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# MORTGAGE FINANCE AND CLIMATE CHANGE: SECURITIZATION DYNAMICS IN THE AFTERMATH OF NATURAL DISASTERS

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**ABSTRACT**

Using the government-sponsored enterprises' sharp securitization rules, this paper provides evidence that, in the aftermath of natural disasters, lenders are more likely to approve mortgages that can be securitized; thereby transferring climate risk when learning the 'new news' of default. The identification strategy uses the GSEs' time-varying conforming loan limits at which mortgages bunch. Natural disasters increase bunching, suggesting an increased option value of securitization. The increase is lower where flood insurance is required. A model identified using indirect inference simulates increasing disaster risk without GSEs. Mortgage credit supply would decline in flood zones. Endogenous guarantee fees are estimated.

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# 1 Introduction

Hong, Karolyi & Scheinkman (2020) highlights the key role of financial institutions, such as lenders, in the climate change adaptation process. Lenders held 11.2 trillion dollars of residential mortgage debt as of 2019 (Goodman 2020), hence lenders could emerge as key financial institutions helping households navigate through increasing climate risk. Bender, Knutson, Tuleya, Sirutis, Vecchi, Garner & Held (2010) predicts a doubling of category 4 and 5 storms by the end of the 21st century; Kossin, Knapp, Olander & Velden (2020) projects increased tropical cyclone intensity under continued warming. After hurricane Katrina, the substantial payments of the National Flood Insurance Program (NFIP) mitigated a potential rise in mortgage defaults (Gallagher & Hartley 2017). Since 2006 however, the number and dollar amount of NFIP flood insurance policies have declined substantially (Kousky 2018); and damages due to hurricane storm surges have affected areas far beyond FEMA's Special Flood Hazard Areas where flood insurance is required. A key empirical question is whether the risk of mortgage defaults due to climate change is borne by lenders or securitizers: in 2019, the government-sponsored enterprises (GSEs) guaranteed $6.88 trillion in home mortgage debt without pricing flood risk in their guarantee fees.[1] Have and will the GSEs act as *de facto* insurers? Understanding whether lenders originate and distribute their climate risk requires (i) estimating the causal impact of flood risk "new news" on lenders' securitization activity; (ii) estimating whether lenders would originate risky mortgages in a counterfactual world where the GSEs either did not securitize in flood risk areas or charged guarantee fees that match the GSEs' potential losses; and (iii) whether the GSEs' securitization activity incentivizes borrowers to locate to flood-prone areas.

This paper addresses these three challenges by estimating the impact of 15 billion-dollar disasters' "new news" on the bunching of mortgage originations and securitizations at the conforming loan limit. Fannie Mae and Freddie Mac have adopted specific sets of observable rules when screening mortgages for purchase. One such rule is based on the size of the loan: the GSEs purchase loans whose amount do not exceed a county- and year-specific *conforming loan limit*. This generates a substantial discontinuity in lending and securitization standards, suggesting that agency securitiza-

[1] Fannie Mae, Freddie Mac, and Ginnie Mae's guaranteed a total amount of $6.9t, more than double the volume of unsecuritized first liens ($3.23t). The non-agency share of mortgage securitizations is about 4.96% as of 2019.

tion has significant option value for lenders.[2] Lenders' perception of increased flood risk may lead to more bunching. Billion-dollar events provide lenders with additional information about the location of flood risk. Lenders can observe and use flood risk information in their underwriting and securitization decisions. In contrast, Fannie Mae and Freddie Mac do not adjust their securitization rules or their guarantee fees in response to flood risk information. They rely on FEMA maps of Special Flood Hazard Areas (the "100-year floodplain") when requiring flood insurance. The prior literature suggests that SFHAs do not typically match actual damage (Morrissey 2006, Kousky 2018); and that a significant share of at-risk communities do not participate in the NFIP. A '*market for lemons*' in climate risk could develop as lenders are able to securitize risky mortgages when they obtain new information about local mortgage default. The paper identifies "new news" about flood risk by estimating the heterogeneity of securitization responses depending on (i) the historical probability of being affected by hurricanes since 1851 and (ii) whether the neighborhood is in FEMA's 100-year floodplain.

The paper's identification strategy relies on estimating the impact of natural disasters on the discontinuity in approval, origination, and securitization rates, as well as in the bunching in a window around the conforming loan limit (±20%, ±10%, and ±5%). First, focusing on a tight window allows the estimation to compare mortgages with arguably similar characteristics yet very significant differences in securitization probabilities. Second, the paper uses a longitudinal panel at the window with 5-digit zip code fixed effects, year fixed effects, pre- and post-treatment indicators, and controls for the evolution of the conforming loan limit in the mortgage market independently of the natural disaster. Thus the impact of the natural disaster on the discontinuity is estimated over and above the baseline impact of the disaster, aggregate confounders, and year-level marketwide fluctuations in the conforming limit. The specification provides a "placebo" test for the existence of pre-trends in the four years prior to the event. Third, the conforming loan limit is county- and year- specific, moving in arbitrary fashion and provides identification at different margins of the distribution of houses, mortgages, and households. As the limits are set nationally either by the FHFA or by Congress, they are less likely to be confounded by other regional discontinuities that would also affect the mortgage market for loans of similar amounts. Fourth, the 5-digit zip

[2] DeFusco & Paciorek (2017) uses the discontinuity in interest rates at the limit to estimate borrowers' elasticity of demand with respect to interest rates.

location of a hurricane is typically an idiosyncratic event when controlling for the history of hurricane occurrence as well as the intensity of the hurricane season.

The results suggest that after a billion-dollar event, lenders are significantly more likely to increase the share of mortgages originated and securitized right below the conforming loan limit. After a billion-dollar event, the difference in approval rates for conforming loans and jumbo loans increases by up to 7.3 percentage points. The probability of securitization increases by up to 19.3 percentage points. The discontinuity in the number of originations at the limit increases by up to 18.5 ppt 4 years after the event. This could be driven by either a retreat to safer mortgages if conforming loans are safer or increasing adverse selection if the mortgages sold to the GSEs are riskier. Evidence from the national-level McDash dataset suggests that conforming loans are likely riskier than jumbo loans and that adverse selection into the conforming loan segment increases after a natural disaster: borrowers are more likely to experience foreclosure at any point postorigination; they are more likely to be 60 or 120 delinquent, and they have lower FICO scores.[3] Bank lenders that originate conforming loans typically hold less liquidity on their balance sheet, and bank lenders that originate conforming loans are less likely to be FDIC-insured commercial banks. Interestingly, while the GSEs' guarantee fee (paid by lenders) is a function of observable characteristics such as FICO scores and loan-to-value ratios, there is likely significant unpriced unobservable flood risk in agency RMBSs.

While analysis suggests no evidence of significant trends in the four years prior to a billion-dollar event, there is a statistically and economically significant increase in securitization volumes at the conforming loan limit in years following the event. The impact of the billion-dollar event is significant at the limit and is not significant further away from the limit: a series of identical regressions on a grid of points $-5\%$ to $+5\%$ of the limit reveals an impact on bunching at the limit only, suggesting that the increasing bunching at the limit is due to the response of lenders. This paper's baseline result is economically significant: a billion-dollar event has a similar effect on securitization activity as a 17% employment decline, which is approximately twice the standard deviation of employment growth.

Evidence suggests that such selection into the conforming segment and the corresponding increase in securitization volumes are consistent with lenders learning about future flood risk from

[3] For contrasting evidence on securitization and loan performance, see Jiang, Nelson & Vytlacil (2014).

the observation of past events (the learning hypothesis). The impact of disasters on securitization volume is greater in neighborhoods that have a historically low frequency of hurricanes since 1851. Thus, a hurricane provides "new news" that may affect lenders' internal forecasts. Evidence also suggests that the effect is likely smaller in Special Flood Hazard Areas, where flood insurance is required.

The impact of billion-dollar events on securitization activity is estimated using five different sets of data:[4] [5] The first is a national dataset of mortgage applications, originations, and securitization purchases between 1995 and 2017 collected according to the Home Mortgage Disclosure Act (HMDA). Such HMDA data can be matched to the neighborhood (Census tract) of the mortgaged house. The second dataset is the McDash loan-level payment history dataset with approximately 65% of the mortgage market since 1989, including household FICO scores, foreclosure events, delinquency, prepayment, and with 5-digit zip code information. The paper's analysis is conducted at the 5-digit zip level throughout. Third, the treatment group of affected neighborhoods is estimated by using the path and impact of hurricanes (wind speed data every 6 hours for all major hurricanes) from NOAA's Atlantic Hurricane Database HURDAT2, combined with high-resolution USGS elevation and land cover data, and a survey of hurricane damages that identify disaster-struck coastal areas. Fourth, FEMA's National Flood Hazard Layer provides the boundaries of Special Flood Hazard Areas, where flood insurance is mandated for agency mortgages. The combination of these four data sources enables a neighborhood-level analysis of the impact of 15 billion-dollar events on securitization activity, lending standards, and household sorting. The fifth and last dataset relates to the lender's identity, obtained by matching HMDA loan-level files with their transmittal sheets. This enables an estimation of the differential response of bank and nonbank lenders.

This paper's second and third challenges are to estimate whether lenders would originate risky mortgages if the GSEs either did not securitize in areas at risk of flooding or charged guarantee fees that match the GSEs' potential losses and whether Fannie and Freddie's role incentivizes borrowers to locate to flood-prone areas. The paper develops a model of mortgage pricing with asymmetric information, household location choice, and the dynamics of mortgage default.[6] The paper's

[4] Overall the paper uses 13 different datasets, described in detail in Appendix Section B.

[5] Appendix Figure A displays the level of granularity of the McDash data used in this paper.

[6] We discuss Elenev, Landvoigt & Van Nieuwerburgh's (2016) important insights on the phasing out of the the GSEs in the latter part of the introduction.

discontinuity in securitization probabilities at the conforming limit is a quasi-experimental source of identification for the structural parameters, in the spirit of indirect inference of Fu & Gregory (2019) and Gourieroux, Monfort & Renault (1993). A key insight is that disaster risk (Barro 2009) substantially affects lenders' mortgage payoffs over and above the other drivers of default such as individual unemployment or divorce, which do not affect the payoff of foreclosure auctions. Disaster risk is thus a key driver of bunching at the conforming loan limit, which enables an identification of the model's structural parameters. The model's out-of-sample simulations increase the probability of disaster risk and estimate the impact on approval rates for mortgage applications, securitization rates for originated mortgages, location choices, and default rates.

The simulations suggest that the the GSEs' securitization activity, without increasing guarantee fees, stabilizes the mortgage market with little change in interest rates and location choice probabilities. In contrast, increasing disaster risk without the GSEs' securitization activity[7] leads to substantial declines in mortgage credit supply, disincentivizing location choices within risky areas. The model's findings thus suggest that the GSEs partially act as a *de facto* substitute for the National Flood Insurance Program outside of mandated flood insurance zones. The model simulations also suggest that the GSEs do not provide significant incentives to either lenders or households to choose different locations and mortgage amounts when facing increasing climate risk.

This paper contributes to three key strands of literature. First, the paper provides evidence consistent with the literature on adverse selection in the mortgage securitization market (Downing, Jaffee & Wallace 2009, Keys, Mukherjee, Seru & Vig 2010, Demyanyk & Van Hemert 2011, Keys, Seru & Vig 2012, Adelino, Gerardi & Hartman-Glaser 2019). Such market is large: the amount of debt guaranteed by the GSEs is \$6.9t, comparable to the total amount of outstanding corporate debt of non-financials.[8] This paper suggests that when mortgage lenders cannot sell mortgages to the two GSEs, they have strong incentives to assess what risks are entailed by lending funds for mortgages. Other papers suggest that, in contrast to the agency MBS market, the commercial MBS market responds strongly to disaster risk (Garmaise & Moskowitz 2009). The results of this paper suggest that the ability to securitize to the GSEs may weaken the discipline brought about

[7]Elenev et al. (2016) designs an important general equilibrium model that simulates a phasing-out of the GSEs. This paper focuses on the impact of such phasing out on borrowing and location decisions within a city, where neighborhoods have different flood risk levels.

[8]Q4 2019, Series TDSAMRIAONCUS of the Federal Reserve Bank of St Louis.

by the mortgage finance industry in fostering climate change adaptation. This paper focuses on the defaults implied by the strongly correlated, arguably upward-trending climate risk that is likely more difficult to hedge than idiosyncratic household-specific income shocks.[9] Remedies to this adverse selection include (a) the pricing of guarantee fees by Fannie and Freddie to reflect climate risk, an extension of the seminal literature on the pricing of mortgage-backed securities (Boudoukh, Whitelaw, Richardson & Stanton 1997) and (b) fintech approaches (Fuster, Plosser, Schnabl & Vickery 2019), which may help securitizers integrate flood risk data in their underwriting process. Such market pricing would take into account the ambiguous risk and heterogeneity among buyers in their risk assessments (Bakkensen & Barrage 2017).

This paper also contributes to the literature analyzing the impact of natural disasters on bank portfolio reallocation. Cortés & Strahan (2017) documents that banks reallocate capital to more prosperous local markets in the aftermath of disasters. The mechanism at work here may be that banks update their beliefs about future risk in the area that was recently hit. In our setting, lenders' reallocation is affected by their option to securitize the loans and sell them to the GSEs at a fixed price, the guarantee fee. In contrast to Cortés & Strahan (2017), this paper's capital re-allocation may generate inefficient risk sharing as flood risk remains unpriced in guarantee fees.

Finally, this paper contributes to the literature estimating the pricing of natural disaster risk in the housing market. An expanding stream of the literature has studied the impact of natural disaster risk on the equilibrium pricing of real estate (Bakkensen & Barrage 2017, Ortega & Taṣpınar 2018, Zhang & Leonard 2018), yet most houses are bought using credit with 11.2 trillion dollars of outstanding debt as of 2019 (Goodman 2020). Mortgage credit supply affects the demand for housing (Ouazad & Rancière 2016, Guren, Krishnamurthy & McQuade 2018, Ouazad & Rancière 2019, Guren & McQuade 2020). The structural model introduces the role of mortgage credit in driving location choices in risky neighborhoods. In the simulation without the GSEs, disaster risk leads to a decline in originations in risky neighborhoods.

