,t-1}$ measures whether the location has at least one fatal disaster with multiple direct deaths. MSA controls are those from Table 2. The p-values are in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level. Each observation is an MSA. The standard errors are clustered at the MSA level. The Data Appendix discusses these variables.

Table A3. Frequency of the Natural Disasters

	Δlog(Rent-to-Price)	Δlog(Rents)	Δlog(Prices)
	(1)	(2)	(3)
High Freq Large$_{i,t-1}$	0.0183***	0.00986**	-0.00840**
	(0.001)	(0.041)	(0.028)
High Freq Small$_{i,t-1}$	-0.00347	-0.00141	0.00206
	(0.666)	(0.837)	(0.648)
MSA Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes
R^2	0.265	0.036	0.495
Observations	1079	1079	1079

The dependent variables Δlog(Rent-to-Price) and $\Delta log(Rents)$, $\Delta log(Prices)$ are the growth rates of the rent-to-price ratio, rents and housing prices are respectively. High Freq Large$_{i,t-1}$ equals to 1 if the frequency of large disasters is above the its year median frequency and the High Freq Small$_{i,t-1}$ equals to 1 if frequency of small disasters is above its median frequency. MSA controls are those from Table 2. The p-values are in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level. Each observation is an MSA. The standard errors are clustered at the MSA level. The Data Appendix discusses these variables.

Table A4. Mortgages Applications, Originations and Denials for all Home Purchase Mortgage. Including the multiple family units

	Δlog(Applications) (1)	Δlog(Originations) (2)	Denial Rate (3)
Disaster Damage$_{i,t-1}$	-0.00339**	-0.00330**	-0.000223
	(0.022)	(0.044)	(0.369)
MSA Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes
R^2	0.409	0.400	0.156
Observations	1079	1079	1079

The dependent variable $\Delta log(Applications)$, $\Delta log(Originations)$ and *Denial Rate* are respectively, the growth rates of the number of mortgages applications, number of mortgages originations and mortgage denial rate at the MSA level. MSA controls are those from Table 2. The p-values are in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level. Each observation is an MSA. The standard errors are clustered at the MSA level. The Data Appendix discusses these variables.

Table A5. Conforming and Jumbo Mortgages. Including the multiple family units

(a) Conforming Mortgages

	Δlog(Applications) (1)	Δlog(Originations) (2)
Disaster Damage$_{i,t-1}$	-0.00350**	-0.00339**
	(0.019)	(0.041)
MSA Controls	Yes	Yes
Year FE	Yes	Yes
MSA FE	Yes	Yes
R^2	0.407	0.399
Observations	1079	1079

(b) Jumbo Mortgages

	Δlog(Applications) (2)	Δlog(Originations) (4)
Disaster Damage$_{i,t-1}$	0.0155*	0.00951
	(0.051)	(0.278)
MSA Controls	Yes	Yes
Year FE	Yes	Yes
MSA FE	Yes	Yes
R^2	0.078	0.081
Observations	1033	1004

The dependent variable $\Delta log(Applications)$ and $\Delta log(Originations)$ are respectively, the growth rates of the number of applications and number of originations at upper panel and for the jumbo mortgages at the lower panel. MSA controls are those from Table 2. The p-values are in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level. Each observation is an MSA. The standard errors are clustered at the MSA level. The Data Appendix discusses these variables.

Table A6. Mortgage Applications and Originations per Loan Size. Including the multiple family units

(a) Mortgage Applications per Loan Size

Δlog(Applications) in	\$ 0-100k (1)	\$ 100k-417k (2)	\$ 417k+ (3)
Disaster Damage$_{i,t-1}$	-0.00203	-0.00401**	0.0138*
	(0.453)	(0.013)	(0.084)
MSA Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes
R^2	0.085	0.472	0.077
Observations	1079	1079	1033

(b) Mortgage Originations per Loan Size

Δlog(Originations) in	\$ 0-100k (1)	\$ 100k-417k (2)	\$ 417k+ (3)
Disaster Damage$_{i,t-1}$	-0.00222	-0.00398**	0.00747
	(0.465)	(0.017)	(0.396)
MSA Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes
R^2	0.077	0.456	0.076
Observations	1079	1079	1005

The dependent variables $\Delta log(Applications)$ and $\Delta log(Originations)$ are the growth rates of the number of mortgage applications and originations for the three loan size groups from 0 to \$100 thousands, from \$100 thousand to \$417 thousand, above \$417 thousand. MSA controls are those from Table 2. The p-values are in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level. Each observation is an MSA. The standard errors are clustered at the MSA level. The Data Appendix discusses these variables.