[9] See Cotter, Gabriel & Roll (2015) for an analysis of the diversification of housing investment risk.

# 2 Datasets and Treatment Area Geography

Estimating the causal impact of natural disasters on mortgage securitization and thus the transfer of risk from lenders to the agencies requires matching local, neighborhood-level, measures of damage due to these disasters, with data on mortgage applications, originations and securitizations. Understanding which banks respond to the natural disaster requires a match between mortgage originations and the lender's identity and balance sheet. Finally, measuring the impact of "new news" requires building a long-run history of hurricane damage. We describe the two sets of data used in this paper: natural disasters and mortgage credit. Additional details are provided in Appendix Section B.

## 2.1 Natural Disasters: Billion-Dollar Events and the Treatment Group

**15 Billion-Dollar Events**

The paper focuses on disasters that have caused more than 1 billion dollars in estimated damage. The estimates come from Weinkle, Landsea, Collins, Musulin, Crompton, Klotzbach & Pielke's (2018) computations between 1900 and 2017 and suggest that the top 15 events are hurricanes. We thus focus on hurricanes occurring between 2004 and 2012, which allows for (i) following hurricane coordinates and wind radii at a granular level since 2004 and (ii) following mortgages for up to 4 years after the disaster, i.e., up to 2017. These events are presented in Table 1, in decreasing order of normalized damage. Hurricane Katrina is the third costliest event over the entire 1900–2017 period, after the Great Miami Hurricane of 1926 and the Galveston Hurricane of 1900. The damage is calculated as the product of the reported damage in current-year US dollars, the inflation adjustment, a real-wealth per-capita adjustment, and a county-population adjustment. Such damage estimates encompass a broader range of damage than those of residential real estate. More details are provided in Weinkle et al. (2018).[10]

[10] Appendix Section A presents evidence that billion-dollar disasters lead to increased mortgage default.

### Definition of Treated Areas

The Atlantic Hurricane Dataset of NOAA's National Hurricane Center includes hurricanes' geocoded latitude/longitude position every six hours.[11] The events post-2004 provide wind radii by speed at this frequency, enabling the computation of the set of blockgroups within the 64 knot hurricane wind path. We start with hurricanes post 2004 as these events' wind speed radius is geocoded.[12] This wind speed maps naturally into the Saffir Simpson hurricane intensity scale (Simpson & Saffir 2007).

Damage to real estate property is unevenly distributed within any of the hurricane's wind paths, and substantially exceeds and/or does not match the boundaries of FEMA's 100-year floodplain, the Special Flood Hazard Areas (SFHAs).[13] This is observable in the case of Hurricane Sandy, using housing inspections performed by HUD. These data are provided as part of FEMA's IA Registrant Inspection Data performed on both rental and owner property. The file reports damages for blockgroups with 10 or more damaged units. The inspector measured the height of the flooding, the highest floor of the flooding, and the height of the flooding in that room. In addition HUD estimated minor/major/severe damage based on such inspections. The data is described in Ingargiola, Francis, Reynolds, Ashley & Castro (2013).[14]

We combine this damage data on observed damages from Hurricane Sandy with blockgroup-level USGS elevation, land cover data, and distance to the coastline. By combining damages with elevation and land cover, we build a classifier to predict the granular location of damages due to any of the other 14 hurricanes. Elevation data come from the USGS's digital elevation model, at 1/3 of an arc second precision (approximately 10 meters). The USGS's 2001 National Land Cover Database provides the location of wetlands. The classifier is built using Ripley's (2007) tree-structured classifier. It predicts that blockgroups within the 64 kt wind path are hit if (i) their minimum elevation is below 3 meters, (ii) they are within 1.5 km of wetland, and (iii) they are within 1.5 kilometers of the coastline. We use this criterion to build a blockgroup-level prediction

[11] Accessed in 2018.

[12] The geographic position of the hurricane's eye is coded for all hurricanes since 1851. The dimension of the wind speed radius is geocoded since 2004.

[13] "Most homes damaged by Harvey were outside flood plain, data show" Houston Chronicle, (Hunn, Dempsey & Zaveri 2018). Three-fourths of houses damaged during Hurricane Harvey were outside of the 100-year floodplain (Pralle 2019); 50% of the buildings in New York City affected by Sandy were outside of the 100-year floodplain. Kousky (2018) discusses the design of flood insurance rate maps. Kousky & Kunreuther (2010) also discusses the mismatch between flood insurance maps and realized flooding in St Louis.

[14] Sandy Damage Estimates Based on FEMA IA Registrant Inspection Data.

of the set of damages due to the 14 hurricanes.[15]

The set of blockgroups with predicted damages is displayed on Figure 1 for hurricane Sandy. It is also estimated for the other 14 disasters. The dark gray area is the hurricane's 64 kt wind path. The blue area is the set of coastal areas or areas close to wetlands. The red boundaries correspond to blockgroups whose elevation is less than 3 meters. This paper's analysis proceeds at the 5-digit zip code level, the common geography for both climate and mortgage data. A zip is treated if more than 40% of its blockgroup surface area has predicted damage. This paper's results are robust to the use of different thresholds for the definition of treated zip codes.

## 2.2 Mortgage-Level Data and Geographic Match

**Home Mortgage Disclosure Act Data**

The first data source is the universe of mortgage applications and originations from the Home Mortgage Disclosure Act, between 1995 and 2017 inclusive. The data are collected following the Community Reinvestment Act (CRA) of 1975 (codified as 12 U.S.C. 2901, Regulations 12 CFR parts 25, 228, 345, and 195) and includes information from between 6,700 and 8,800 reporting institutions on between 12 and 42 million mortgage applications annually. The law mandates reporting by both depository and nondepository institutions. It mandates reporting by banks, credit unions, and savings associations, whose total assets exceed a threshold, set to 45 million USD in 2018,[16] with a home or branch office in a metropolitan statistical area; which originated at least one home purchase loan or refinancing of a home purchase loan secured by a first lien on a one-to-four-family dwelling; and if the institution is federally insured or regulated. The following nondepository institutions are required to report: for-profit institutions for which home purchase loan originations equal or exceed 10 percent of its total loan originations or 25 million USD or more, whose assets exceed 10 million dollars, or who originated 100 or more home purchase loans.

HMDA data include the identity of the lender,[17] loan amount, the income, race, and ethnicity

[15] An alternative approach for the definition of the treatment group involves using the NOAA's Sea, Lake, and Overland Surges from Hurricanes (SLOSH) dataset, which provides storm surge heights as predicted by a computational model of fluid dynamics. While this has the benefit of granularity and comprehensiveness, the SLOSH model's predictions correlate imperfectly with actual property damages.

[16] The minimum asset size threshold is typically adjusted according to the CPI for urban wage earners (CPI-W), is currently set by the Consumer Financial Protection Bureau, and published in the Federal Register.

[17] A unique identifier, the `respondentid`, can be matched to the `RSSDID` of the Federal Reserve of Chicago's Commercial Bank Data using Transmittal Sheets.

of the borrower, the census tract of the house, the property type (1-4 family, manufactured housing, multifamily), the purpose of the loan (home purchase, home improvement, refinancing), owner-occupancy status, preapproval status, and the outcome of the application (denied, approved but not accepted, approved and accepted, widthdrawn by the applicant).

HMDA uses 1990 census borders from 1995 to 2002 and 2000 Census borders from 2003 to 2011, and 2010 Census borders for years 2012 onward. Borders are made consistent using census tract relationship files. The census tract of the loan can be matched with the corresponding ZCTA5s. This determines the treatment status of an area (whether hit by a billion-dollar event). While HMDA enables an analysis at the census tract level, the McDash data described below provides 5-digit zip codes. We use ZCTA5s consistently throughout this paper in both the HDMA and the McDash analysis.[18]

This paper focuses on conventional loans, i.e., any loan other than FHA, VA, FSA, or RHS loans, on one to four family housing (other than manufactured housing), and on owner-occupied home purchase loans. We consider loan purchases (i.e., securitizations) for mortgages originated in the same year or in previous years. We exclude the small number of mortgages with applicant incomes above 5 million dollars or with loan-to-income (LTI) ratios above 4.5 or below 1.

**McDash Data**

The McDash data files are collected by Black Knight Financial. They follow each loan's history from origination and/or transfer of servicing rights to either full payment, prepayment, foreclosure, bankruptcy, or another transfer of servicing rights. The dataset follows about 65% of the market on average across observation years, and includes the borrower's FICO score, the interest rate, the interest rate type, the term, the loan amount, the property value, the LTV, the debt-to-income ratio, and other features of the mortgage.

This paper's McDash data include the home's 5-digit zip code. Appendix Figure A shows that counts are well distributed across 5-digit zip codes. The postal 5-digit zip codes are matched to their corresponding ZCTA5 Census identifier. We use the terms zip or ZCTA5 interchangeably in

[18]While ZCTA5s and zip codes differ marginally, the results using either HMDA at the ZCTA5 level or McDash at the zip code level are similar, suggesting that these differences do not have significant qualitative implications. See "ZIP Code Tabulation Areas (ZCTAs)", from the U.S. Census Bureau. In what follows, zip code and ZCTA5 are used interchangeably.

the paper. The 5-digit zip code is matched to the treatment group definition presented earlier in this section.

This paper uses the following filters for the McDash data and excludes home equity loans, focusing on new loans originated by the client organization, as opposed to transfers of servicing rights. It includes conventional loans with or without private mortgage insurance (PMI). It focuses on loans for purchase, and excludes loans for construction, rehabilitation, remodeling, rate/term refinance, cash-out refinance and other refinancing. It includes mortgages for single family homes. In this paper, the McDash data cover the same time period as that for the Home Mortgage Disclosure Act data.

# 3 Empirical Strategy

## 3.1 Identification Challenges

Estimating the impact of natural disasters on lenders' decisions to transfer risk by securitization is challenging for a number of reasons.

First, mortgages that are securitized differ in a number of observable and unobservable dimensions from mortgages that are originated and held. In the HMDA data, the median loan amount for mortgages that are originated and securitized is approximately $62,000 higher than for those that are originated and held. The median income of borrowers of mortgages originated and held is 4.4 higher than those that are originated and securitized. The share of white borrowers is also 1.6 percentage points higher for loans that are originated and held. The share of mortgages with missing income is also 3.9 percentage points lower for securitized mortgages. The uneven distribution of securitization volumes across states also implies a correlation between state laws and the characteristics of mortgages (Pence 2006). These strong baseline differences in simple observable characteristics of originated-and-securitized vs. originated-and-held mortgages suggest that estimating the impact of disasters on the overall probability of securitization is unlikely to yield a causal impact.

Second, the mortgage market experiences shifts due to financial conditions independent from natural disasters and related to macroeconomic conditions (Bassett, Chosak, Driscoll & Zakrajšek 2014) such as the global savings glut (Bernanke 2015), changes in consumer income (Ackerman, Fries & Windle 2012) due to a variety of factors such as shifts in industrial specialization, or due to lenders' losses in other parts of the United States or in other credit segments (Ramcharan, Verani & Van den Heuvel 2016). The secular growth of the share of non-bank lenders (Center 2019) may lead to increases in securitization volumes, as bank lenders tend to originate and hold significantly more than nonbank lenders.

Third, households and lenders may anticipate which areas are at risk of flooding (independently of SFHA areas) and may take on either less debt (if lenders tighten lending standards in this area prior to the event) or more debt (if households load on more debt in expectation of low future levels of equity).

Fourth, there may be general equilibrium spillovers from treated areas to untreated areas, as borrowers' demand for "flood-safe" locations increases; such general equilibrium effects of place-based shocks may follow the mechanisms of Sieg, Smith, Banzhaf & Walsh (2004).

Fifth, housing prices may respond to natural disasters and lead to shifts in the demand for debt. Hence shifts in the amount of securitized debt may shift due to shifts in house prices at constant lending standards and constant LTV. In addition, housing prices may respond to the supply of credit (Favara & Imbs 2015, Ouazad & Rancière 2019). Lenders may also aid in rebuilding by providing credit (Cortés 2014).

Hence an ideal experiment consists of presenting a lender with otherwise identical mortgages in both observable and unobservable dimensions and estimating the impact of a natural disaster on their securitization activity. While this ideal experiment presents practical challenges, the set of securitization rules that the GSEs use presents us with an opportunity to estimate an impact that may arguably address a number of the identification concerns.

### 3.2 Identification Strategy

This paper combines three features to identify the impact of natural disasters on mortgage securitization.

First, the paper focuses on the set of mortgages in a narrow window around the conforming loan limit. The conforming loan limit is the maximum loan amount that Fannie Mae and Freddie Mac will securitize. When focusing on loans in the window around the conforming loan limit, observable differences in borrower and mortgage characteristics narrow significantly. For instance, in the $\pm 5\%$ window, the difference in the share of white borrowers is only 0.1 percentage points, in the share of black borrowers of only 0.1 ppt, in the share of missing incomes is 1.3 ppt (compared to 3.9 ppt in the overall sample), and in applicant incomes is 3.4% (compared to 4.4%) in the overall sample. However, the share of securitized mortgages experiences a sharp drop from 86% to less than 11%, as loan amounts cross the discontinuity.

Second, the paper combines such a bunching strategy with a longitudinal panel data approach, estimating the impact of natural disasters on discontinuities controlling for year fixed effects (for the overall evolution of the mortgage market), time fixed effects (for the evolution of the control group around the natural disaster), and neighborhood fixed effects (as neighborhoods hit by a natural disaster may be observationally different) as well as controlling for the *evolution* of bunching at the conforming limit in the U.S. mortgage market.

While the intensity of hurricane seasons is typically forecast by NOAA in its Atlantic Hurricane Season Outlook, issued in May, it is difficult to predict the specific location of damage caused by hurricanes. Indeed, NOAA suggests that a large share of the year-to-year variation in local hurricane risk is idiosyncratic. "*NOAA's Seasonal outlook [...] predicts the number of [...] major hurricanes expected over the entire Atlantic basin during the six-month season. But that's where the reliable long-range science stops. The ability to forecast the location and strength of a landfalling hurricane is based on a variety of factors, details that present themselves days, not months, ahead of the storm.*[19]."

Third, the conforming loan limit varies both across years and across counties in discrete and, to a large extent, in an arbitrary fashion that is not tailored to the specific composition or housing of an area. In the sample, 91% of counties experience shifts in their associated county-specific conforming limit at some point in the time period. These shifts are large: when a county goes from general to high-cost, its limit increases up to $320,775. Conforming loan limits go from $203,150 in the early part of the sample to $625,500 for high-cost counties in the last years of the sample. Such policy-driven variation in the limit creates a natural experiment in shifting the marginal house and the marginal borrower at which bunching occurs.

Finally, the paper's identification strategy estimates the impact of "new news" by estimating the heterogeneity of the securitization response to the long-run history of hurricane occurrence in each neighborhood. The methodology and results for this heterogeneity test are presented in Section 4.4.

[19] `https://www.noaa.gov/stories/what-are-chances-hurricane-will-hit-my-home`

### 3.3 Econometric Specification

This is summarized in the following econometric specification, where the outcome variable is the approval of a mortgage, the securitization of an approved mortgage, the characteristics of the mortgage (LTI, term), the characteristics of the applicant (income, credit score, and race), and the payment history of the mortgage (foreclosure, 30-, 60-, 90-, or 120-day delinquency at any point, and voluntary payoff).

$$
\begin{aligned}
Outcome_{it} = \alpha \cdot \text{Below Conforming Limit}_{ijy(t,d)} + \gamma \text{Below Conforming Limit}_{ijy(t,d)} \times \text{Treated}_{j(i)} \\
+ \sum_{t=-T}^{+T} \xi_t \cdot \text{Treated}_{j(i)} \times \text{Time}_{t=y-y_0(d)} \\
+ \sum_{y=1995}^{2016} \zeta_y \cdot \text{Below Conforming Limit}_{ijy(t,d)} \times \text{Year}_{y(t)} \\
+ \sum_{t=-T}^{+T} \delta_t \cdot \text{Below Conforming Limit}_{ijy(t,d)} \times \text{Treated}_{j(i)} \times \text{Time}_t \\
+ \text{Year}_{y(t,d)} + \text{Disaster}_d + \text{ZIP}_{j(i)} + \varepsilon_{it}, \qquad (1)
\end{aligned}
$$

The regression is at the mortgage level $i$. $j(i)$ is the zip code of mortgage $i$. $d = 1, 2, \ldots, D$ indexes disasters. $y_0(d)$ is the year of disaster $d$. $y(t,d) = t + y_0(d)$ is the year when the time is $t$ relative to disaster $d$. This relative time runs from $t = -5$ years prior to the event to $t = +4$ years after the event. In each sum $\sum_{t=-T}^{+T}$, the summation excludes $t = -1$, the reference year. The regressions consider mortgages for which the loan amount is in a $\pm 10\%$, $\pm 5\%$, or $\pm 2.5\%$ window around the conforming limit, $|\log(\text{Loan Amount})_{it} - \log(\text{Conforming Limit})_{iy(t,d)}| < 0.10$, 0.05, or 0.025, where $\log(\text{Conforming Limit})_{iy(t,d)}$ is the year- and county-specific conforming limit (Weiss, Jones, Perl & Cowan 2017). Below Conforming $\text{Limit}_{ijy(t,d)}$ is equal to 1 when the loan amount is below such conforming loan limit.

This specification addresses the key identification challenges presented in the previous subsection. Year fixed effects control for the overall evolution of mortgage characteristics across years, which may be a concern for hurricanes occurring at the peak of the housing boom or at the trough of the housing bust. The coefficients $\xi_t$ identify the evolution of mortgage and borrower characteristics in the treated areas, both below and above the conforming loan limit. The specification also controls for the overall evolution of the discontinuity at the conforming-loan limit. The coefficients $\zeta_t$ identify the overall evolution of the conforming loan limit discontinuity independently of its evolution driven by each natural disaster. Five-digit zip code fixed effects $\text{ZIP}_{j(i)}$ capture the average differences in mortgage characteristics across locations. Disaster fixed effects $\text{Disaster}_d$ capture disaster-specific differences in averages. They are identified separately from zip fixed effects as a neighborhood may appear in multiple disasters (e.g. Katrina and Ivan).

The paper's coefficients of interest are $\delta_t$. They measure the evolution of the conforming loan limit in the treated areas over and above the evolution of the conforming loan limit overall during the same time period. In particular, the $\delta_t$ for $t \geq 0$ measure how the natural disaster causes an increase or a decline in, for instance, approval rates for mortgages on the left side of the conforming loan limit compared to the right side of the conforming limit.

A threat to identification could be the presence of time-varying local confounders preceding the disaster; this would occur if, for instance, mortgage credit anticipates the location of natural disasters. The predisaster coefficients $\delta_t$, $t < 0$ provide a placebo test for such predisaster trends. As we estimate the coefficients on a window around the conforming loan limit, the specification measures the impact of the disaster on the discontinuity in that location-specific and time-specific window.

The control group is the set of mortgages (i) in the zip codes in states of the Atlantic coast and the Gulf of Mexico, i.e. 18 states from Maine to Texas, and (ii) not affected by any of the 15 billion-dollar events, i.e. not in one of the 15 treatment groups defined in Section 2. The control group contributes to the identification of the baseline discontinuity $\alpha$, the evolution of the jumbo discontinuity $\zeta_t$, the year fixed effects $Year_y$, and the fixed effects of control group neighborhoods. The observations of the control group have a value of $t$ conventionally set to $t \equiv -1$ while the year $y$ varies between 1995 and 2017. The next section discusses the robustness of the results to the alternative definitions for the control group.

Standard errors are two-way clustered by zip code and by year, as in Cameron, Gelbach & Miller (2008).

The robustness checks presented later in this paper replace the "below the Conforming Limit" variable by "Below $x\%$ of the Conforming $\text{Limit}_{it}$" where $x$ ranges from $-5\%$ to $+5\%$, to estimate whether the impacts are *at* the discontinuity rather than far from the discontinuity. Another set of robustness checks performs volume regressions rather than regressions with the percentage of approvals or securitizations.

We also consider bunching regressions. When $Outcome_{it}$ is approval, increases in approval rates may not correspond to increases in total originations if the volume of applications declines at the conforming limit. Hence bunching regressions estimate the impact of disasters on the number of mortgage originations, approvals, and securitizations relative to their total number in the segment.

$$\frac{\#\,Below\,Limit_{jt} - \#\,Above\,Limit_{jt}}{\#\,Below\,Limit_{jt} + \#\,Above\,Limit_{jt}} = \gamma^v \text{Treated}_j + \sum_{t=-T}^{+T} \xi_t^v \cdot \text{Treated}_j \times \text{Time}_t$$
$$+ \text{Year}_{y(t,d)}^{volume} + \text{Disaster}_d^{volume} + \text{ZIP}_j^{volume} + \varepsilon_{jt}^v, \qquad (2)$$

where $\#\,Below\,Limit_{jt}$ ($\#\,Above\,Limit_{jt}$) is the number of mortgages with loan amounts in the 10% segment below (above) the conforming limit. The coefficients of interest are the $\xi_t^v$, $t \geq 0$, the impact of the natural of the disaster for each postdisaster year $t = y - y_0(d)$. As in the previous specification, $t = -5, \ldots, +4$. The coefficients $\xi_t^v$, $t < 0$, are placebo tests for the existence of trends in the discontinuity prior to the disaster. The coefficient $\gamma^v$ measures the average difference in the size of the discontinuity between the treated and untreated zip codes. The year fixed effects $\text{Year}_{y(t,d)}^{volume}$ measure the overall evolution of the discontinuity in the treatment and control groups. Disaster-specific fixed effects $\text{Disaster}_d^{volume}$ for $d = 1, 2, 3, \ldots, 15$ capture disaster-specific differences in the magnitude of the discontinuity. Zip code fixed effects are included. Standard errors are double-clustered by zip code and by year to account for common unobservable shocks.

## 3.4 Descriptive Evidence at the Conforming Loan Limit: Bunching, Discontinuities, and Selection

This section presents cross-sectional descriptive evidence at the conforming loan limit, prior to the estimation of the paper's main specification in the next section.

### Regulatory Framework

Section 1719 of the National Housing Act empowers government-sponsored enterprises to set the standards that determine eligibility of mortgages for securitization. This paper focuses on the time-varying and county-specific observable, the conforming loan limit, set by the Federal Housing Finance Agency or by Congress (Weiss et al. 2017). Three interesting features enable the identification of the impact of such limit on the market equilibrium: first, the limit is time-varying, thus enabling an estimation of the impact of the *change* in the limit on origination, securitization volumes. Second, the limit is also county-specific after 2007, implying that the limit bites at different margins of the distribution of borrower characteristics. Finally, the limit for second mortgages (last column) is high, allowing homeowners to combine a first conforming mortgage with a second mortgage to increase the combined loan-to-value (CLTV) ratio, while maintaining a loan amount within the upper bound of the conforming loan limit.

The observable loan characteristics of the government-sponsored Enterprises use also pin down the guarantee fee that is charged to primary lenders in exchange for purchasing the mortgage. The loan level price adjustment matrix (LLPA) maps the applicant's credit score and loan-to-value ratio into a guarantee fee ranging in 2018 for fixed-rate mortgages (FRM) from 0% (for applicants with a FICO score above 660 and an LTV below 60%), to 3.75% (for applicants with a FICO score below 620 and an LTV above 97%). Specific guarantee fees also apply to adjustable rate mortgages, manufactured homes, and investment property, where fees can reach 4.125% as of 2018.

#### At the Conforming Loan Limit: Discontinuities in Approval Rates, Securitization Rates, and Adverse Selection

If guarantee fees were substantially above the maximum risk premium that lenders are ready to pay, then securitization volumes would not affect origination volumes. Figure 2 presents evidence that lenders' ability to securitize mortgages by selling them to GSEs has option value. It uses data from the Home Mortgage Disclosure Act. In each year and each county, loans with an amount between 90 and 110% of the conforming loan limit are considered. Such loans are grouped into bins of 0.5%, and the number of applications is computed. The blue line is the curve fitted using a general additive model. The vertical axis is log-scaled. Figure (a) suggests that there is a discontinuity in the volume of applications at the limit, with significant bunching exactly on the left side of the limit: the count of applications exactly at the limit is up to twice the volume of applications on the right side of the limit. Figure (b) suggests that, despite the higher count of applications, the approval rate of applications is substantially higher for conforming loans, with a discontinuity of 4 to 8 percentage points. Figure (c) shows a large discontinuity in the fraction of securitized originations, of up to 50 percentage points at the limit. Figure (d) matches the HMDA application and origination file to the balance sheet of bank lenders. The figure suggests that lenders' liquidity is 1.1 ppt higher for originators of jumbo loans, who originate and hold such loans. This is consistent with Loutskina & Strahan (2009) as the ability to securitize loans led to the expansion of mortgage lending by banks with low levels of liquidity. In addition, the preferential capital treatment given to securitized products incentivizes mortgage securitization.

The evidence presented in this figure also suggests that private label securitizers (PLSs) are an imperfect substitute for the GSEs. Indeed, while PLSs do take on the risk of nonconforming, i.e. jumbo, loans, the size of the market is smaller and fees are higher, which generates a discontinuity at the conforming limit.

**Descriptive Evidence of Negative Selection into Securitization in the Cross-Section**

The evidence present in HMDA and in publicly available GSE loan files does not provide sufficient information to assess the welfare impact of the GSEs' securitization program. Indeed, different policy implications would follow from either positive or negative selection into securitization, i.e. the self-selection of safer or riskier borrowers into securitization.

Figure 3 presents evidence from McDash's loan-level files. Such files provide data on the FICO credit score at origination, and on detailed payment history, which are typically absent from publicly available files. Bunching in loans at the conforming loan limit is also present in this different dataset. Figure 3 builds and presents four indicators of ex post mortgage performance. Indeed, McDash reports monthly updates on each loan covered by its network of servicers. Loans are either current, delinquent (90 or 120 days) or in foreclosure, or the household is going through a bankruptcy process. Figure (a) suggests that conforming loans are more likely to foreclose at any point after origination. The difference is about 2 to 1.4 percentage points depending on the window (+-10% down to 0.5%). Figure (b) presents a larger discontinuity in hazard rates. Figure (c) suggests that conforming loans are more likely to be 60 days delinquent at any point. The most visually striking discontinuity is in voluntary prepayment: Figure (d) suggests that conforming loans are more likely to experience a voluntary payoff. Such prepayment is a risk for the lender, which forgoes interest payments.

Overall, the evidence presented in Figure 3 is consistent with the negative selection of borrowers into conforming loans. Such negative selection occurs along unobservable dimensions: while GSEs' rules ensure positive selection along observable characteristics, residual variance in borrower quality is sufficient to offset the national selection criteria enforced by federal regulators.

# 4 Main Results

## 4.1 Baseline Impacts

We now turn to the estimation of the paper's baseline specification (1), the impact of billion-dollar disasters on the discontinuity in approval, origination, and ultimately securitization rates at the conforming loan limit. The estimation results are presented in Table 2. The unit of analysis is a mortgage application in columns 1–7, i.e., for the approval decision (columns 1–3) and for the origination decision (columns 4-6).[20] The unit of analysis is an originated mortgage in columns 7–9 for the securitization decision as the dependent variable. For each dependent variable, we estimate the results including only mortgages whose loan amounts are within 20% of the conforming loan limit (columns 1,4, and 7), within 10% of the conforming loan limit (columns 2,6, and 8), and within 5% of the conforming limit (columns 3,6, and 9). The results using the 2.5% window are also available, statistically significant, and in line with the other results. Each regression also includes the controls of specification (1): treatment dummies for each time period $t = -4, \ldots, +4$, year fixed effects, disaster fixed effects, ZCTA5 fixed effects, and year fixed effects interacted with the "below conforming limit" indicator that captures the evolution of the mortgage market's overall discontinuity at the limit.

Placebo coefficients suggest little evidence of significant pretrends in the four years that precede the billion-dollar disaster: the coefficients for the "below Limit" variable interacted with the pre-disaster year indicator variables are not significant at 10%, except for the $-4$ variables in columns 7,8, and 9, yet the $-3$ and $-2$ coefficients are not significant and are even negative. Approval, origination, and securitization rates in the year before the disaster ($t = -1$) are set as the reference year.

Postevent variables display statistically and economically significant impacts of the disaster:

[20] In all columns the dependent variable is 0,1. The results of the estimation of a conditional logit with fixed effects are similar and available from the authors. We choose the linear probability model for the sake of simplicity.

approval rates increase between 2.4 and 7.3 percentage points in years +1 to +3 after the disaster. Origination rates increase by between 2.4 and 8.0 percentage points. Securitization rates increase by between 4.5 and 19.3 percentage points. For statistically significant coefficients, the impact on securitization rates conditional on originations is systematically higher than the impact on origination and approval rates: while higher securitization rates contribute to the increase in approval rates, there is also an independent movement at the intensive margin to securitize a larger share of the usual flow of mortgages.

Importantly, securitization rates both stay significant and increase for the 1 to 4-year range after the disaster. This is depicted in Figure 4a. In contrast, approval and origination rates experience some decline in year +4. This is driven by (i) the higher numbers of mortgage applications (ii) with lower credit quality in year +4. We describe both features below in detail.

Table 3 presents evidence that the year +4 decline in approval and origination rates is driven by the increase in application rates. When focusing on discontinuities in *numbers* rather than in rates, the discontinuity in approvals, originations, and securitizations is large and significant. In this table, the unit of analysis is a zip code × year (of which there are between 173,255 and 171,115). The dependent variable takes values between 0 (no discontinuity) and 1 (100% discontinuity). We consider discontinuities for which there are at least 20 mortgages on either side, and observations for 2 years before and 2 years after the event. This table uses the coarsest 5% window around the conforming loan limit, as in previous tables' columns (3), (5), and (9). The discontinuity in approval numbers increases up to 18.1 percentage points in year +4 after the disaster. The discontinuity in origination numbers increases by up to 18.5 percentage points. The discontinuity in securitization numbers increases by 17 percentage points 4 years after the event. The regression in numbers also does not display a significant pretrend before the event. The coefficients are depicted in Figure 4b.

Overall, the results suggest that while there is no evidence of pretrends, disasters tend to lead to significantly higher securitization, approval, and originations in the conforming segment vs. in the jumbo segment, regardless of the size of the window from 20% to 5%.

## 4.2 Impact of Disasters on Adverse Selection into Securitization

The results of specification (1) suggested a greater volume of applications at the limit on the conforming segment after a natural disaster. This section presents results that suggest that the creditworthiness of such applicants also declines after such a disaster.

As HMDA data do not contain ex-post performance measures or credit scores, we turn to the McDash dataset to estimate specification (1). Table 4 presents the results on the 1,697,650 observations of the McDash dataset with a ±10% window.[21] As in the previous regressions, standard errors are double-clustered at the zip code and year levels and include the same set of controls. Results suggest that the discontinuity in credit scores increases significantly after the event, with borrowing at the conforming limit having a credit score 3.4 points lower than in the jumbo segment. Mortgage maturity becomes marginally longer. However, it is in the measures of mortgage performance that the results are perhaps more economically significant. Six measures of ex post mortgage performance are used: foreclosure at any point, 30-, 60-, 90-, 120-day delinquency, and voluntary payoff. The results suggest that the discontinuity in performance at the conforming limit is significantly worse after the disaster. The foreclosure probability is 4.9 percentage points higher 3 years after the event. The probability of a 60-day delinquency at any point after origination is 2.2 percentage points higher. The probability of a 90-day delinquency is 2.4 percentage point higher, the probability of a 120-day delinquency is 1.3 percentage points higher. The probability of an early prepayment (voluntary payoff) is 2.3 percentage points lower. The results also suggest the absence of pretrends in the McDash dataset as in the HMDA dataset (first row, $t = -2$ coefficients).

### 4.3 Robustness Checks

**A Test of the Identification Strategy:**

**Effects Far From the Conforming Loan Limit vs. Effects at the Conforming Loan Limit**

A second set of regressions identifies whether the estimated $\delta_t$, for $t = -2, \dots, 3$, are due to observations *at* the conforming loan limit or far from the limit. The results of specification (1) may be driven by observations away from the conforming loan limit. For instance, declining house prices may lead to an increase in the volume of conforming loans in a wide segment below the conforming loan limit rather than affecting discontinuity at the limit.

We thus design an additional test that applies to our main specifications (1) and (2). In the case of specification (1), we run 15 separate estimations where the Below Conforming Limit$_{it}$ variable is

[21] Results with the 20% and the 5% windows available from the authors.

replaced by an indicator for Below p% of the Conforming Limit$_{it}$, with $p$ ranging from 95% to 105% of the conforming limit, on a grid of 15 equally spaced points. This yields estimates of the treatment effects $\delta_t(p)$ for 15 values $p \in [95\%, 105\%]$, which should be highest at $p = 0$ if the discontinuity at conforming limit is driving our result. For specification (2), the discontinuity in numbers, we rebuild the dataset of discontinuities 15 times with 15 different thresholds with the same range of $p$.

The results of these estimations are presented in Figure 6, Panels (a), (b), (c) for specification (1): for the approval rate, the origination rate, and the securitization rate. The impacts are presented in the year following the disaster and in the 1st, 2nd, and 3rd years after the disaster. The results for specification (2) are presented in panels (d), (e), and (f).

The results suggest that the impact of billion-dollar disasters is greatest at the conforming limit, with approval rates increasing significantly at the conforming limit but not far from it in the year following the disaster. The impact of a disaster grows significantly over time, up to 3 to 5 times as high as the impact in the year of the disaster; such higher treatment happens exactly at the conforming loan limit. This suggests that the results are driven by the discontinuity in lenders' ability to securitize at the limit rather than an across-the-board increase in the volume of loans in the conforming segment.

**Impact of the Control Group on Results**

An appropriate control group provides counterfactual observations, i.e. observations where the state of the mortgage market prior to the natural disaster is comparable in both control and treatment zip codes. The paper suggests the absence of significant pretrends in both specifications (1) and (2). Another condition is that the control group should not be affected by general equilibrium price spillovers. Such violations of the SUTVA[22] identification assumption would occur if mortgage lending and securitization standards in unaffected areas responds in a general equilibrium fashion to mortgage lending and securitization standards in affected areas.

To test for such confounding effects, we run the regression excluding control group zip codes in CBSAs ($\mu$SAs and MSAs) for which there is at least one zip code hit. This leaves 328 CBSAs in total, 53 in the treatment group, 276 in the control group (vs. 328 in the control group in

[22] For a discussion of the Stable Unit Treatment Value Assumption, see Rubin (1986).

the baseline sample). The results are not significantly different than those presented in Table 2, suggesting that spillovers from the treatment to the control group are not driving the results.

#### Difference-in-Differences with Multiple Treatments

Another concern may stem from the multiple treatments occurring at different points in time. Goodman-Bacon (2018) suggests that neighborhoods that experience early treatment are (inadequately) part of the control group for neighborhoods that are treated later in the period of analysis. With only 18% of the dataset treated, the fixed effects for years, neighborhoods, and the time dummies are identified on the 82% of the untreated observations, suggesting that this concern may be less relevant than with state-level difference-in-differences. However Goodman-Bacon's (2018) point may affect zip code tabulation areas that experienced multiple treatments in the 2005-2012 period, in which case a subset of post-disaster observations would serve as controls for future treatements. To assess the robustness of the results to this concern, we run two different sets of regressions. We consider zip codes as treated only for their first hurricane in the 2005-2012 period. We also consider a similar regression for zip codes treated only for their last hurricane in the 2005-2012 period. The results are not significantly different than those presented in Table 2.

### 4.4 Documenting the Mechanism: New News, the Insurance Mandate

#### Heterogeneous Effects by the Local 1851-2017 Frequency of Hurricanes

If lenders learn about the future location of disasters when observing the geography of a new disaster's damages, then the impact of disasters on securitization probabilities may be higher in areas with a long history of hurricanes. We build such a history to estimate the heterogeneous impact of disasters.

The hurricane history is built as follows. For each hurricane since 1851 in NOAA's Atlantic Hurricane Database, we obtain the coordinates of the hurricane's path and wind radius. When such a radius was not available, e.g., for 19th century hurricanes, we impute it using the typical 64kt wind radii of the area. For each blockgroup of the coastal states from Maine to Texas, we count the number of times such a hurricane's wind path crosses the blockgroup. The historical frequency is aggregated from the blockgroup to the zip code level. This provides us with a zip-code-level measure of hurricane frequency since 1851, ranging from 0 (for northern and western Texas) to 0.405, or 4.1 times per decade (for the New Orleans basin, Florida, the eastern part of the Carolinas). This is depicted in Figure C. Hence, hurricanes occurring in Texas tend to provide more "new news" than hurricanes occurring in the New Orleans or South Florida basins.[23] The granularity of the measure combined with the use of fixed effects in the regression, however, allows for an identification based as much on within-MSA heterogeneity in frequency as on broad differences in hurricane frequencies across states or MSAs.

Table 5 presents the coefficients of the interaction of $Below\,Limit_{it} \times Treated_{jt}$ with such historical frequency, in the paper's main specification (1). The historical frequency is demeaned. We present the results for the $\pm 10\%$ window and report the interaction. The results suggest that indeed, there is a smaller response of approval and origination rates (respectively, columns (1) and (2)) in areas with a high frequency of hurricanes. In zip codes in the upper quartile of hurricane frequency (0.046 or 0.46 hurricanes per decade), the impact is approximately half the baseline impact in the average zip code: for originations in year $+3$, the impact is $-0.507 \times 0.046 = 0.023$, or 2.3 percentage points lower than in the baseline of $+5.9$ percentage points.

### Heterogeneous Effects in Special Flood Hazard Areas

The two government-sponsored enterprises require flood insurance for agency-backed mortgages in Special Flood Hazard Areas.[24] An SFHA is in principle defined as an area that will be inundated by a flood having a 1-percent chance of being exceeded in any given year. This requirement has been in place since the 1973 Flood Disaster Protection Act[25] but take-up has been limited and declining since 2006 and evidence suggests significant mismatches between affected areas and SFHAs.[26] The flood insurance coverage extends up to \$250,000, which is below the conforming loan limit by at least \$167,000 and up to \$375,500 between 2005 and 2016.

[23] One approach to "new news" is by considering lenders and borrowers' beliefs about the local probability of flooding.

[24] Fannie Mae Selling Guide, B7-3-07 Flood Insurance Coverage Requirement

[25] Section 103, (3), (B) "Government-Sponsored Enterprises for Housing. -- The Federal National Mortgage Association and the Federal Home Loan Mortgage Corporation shall implement procedures reasonably designed to ensure that, for any loan that is-- [...] purchased by such entity, the building or mobile home and any personal property securing the loan is covered for the term of the loan by flood insurance in the amount provided in paragraph (1)(A)."

[26] See footnote 13 .

The paper's main result, i.e. the shift toward the conforming segment, should be lower in SFHAs for at least two reasons: (i) the flood insurance mandate implies higher costs for households willing to borrow in the conforming segment, and thus, lenders may be less able to shift demand away from the jumbo segment, and (ii) SFHA delineations are well known to households, who can display the National Flood Hazard Layer and its SFHAs using a publicly available website. Flooding in SFHAs is less likely to bring new information on disaster probabilities. Flooding occurs regularly outside of SFHAs. Appendix Figure B zooms in on parts of the New York MSA to illustrate potential discrepancies between realized flooding and the SFHA. [27]

We test the hypothesis that the paper's baseline impact is smaller in SFHA areas by building a zip-code-level measure of the share of a zip code that is in the SFHA of the National Flood Hazard Layer. The bottom panel of Table 5 presents the results when adding the interaction of $Below\,Limit_{it} \times Treated_{jt}$ with the $[0, 1]$ share of a zip code in an SFHA. Three of the coefficients are negative and significant at 10 and 5%, suggesting evidence that the impact of disasters on mortgage securitization is smaller in SFHAs.

## 5 Mortgage Credit Supply in Disaster Areas without the Government Sponsored Entreprises: A Structural Approach

We need a model to assess the impact of disaster risk on mortgage origination and securitization volumes when catastrophic risk raises the risk of default above idiosyncratic default risk. We also need a model to simulate the impact of a potential withdrawal or decline of the government-sponsored enterprises' securitization activity.

This section introduces a stylized model of monopolistic mortgage pricing and approval with (i) a differentiated menu of locations exposed to flood risk, and a flood-safe outside option, (ii) the sorting of households by their idiosyncratic default risk (e.g. divorce and unemployment) into locations and into the outside option, (iii) the lender's choice of mortgage pricing in each location, (iv) the lender's option of securitizing mortgages in areas where loan amounts are less than the conforming limit, and (v) the lender's decision to approve or deny mortgages based on households' idiosyncratic risk

[27] While flooding outside of the 100-year floodplain can occur without a shift in the 1% probability, the mismatch between the 100-year floodplain and the SFHA can update mortgage market's participants' beliefs about flooding in a specific area.

in each location.

The model generates bunching and adverse selection at the conforming limit and thus replicates the "structure-free" discontinuities estimated in Section 4 for the overall sample. The amount of bunching depends on the sorting of households' idiosyncratic risk in each location. The amount of bunching also depends on catastrophic risk. Catastrophic flood risk affects all locations except the outside option. Out-of-sample increases in the probability of flood risk generate larger bunching and larger adverse selection as in the paper's main tables 2 and 3. Yet it does not generate an overall decline in mortgage credit supply when the GSEs maintain their securitization policy. In contrast, in the counterfactual world where the GSEs withdraw their securitization activity, increases in the probability of flood risk lead to substantial declines in mortgage credit supply in flood risk areas.

### 5.1 A Structural Model of Mortgage Pricing with Asymmetric Information

There are $j = 1, 2, \ldots, J$ neighborhoods, each with amenity level $z_j$. Each of the $i \in [0, N]$ households chooses a neighborhood $j$. Such a continuum of households differs by their idiosyncratic default driver $\varepsilon \in (-\infty, +\infty)$. Such $\varepsilon$ is not observable by lenders.

We model a lender's mortgage pricing choices. The lender's opportunity cost of capital is denoted $\kappa$. The lender offers a fixed rate mortgage with loan amount $L_j$ and maturity $T$ in each location, and chooses an interest rate $r_j$ in each location.[28] The lender chooses a menu of interest rates: the lender sets the interest rate $r_j$ in this segment $j$ to maximize the joint profit over the $j$ locations.

After choosing a location-mortgage contract pair $j \in \{1, 2, \ldots, J\}$, households pay a mortgage with payment $m_j(r_j, T, L_j)$ from $t = 1, 2, \ldots, T$. They can default every year $t = 1, 2, \ldots, T$ or keep paying and deriving utility from neighborhood amenities. For the sake of simplicity we abstract from (i) dynamic prepayment and (ii) households' dynamic location choices.[29]

The annual default probability $\delta(\varepsilon, B_{jt}, p_{jt}) \in [0, 1]$ is driven both by household fundamentals $\varepsilon$, and by the current loan-to-value (LTV), i.e. the ratio of the household's mortgage balance $B_{jt}$ by the house price $p_{jt}$ in year $t$ after origination. Flood risk, which occurs with probability $\pi$, wipes out the value of the house $p_{jt}$, makes the current LTV $\to +\infty$ and thus causes default. The

[28] For the sake of clarity we present the structural approach with fixed rate mortgage (FRM) contracts, but the model is extended and estimated with other contracts such as ARMs and IO loans.

[29] Key papers describe households' dynamic location choices for a given menu of mortgage options (Guren et al. 2018, Guren & McQuade 2020). This paper focuses on the description of the endogenous menu of mortgage options.

latent variable $\text{Default}^*_{jt}(\varepsilon)$ measures the household's propensity to default absent a flood, so that its annual default probability is $\delta = (1-\pi) \cdot P(\text{Default}^*_{jt}(\varepsilon) > 0) + \pi$, with:

$$\text{Default}^*_{jt}(\varepsilon) = \alpha^{default} \log\left(B_{jt}/p_{jt}\right) + \sigma_\varepsilon \varepsilon + \eta_{jt}(\varepsilon) \tag{3}$$

where $\eta$ is extreme-value distributed. The balance evolves according to the usual formula of mortgage amortization:

$$B_{jt+1} = (1 + r_j)B_{jt} - m_{jt} \tag{4}$$

An important driver of mortgage default in equation (3) is the current house price. A household whose balance substantially exceeds the current value of its house is more likely to default (Foote, Gerardi & Willen 2008). Each lender forecasts the path of future prices. At the time of origination, the lender expects that, absent a flood, house prices follow a geometric Brownian motion with constant drift $\alpha$ and volatility $\sigma$ as is typical in the real estate literature (Bayer, Ellickson & Ellickson 2010). The novelty in the dynamics of prices below is that there is a probability $\pi \in [0, 1]$ of flood risk wiping out real estate values in the neighborhood.

$$p_{t+1} = (1 - \pi) \cdot p_t \cdot (\alpha + \sigma \Delta W_t) \tag{5}$$

where $\alpha$ is the house price trend (in logs), $\sigma$ the price volatility. $\Delta W_t$ is an i.i.d normal shock, $\Delta W_t \sim N(0, 1)$. Both $\alpha$ and $\sigma$ are assumed to be common knowledge, while disaster risk $\pi$ is uncertain. When a flood occurs, $p_t = 0$ and $\log(B_{jt}/p_{jt}) = +\infty$, so that $\delta = P(\text{Default}^*_{jt}(\varepsilon) > 0) = 1$.

**Lenders' Optimal Menus of Contracts** The lender chooses a vector of interest rates $\mathbf{r}$ to maximize its total profit, coming from each of the $J$ locations:

$$\Pi(r_1, r_2, \ldots, r_J) = \sum_{j=1}^{J} \Pi_j(r_1, r_2, \ldots, r_J) \tag{6}$$

where the profit in location $j$ is driven by the default probability, the mortgage payment, and the fraction of households choosing $j$:

$$\Pi_j = \{E_j[\xi] \cdot m(r_J^*, T, L_j) - L_j + E_j[\phi(\delta)]\} \cdot P(j) + \epsilon \tag{7}$$

where $\epsilon$ is an unobservable driver of profit. The multiplier $\xi$ of mortgage payments depends on the expected default rate, so:

$$E_j[\xi] \equiv E_j\left[\sum_{t=1}^{T} \frac{\Pi_{s=1}^{t}(1-\delta_{js}(\varepsilon))}{1+\kappa}\right] \tag{8}$$

with $\kappa$ the lender's opportunity cost of capital. For a specific location $j$, the probability of default of households is as follows:

$$E_j[\xi] = \int \xi(\varepsilon) f(\varepsilon|j) d\varepsilon \tag{9}$$

where $f(\varepsilon|j)$ is the consequence of households' sorting and is derived in the next few paragraphs. In the lender's profit (7), the term $E_j[\phi(\delta)]$ is the expected revenue generated by a foreclosure sale in case of default, equal to $\sum_{t=1}^{T} \Pi_{s=1}^{t}(1-\delta_{js})/(1+\kappa)\delta_{jt} \min\{B_{jt}, p_{jt}\}$. If the household defaults indeed ($\text{Default}_{jt}^*(\varepsilon) > 0$), a foreclosure auction yields a payoff $\min\{B_{jt}, p_{jt}\}$, which is at most equal to the current mortgage balance.

At this point, it is clear that households' location choices are a key input in lenders' optimal mortgage menu.

**Households' Location and Contract Choices** A household $\varepsilon$ chooses its location based on local amenities $z_j$ and contract features $r_j, L_j$. It maximizes the indirect utility:

$$U_j(\varepsilon) = \boldsymbol{\gamma} z_j - (\alpha + \beta\varepsilon) \cdot \log(\text{Total Cost}_j) + \eta_j(\varepsilon) \tag{10}$$

where $\eta_j$ is extreme-value distributed, as is common in the discrete choice literature. $\text{Total Cost}_j$ is the mortgage's total cost. As households with worse risk (higher $\varepsilon$) are less likely to pay the total cost of the mortgage, the household's sensitivity to the total cost $\log(\text{Total Cost}_j)$ depends on its unobservable default driver $\varepsilon$ through the interaction coefficient $\beta$. The household can also choose an outside option yielding utility $U_0$, which is not affected by the catastrophic risk of flooding.

Hence the probability of choosing $j$ for household $\varepsilon$ is simply:

$$f(j|\varepsilon) = \frac{\exp(U_j(\varepsilon))}{\sum_k \exp(U_k(\varepsilon)) + \exp(U_0)} \tag{11}$$

The probability of choosing neighborhood $j$ and lender $\ell$ is denoted $f(j|\varepsilon)$ and is a simple multinomial logit that depends on the deterministic part of utility $U_j(\varepsilon)$, denoted $V_j(\varepsilon)$. Households have the outside option of not purchasing a house, which yields utility $U_0 \equiv 0$ by convention.

In turn the expected distribution of unobservable household characteristics $\varepsilon$ in a given location-contract $j$ is given by using Bayes' rule:

$$f(\varepsilon|j) = \frac{f(j|\varepsilon)f(\varepsilon)}{f(j)}, \tag{12}$$

which is a key ingredient in the lender's calculation of its discounting factor $\xi$ described in equation 9. It is also a key ingredient of the lender's first-order condition, as shifts in interest rates affect households' sorting in the unobservable dimension $\varepsilon$.

**The Securitization Option** The introduction of the securitization option is as follows. For mortgages whose amount $L_j$ is below the conforming limit $\tilde{L}$, the lender can sell the mortgage to the agency securitizers at a guarantee fee $\varphi$ at the time of origination.[30] In such a case, the multiplier becomes a simple function $\xi(\varphi)$ of the guarantee fee. This multiplier is independent of the default rate and of the revenue $E_j\left[\phi\right]$ of a foreclosure sale.

$$\tilde{\Pi}_j^h = \left\{E_j\left[\xi\right] \cdot m(r_J^*, T, L_j) - L_j + E_j\left[\phi(\delta)\right]\right\} \cdot P(j) + \epsilon_j^h \tag{13}$$

$$\tilde{\Pi}_j^s = \left\{\xi(\varphi) \cdot m(r_J^*, T, L_j) - L_j\right\} \cdot P(j) + \epsilon_j^s \tag{14}$$

As the lender picks loans for securitization after observing $\varepsilon$, it securitizes mortgages for which the profit $\tilde{\Pi}_j^h = \Pi_j^h + \epsilon_j^h$ of originating and holding (equation (7)) is lower than the profit $\tilde{\Pi}_j^s = \Pi_j^s + \epsilon_j^s$

[30]See Adelino et al. (2019) for an empirical discussion of the dynamic process of securitization.

when originating and securitizing. Then,

$$P(\text{Approval})_j = P\left(\max\left\{\Pi_j^h + \epsilon_j^h, \Pi_j^s + \epsilon_j^s\right\} \geq 0\right), \tag{15}$$

$$P(\text{Securitization})_j = P\left(\Pi_j^s + \epsilon_j^s \geq \Pi_j^h + \epsilon_j^h \,\middle|\, \max\left\{\Pi_j^h + \epsilon_j^h, \Pi_j^s + \epsilon_j^s\right\} \geq 0\right) \tag{16}$$

where $\Pi$ is the observable part of profit. Both the approval rate and the securitization rates by location are observable quantities in Home Mortgage Disclosure Act data.

**Monopoly Pricing with Differentiated Locations** We consider the partial equilibrium of the lender's price setting and household sorting across locations. By offering a menu of interest rates, the lender practices second-degree price discrimination.

**Definition 1.** An equilibrium is a $J$-vector $\mathbf{r}^*$ of interest rates for each location-contract pair $j$ such that (i) the lender chooses a menu $\mathbf{r}^* = (r_1, r_2, \ldots, r_J)$ of interest rates in each location $j$ to maximize its total profit given households' location choices; (ii) in each location, the lender approves loans for which the profit of origination is positive; (iii) in each location, the lender securitizes loans for which the profit of securitization is greater than the profit of holding; and (iv) each household $\varepsilon$ chooses a location-contract pair $j^*(\varepsilon)$ that maximizes his utility.

The structure of this problem is in the class of problems first introduced by Mirrlees (1971) and developed in the case of monopoly pricing by Maskin & Riley (1984).[31] This setup could be extended to multiple lenders.

**Identification at the Conforming Loan Limit** We need to estimate structural parameters in three structural equations: the drivers of household default (3), the drivers of household sorting (10), and the drivers of lenders' profit of originating and holding (13) as well as originating and securitizing (14).

Mortgage default is observed for each loan amount and for each household income in the McDash financial dataset. The set of household characteristics borrowing in each neighborhood is observed in Home Mortgage Disclosure Act data. The approval rates and the securitization rates are observed in HMDA data. The interest rate of mortgages is observed in the McDash data.

[31] A recent structural model of business lending with asymmetric information is presented in Crawford, Pavanini & Schivardi (2018).

We jointly estimate the default parameters $\left(\alpha^{default}, \boldsymbol{\beta}^{default}, \sigma_\varepsilon\right)$ from equation (3), the utility parameters $(\boldsymbol{\gamma}, \Omega, \alpha, \beta)$ from (10), and the lender's profit parameters $\left(\kappa, Var(\epsilon^h), Var(\epsilon^s)\right)$ from (13) and (14) that match, across neighborhoods, (i) the observed default rates, (ii) the share of originations, (iii) the probability of approval, and (iv) the probability of securitization. These three sets of parameters are stacked into a single vector $\boldsymbol{\theta} = (\boldsymbol{\theta}^{default}, \boldsymbol{\theta}^{utility}, \boldsymbol{\theta}^{profit})$. The four sets of predictions are stacked in a vector and denoted $\boldsymbol{Predictions}$, and the corresponding observations are denoted $\boldsymbol{Observations}$.

The following parameters are set exogenously. The conforming loan limit is set as in Section 2. The price trends $\alpha$ and volatility $\sigma$ are estimated using Zillow's zip-code-level time series. The LTV at origination is set to 80%. As the estimation is performed on a majority of neighborhoods outside of flood-prone areas, the probability of catastrophic risk is initially set to $\pi = 0$ in the estimation stage; and increased in counterfactual simulations.

The estimation of parameters is performed in a 90-110% window around the conforming loan limit. We use a two-step GMM approach:

$$\hat{\boldsymbol{\theta}} \equiv \operatorname{argmin} \left(\boldsymbol{Predictions} - \boldsymbol{Observations}\right)' \Psi \left(\boldsymbol{Predictions} - \boldsymbol{Observations}\right) \qquad (17)$$

where $\Psi = Id$ in the first step and $\Psi$ is the positive definite matrix that minimizes the variance of the estimator in the second step. This empirical approach of estimating parameters in a window around the conforming loan limit is similar to one recently used in Fu & Gregory (2019).

## 5.2 Model Fit and Simulations of Increasing Disaster Risk

Figure 7 compares the predictions of the model with the realizations for the largest lender observed in HMDA in the 2004-2016 period. The gray points correspond to observations, and the black points to the realizations of the model. In each figure, the horizontal axis is the difference between the log loan amount in the location and the log of the conforming loan limit. It ranges from 90 to 110% of the conforming loan limit.

The model reproduces the discontinuities in approval rates, securitization rates, default probabilities that were described in Section 3.4, "Descriptive Evidence at the Conforming Loan Limit." By replicating the higher default rate of conforming loans (Figure 7c), the model also accounts for the adverse selection into the conforming segment. In the model, this is generated as households with worse (higher) $\varepsilon$s tend to be more likely to bunch at the conforming loan limit. The model does not account for private label securitization activity above the conforming loan limit. However, it captures the higher approval rate, the higher securitization rate, the higher default rate in the conforming segment.

### 5.2.1 Increasing Disaster Risk

We then simulate the out-of-sample impact of increasing disaster risk from $\pi = 0$ to $\pi = 1\%$ on approval rates, securitization rates, and default rates in each neighborhood. Households' propensity to default, households' preferences, and lenders' profit parameters are kept constant, but optimal interest rates, approval rates, and securitization rates are recomputed in response to the increase in $\pi$. A key question is whether the model can replicate the structure-free results of Specification (1) and Specifications (2). The model can then be used to perform out-of-sample simulations.

Figure 8 compares the baseline scenario (black points) with $\pi = 0$ with the scenario with $\pi = 1\%$. This value of disaster risk matches the assumed risk of flooding in the 100-year floodplain.

As expected, this increasing disaster risk causes a rise in expected default rates across all neighborhoods (subfigure (b)). Default increases from 0.15-0.3% to levels above 1.1%. The approval rate declines (subfigure (a)), but such a decline is mitigated by the increase in securitization rates, that move up in the conforming segment. The model thus generates the increase in the discontinuity of approval rates observed in the quasi-experimental analysis (Table 2, columns (1)–(3)), as well as the increase in the discontinuity in securitization rates (same Table, columns (7)-(9)).

This suggests that the transfer of disaster risk to agency securitizers mitigates the impact of greater disaster risk on mortgage approvals. Hence the share of originations in each location (for this lender) changes only marginally, suggesting that households' location patterns would be more affected without such securitization options. Hence the GSEs' securitization option is likely to benefit households who wish to locate in flood zones.

### 5.2.2 The Withdrawal of the GSEs

A simulation of a similar growth in disaster risk is performed this time while simultaneously removing the securitization option. In particular, the simulation can establish whether the lender would reduce lending volumes, increase interest rates, in the absence of the option to sell risky mortgages. Elenev et al. (2016) predicts that underpriced government mortgage guarantees lead to more and riskier mortgage originations. This paper's model makes spatial predictions: will households move away from homeownership by choosing the "flood-safe" outside option? Will households choose locations with lower loan amounts?

Figure 9 presents the results of such counterfactual simulation where the lender cannot securitize to the GSEs. The orange points depict the equilibrium in the mortgage market when lenders do not have the option to securitize and disaster risk is introduced with a probability $\pi = 1\%$.

The withdrawal of the GSEs causes a substantial decline in approval rate in the conforming segment (subfigure (a)). This stands in contrast with the results of the previous analysis: while the discontinuity in approval rates increases with the option to securitize (as in the paper's main result of Table 2), such discontinuity *declines* when there is no option to securitize. It also causes a substantial decline in the overall fraction of households who choose to buy a home (an increase in the share choosing the outside option) as the total volume of originations shifts down. Without the securitization option (the probability of securitization falls to zero in subfigure (b)), there is no evidence of adverse selection of households into the conforming segment as there is a smooth relationship between default rates and loan amounts (subfigure (c)). Overall simulations suggest that the GSEs' securitization activity mitigates the impact of increasing disaster risk on the number of households purchasing a home.

### 5.3 An Endogenous Guarantee Fee when Facing Rising Flood Risk

The model can be used to estimate the evolution of an endogenous guarantee fee that maintains the securitizers' profit constant even as disaster risk increases. The key question is whether such an endogenous fee would affect the supply of mortgage credit by lenders in the face of a rising disaster risk probability $\pi$.

In the model, the profit-neutral guarantee fee $\varphi^*(\pi)$ is such that the securitizers' profit is unaffected by the probability of disaster risk $\pi$, i.e. is equal to the profit when disaster risk probability is zero, $\pi = 0$. In other words, the securitizers' total profit across all $J$ locations is equal in either the zero-probability of disaster risk scenario and in the $\pi = 1\%$ scenario:

$$\varphi^*(\pi) \quad \text{such that} \quad \sum_{j=1}^{J} \Pi_j^{sec} \left[\varphi^*(\pi)\right] = \sum_{j=1}^{J} \Pi_j^{sec} \left[\varphi(0)\right] \tag{18}$$

Securitizers' profit in location $j$ can be calculated as follows. Securitizers receive borrowers' mortgage payment $m_j$, and face a default probability $\delta_{jt}$ in each period. In case of a foreclosure, the securitizer receives the proceeds of the foreclosure auction. Hence the present discounted value of mortgage payments and foreclosure auction is $E_j[\zeta] \cdot m_j + E_j[\psi(\delta)]$. In this expression, $E_j[\zeta]$ is defined as the multiplier in $j$ given the default probability of mortgages *securitized* in $j$. This differs from the earlier multiplier $E_j[\xi]$ for all originated mortgages, regardless of whether they are held or securitized. The expected proceeds of the foreclosure auction $E_j[\psi(\delta)]$ for securitized mortgages also differ from the expected proceeds of the foreclosure auction $E_j[\phi(\delta)]$ for all originated mortgages in $j$.

Securitizers 'pass through' mortgage payments back to the lenders regardless of default, and receive a guarantee fee $\varphi$, a fraction of the mortgage payment. The profit of the securitizers in location $j$ is thus:

$$\Pi_j^{sec} = E_j[\zeta] \cdot m_j + E_j[\psi(\delta)] - \sum_{k=0}^{T} \left(\frac{1-\varphi}{1+\kappa}\right)^k m_j \tag{19}$$

The table below estimates the endogenous guarantee fee $\varphi^*(\pi)$ defined in equation (18) when the probability of disaster risk increases smoothly from $\pi = 0$ to $\pi = 1.5\%$.

| Disaster Risk $\pi$ | 0.0% | 0.25% | 1.0% | 1.25% | 1.5% |
|---|---|---|---|---|---|
| Guarantee Fee $\varphi^*(\pi)$ | 0.40% | 0.44% | 0.56% | 0.59% | 0.65% |

Actual guarantee fees, detailed every year in the FHFA's Loan Level Price Adjustment matrix, vary according to the borrower's credit score and LTV. Yet this simulation provides an essential mechanism suggesting that credit supply would decline in flood zones as disaster risk increases when the guarantee fee is allowed to adjust, a finding that should be robust to the introduction of heterogeneous guarantee fees.

# 6 Conclusion

This paper describes an arbitrage opportunity in a large debt market where market incompleteness stems from non-comprehensive flood insurance coverage,[32] and where securitization policies do not charge fees related to flood insurance risk. Such arbitrage opportunity implies that the two securitizers Fannie Mae and Freddie Mac may bear the risk of increasing climate risk, and thus have an important role in guiding lenders and households through the climate change adaptation process: as they support liquidity in the secondary U.S. mortgage market to facilitate access to homeownership, they may also encourage lenders to "originate and distribute" their climate risk; and encourage households to locate in flood risk areas. A 30-year fixed rate mortgage contract signed in 2020 matures in 2050, within the forecasting horizon of the IPCC's climate change scenarios.

The ambiguity of climate risk probabilities and the correlation of natural disaster shocks may spark a new research field at the frontier of empirical finance and asset pricing. Correlated defaults[33] may involve the development of new financial techniques for the diversification of climate risk as the volume of at-risk loans increases. Unpriced climate risk may lead to the existence of a large set of arbitrage opportunities, including in the Mortgage Backed Securities market, in addition to those highlighted during the credit boom of the 2000s (Gabaix, Krishnamurthy & Vigneron 2007). Hence this paper's conclusions should be of interest to regulators (Carney 2015, Carney 2016) and stakeholders interested in monitoring the systemic climate risk held onto financial institutions' balance sheets.

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[32]Levine & Zame (2002) shows that aggregate risk (as opposed to idiosyncratic risk) has substantial consequences when markets are incomplete.

[33]Phelan (2017) presents a financial model where one of the purposes of intermediaries (e.g. commercial banks) is to facilitate the monitoring of mortgage default correlation.

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Figure 1: Treatment Area Geography – The Case of Hurricane Sandy

*This figure presents the treatment area geography for Hurricane Sandy. A neighborhood is in the treatment group if: (i) its minimum elevation is less than 3 meters, (ii) its distance to the coastline or its distance to wetland is less than 2 km, and (iii) if it lies in the 64kt wind path. Elevation from USGS' digital elevation model. Distance to wetland from the Land Cover dataset. Wind speed from the Atlantic Hurricane data of the National Hurricane Center. The treatment group is at the intersection of the red and blue areas. Description of the construction of the treatment group in Section 2.1.*

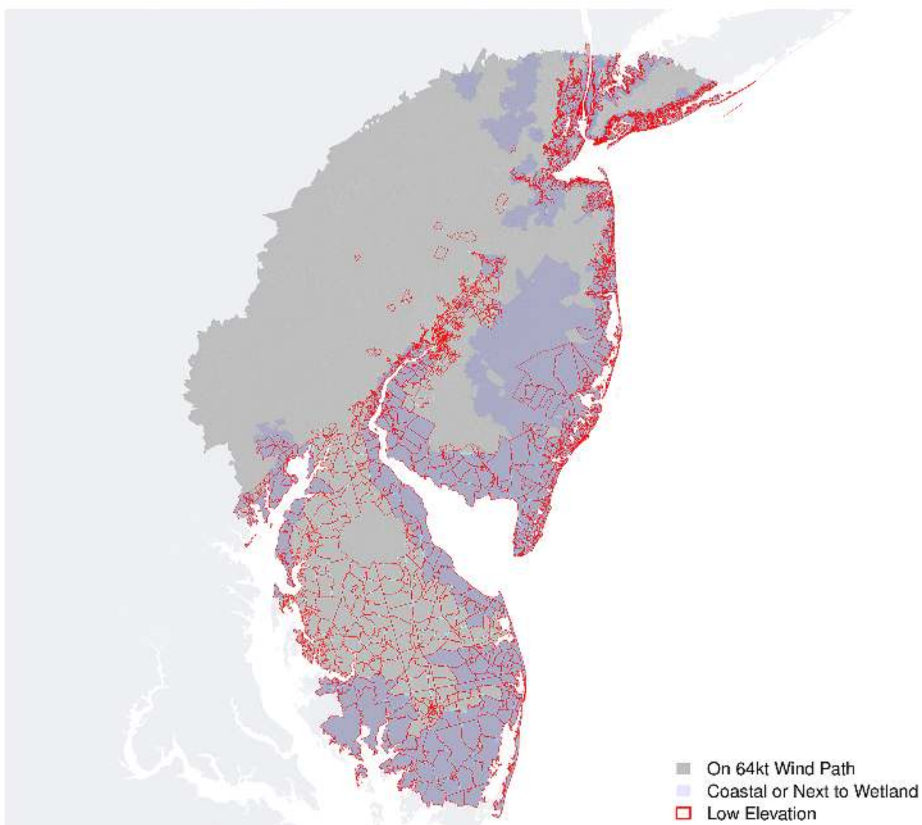
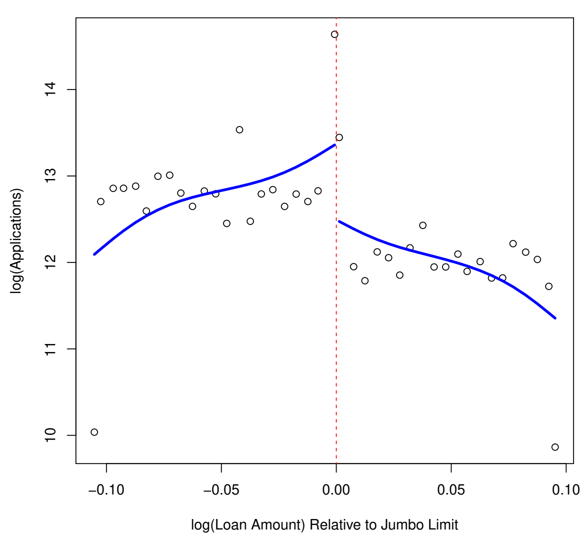


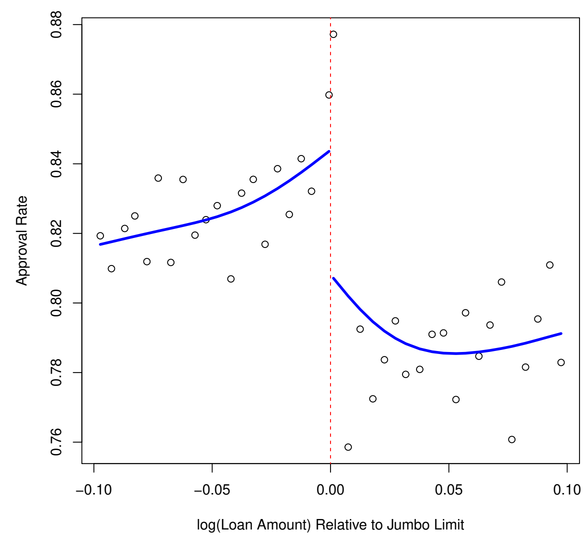
Figure 2: Descriptive Statistics – Baseline Discontinuities at the Conforming Loan Limit – HMDA Analysis

*These figures present the estimates of the impact of the conforming loan limit on the log count of applications, borrowers' ethnicity, the loan-to-income ratio of originations, and the liquidity ratio of the lender. The black points are the value for each 1 ppt bin in the window around the conforming loan limit. The blue lines are the predictions from a generalized additive model. The red dotted line is the conforming loan limit. The horizontal axis is the difference between the log loan amount and the log conforming loan limit. The conforming loan limits are year- and county-specific.*

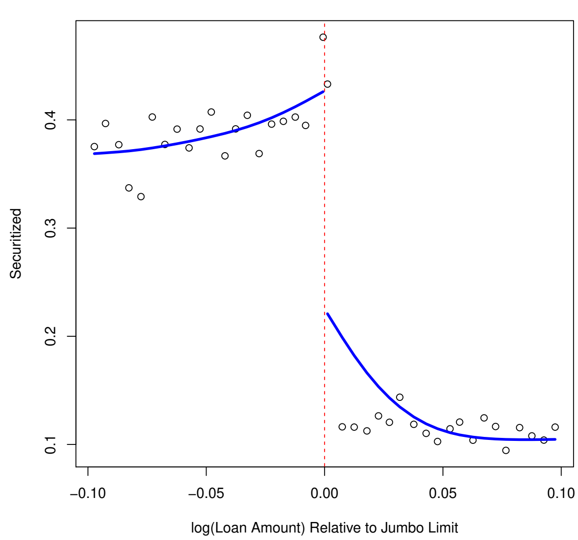
(a) Counts of Applications




(b) Approval Rates




(c) Securitization Rates




(d) Lender's Balance-Sheet Liquidity

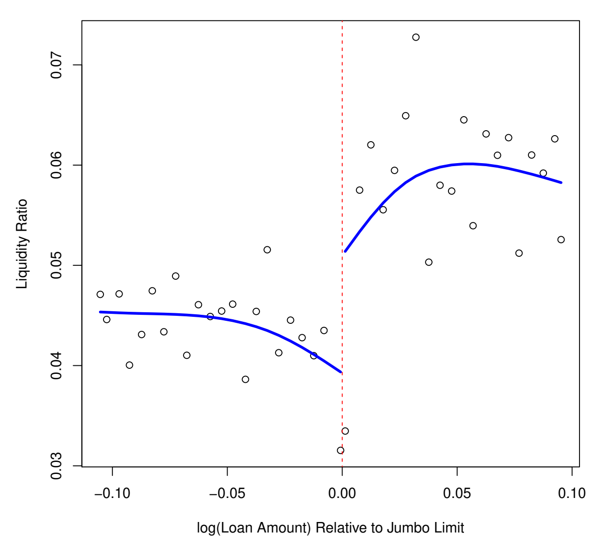
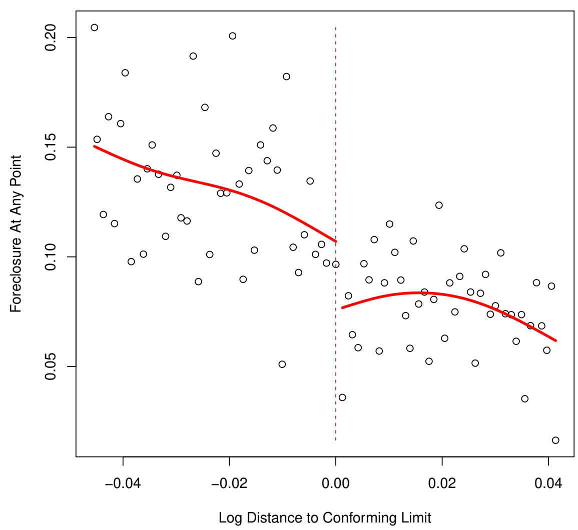


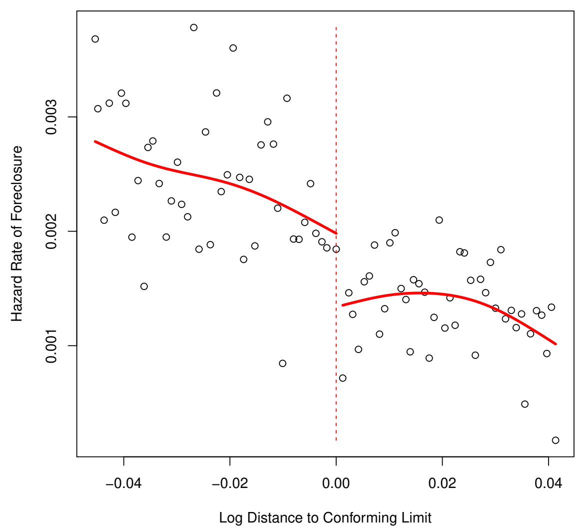
Figure 3: Descriptive Statistics – Default and Prepayment Around the Conforming Limit – McDash Data Analysis

*These figures estimates delinquency, foreclosure, and bankruptcy probabilities around the conforming loan limits.*

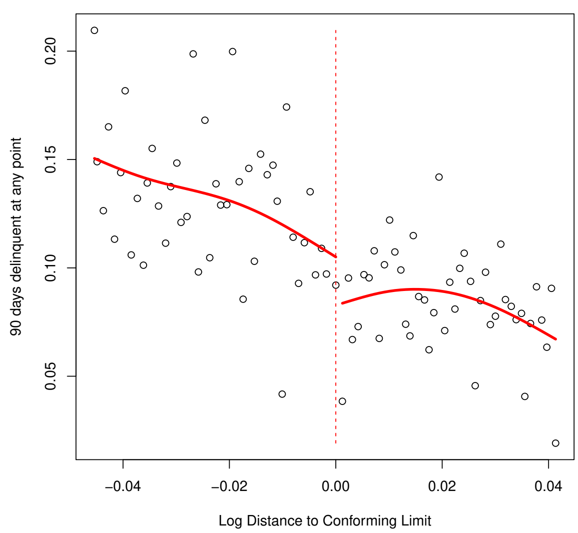
(a) Foreclosure at any point after origination




(b) Hazard Rate of a Payment Incident (Delinquency, Foreclosure)




(c) 60 Days Delinquent At Any Point




(d) Voluntary Payoff

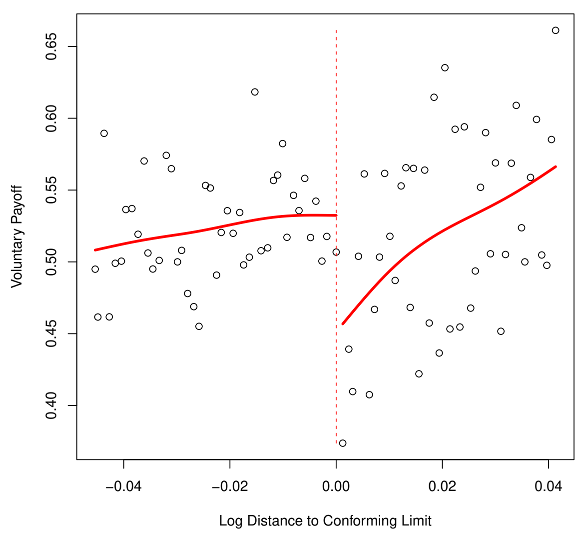
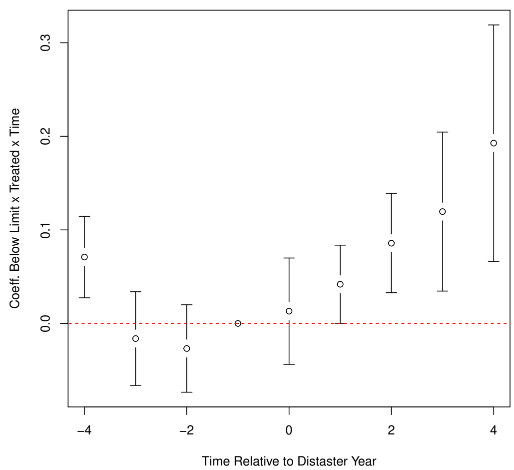


Figure 4: Main Results – Impact of Billion-Dollar Events

*This figure presents (i) the coefficients of interest in specification (1) with securitization as the dependent variable, and (ii) the coefficients of interest in specification (2) with the discontinuity in the number of securitizations as the dependent variable. The bottom figure presents results for OCC- and FRS-regulated lenders, that are more likely to arbitrage between "originate-and-hold" and "originate-and-distribute." The bars are 95% confidence intervals.*

(a) Evolution of the Probability of Securitization (Specification (1))




(b) Evolution of the Discontinuity in the Number of Securitizations (Specification (2))

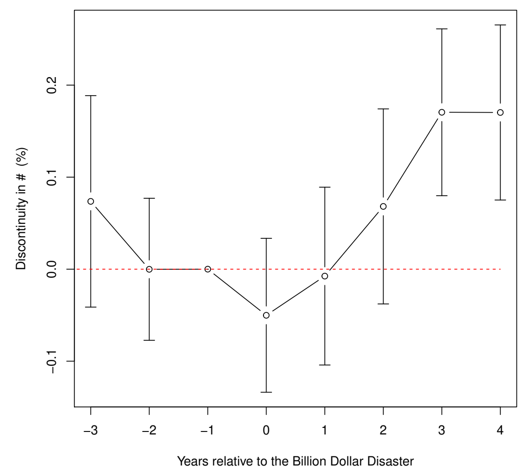
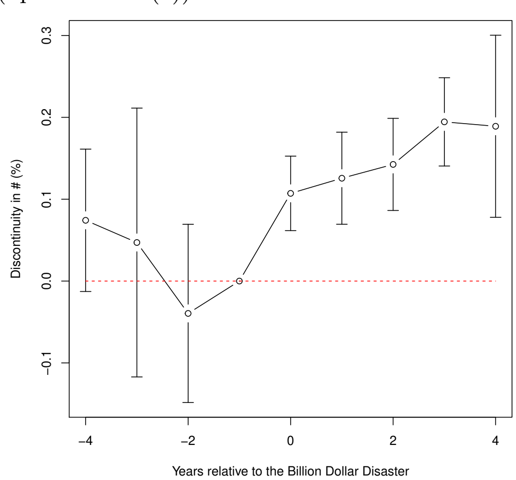



Figure 5: Result for OCC and FRS Regulated Lenders – Impact of Billion-Dollar Events

(a) Evolution of the Probability of Securitization (Specification (1))




(b) Evolution of the Discontinuity in the Number of Securitizations (Specification (2))

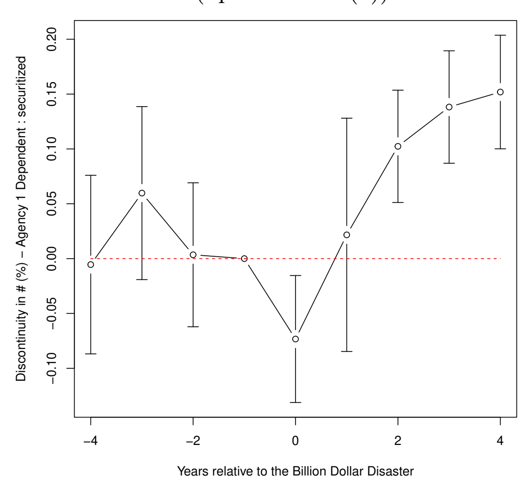
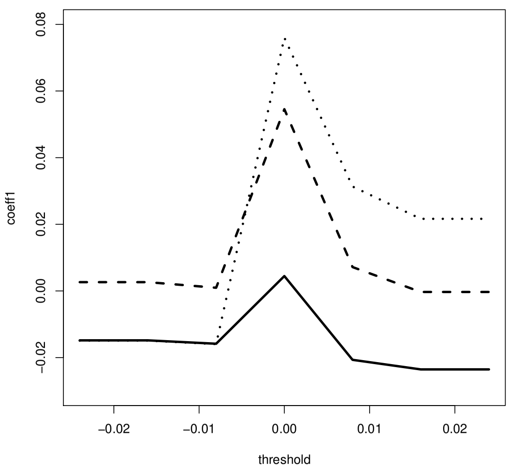


Figure 6: Robustness Check – Artificial Shifting the Position of the Discontinuity

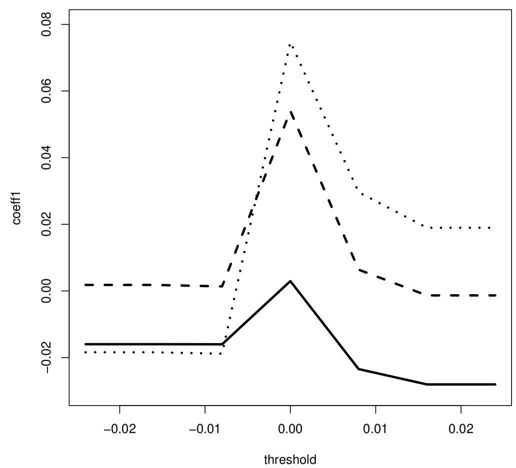
*This figure presents the results of the reestimation of both specifications (1) and (2) . The vertical axis is the* $\xi_t$ *(resp.* $\xi_t^v$*), the horizontal axis is the threshold. The line is drawn using the outcome of 15 different regressions each, where* $Below\,Limit$ *is replaced by* $Below\,Threshold$*, with a threshold set according to the horizontal axis.*

Robustness Check for Specification (1) – Discontinuities in Lending and Securitization Standards

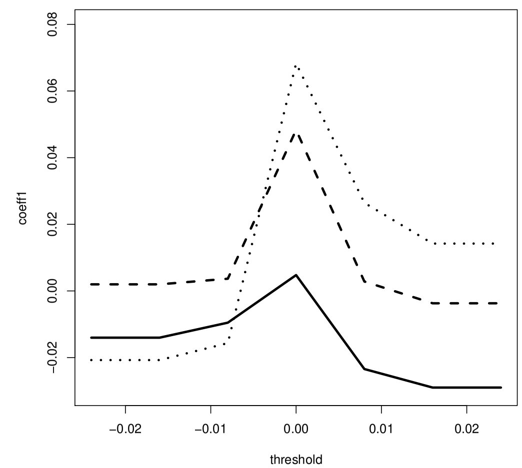
(a) Approved.




(b) Originated.

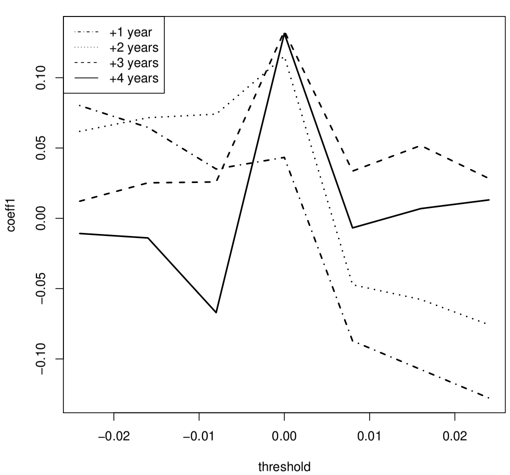



(c) Securitized conditional on originated

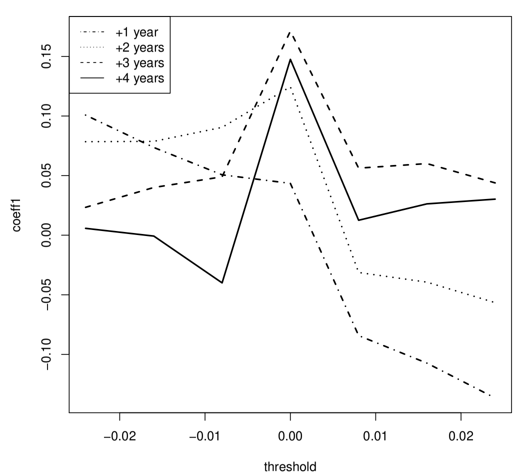



Robustness Check for Specification *(2)* – Discontinuities in Approval, Origination, Securitization Numbers

(d) Discontinuity in Approval Numbers.




(e) Discontinuity in Origination Numbers.




(f) Discontinuity in Securitization Numbers.

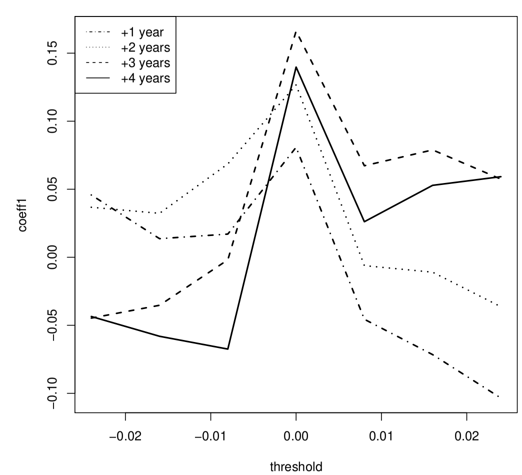
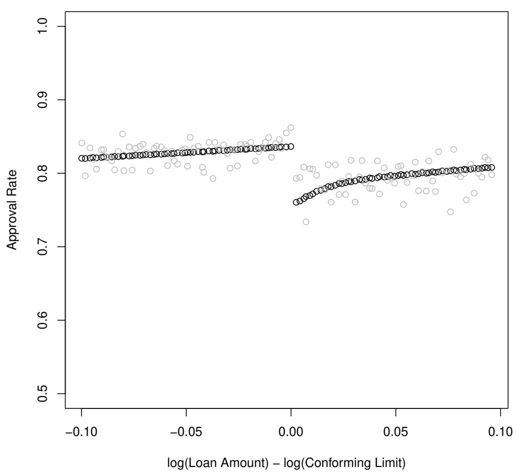


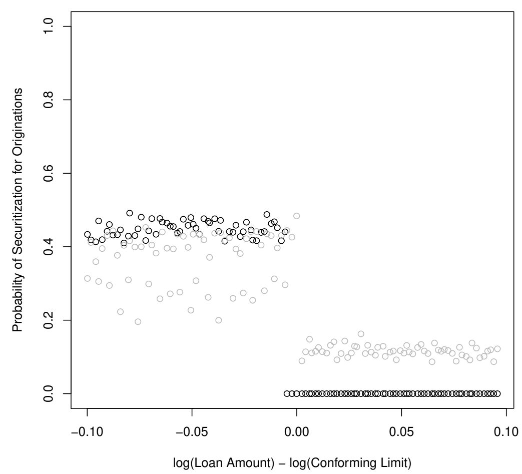
Figure 7: Structural Modeling – Model Fit: Computed Equilibrium at Estimated Parameters vs. Observations

*This set of figures compares the predictions of the estimated model of optimal origination, securitization, and mortgage pricing. The lender chooses interest rates, makes mortgage approval decisions, and securitizes mortgages optimally given households' self-selection and future default probabilities. In the graphs below each grey point comes from either HMDA data (subfigures (a), (b), (d)) or from McDash data (subfigure (c)). The black points are the predictions of the estimated model.*

(a) Probability of Approval




(b) Probability of Securitization




(c) Default Probability

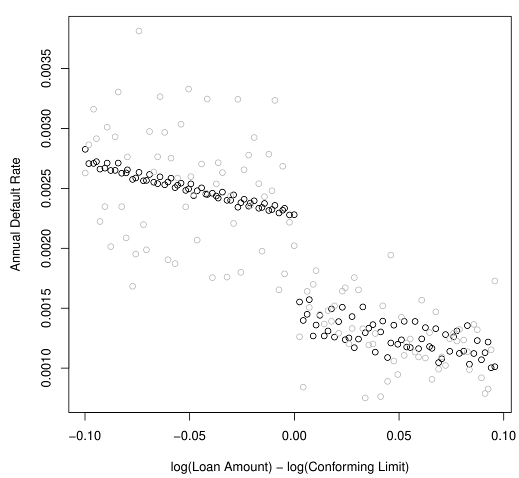
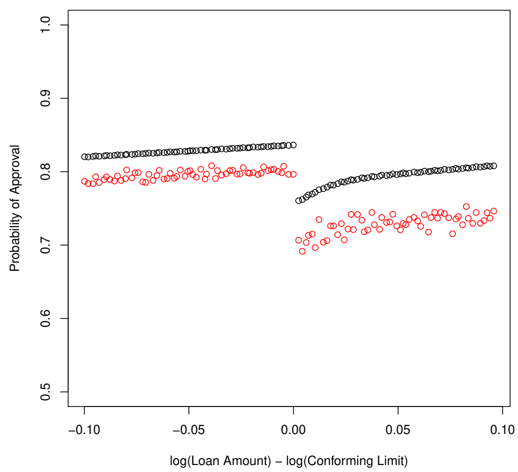


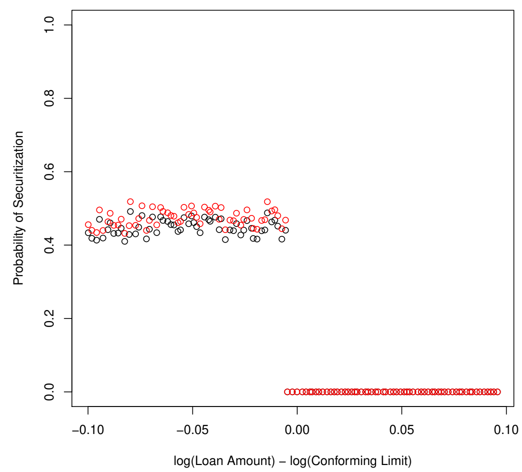
Figure 8: Structural Modeling – Impact of Increasing Disaster Risk on the Equilibrium of the Mortgage Market – with the GSEs' Securitization Activity

*Keeping the cost of capital, neighborhood amenities, household preferences, and the dynamics of default constant, these figures present the simulation of an increase in disaster risk* $\pi$ *on the equilibrium of the mortgage market. This is described in Section 5.2.1. The black points correspond to* $\pi = 1\%$*, and the red points are for* $\pi = 1.5\%$*.*

(a) Probability of Approval




(b) Probability of Securitization




(c) Default Risk

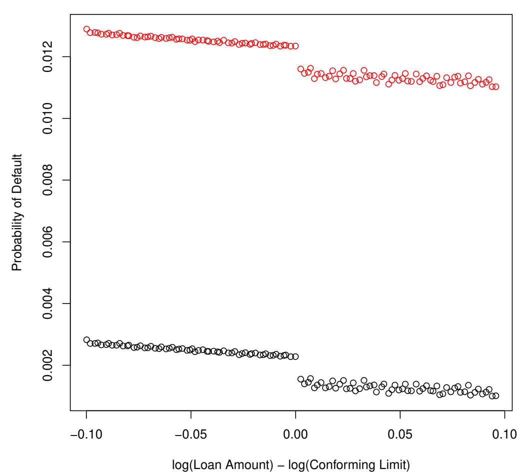
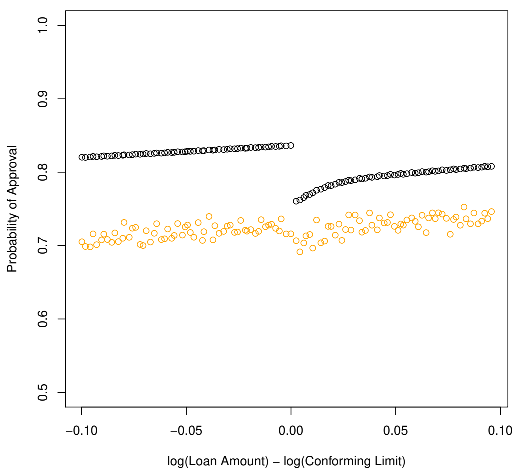


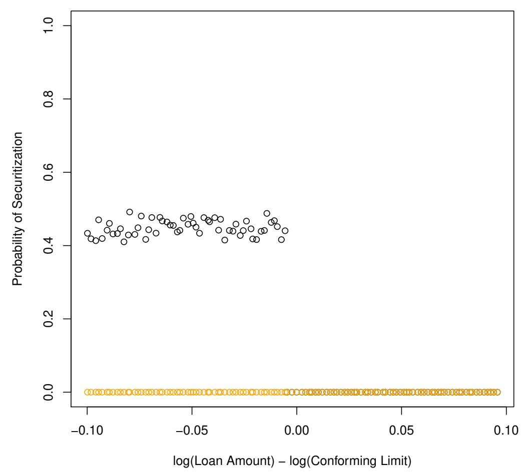
Figure 9: Structural Modeling – Increasing Risk and the Withdrawal of the GSEs

*Keeping lenders' parameters, household preferences, and the dynamics of default constant, these figures simulate the impact of increasing climate risk and, simultaneously, the withdrawal of the option to securitize to the GSEs. The black point correspond to the initial equilibrium, with no disaster risk and the option to securitize. The orange points correspond to the new equilibrium with a probability of disaster risk of $\pi = 1\%$ and no option to securitize to the GSEs. This is described in Section 5.2.2.*

(a) Probability of Approval




(b) Probability of Securitization




(c) Default Risk

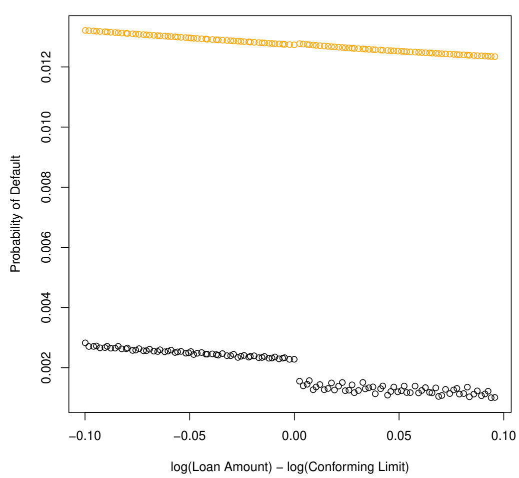


Table 1: Billion-Dollar Events

*This table describes this paper's 15 'billion-dollar' natural disasters occurring between 2004 and 2012. These are used as a series of natural experiments. Damage calculations from Weinkle et al.'s (2018) data base. Events are ranked in decreasing order of their damages. The zip-code-level treatment group for each billion-dollar event is described in Section 2.1.*

| Year | Name | From | To | Category | States | Normalized PL‡ USD b$, 2018 |
|---|---|---|---|---|---|---|
| 2005 | Katrina | 25-Aug | 30-Aug | 5 | FL, LA, MS, AL | $116.88 |
| 2012 | Sandy | 30-Oct | 31-Oct | 3 | NY | $73.49 |
| 2008 | Ike | 12-Sep | 14-Sep | 4 | TX, LA | $35.15 |
| 2005 | Wilma | 24-Oct | 24-Oct | 5 | FL | $31.90 |
| 2004 | Charley | 13-Aug | 14-Aug | 4 | FL, SC | $26.93 |
| 2004 | Ivan | 12-Sep | 21-Sep | 5 | AL, FL | $25.89 |
| 2004 | Frances | 03-Sep | 09-Sep | 4 | FL | $16.48 |
| 2005 | Rita | 20-Sep | 24-Sep | 5 | LA, TX | $14.89 |
| 2004 | Jeanne | 15-Sep | 29-Sep | 3 | FL | $13.57 |
| 2011 | Irene | 26-Aug | 28-Aug | 3 | NC | $10.79 |
| 2008 | Gustav | 31-Aug | 03-Sep | 4 | LA | $5.45 |
| 2005 | Dennis | 04-Jul | 18-Jul | 4 | FL, AL | $3.54 |
| 2005 | Ophelia | 09-Oct | 18-Oct | 3 | NC | $2.48 |
| 2012 | Isaac | 21-Aug | 03-Sep | 1 | LA | $2.36 |
| 2008 | Dolly | 20-Jul | 27-Jul | 1 | TX | $1.48 |

‡*PL: Pielke Landsea methodology, described in Weinkle et al. (2018).*

Table 2: Impact of Billion-Dollar Events on Approvals, Originations, and Securitization Probabilities

*This table presents the estimates of the impact of billion-dollar events on the discontinuity in mortgages' approval rates, origination rates, and in securitization conditional on origination. Mortgages with amounts in the ±20%, ±10%, and ±5% window of the conforming loan limit are considered in every year and every area between 1995 and 2016 inclusive. Pre- and post-treatment indicator variables estimated in the −4 to +4 period. The conforming loan limit is determined annually and differs between high cost and general counties. Standard errors 2-way clustered at the ZIP and year level. The unit of observation is the mortgage application. The control group is the set of mortgages in Zips of Atlantic states and states of the Gulf of Mexico.*

| | *Dependent variable:* | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Approved | | | Originated | | | Securitized | | |
| | ±20% | ±10% | ±5% | ±20% | ±10% | ±5% | ±20% | ±10% | ±5% |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Below $\text{Limit}_{it}$ × Treated $_{t=-4}$ | 0.003 | 0.001 | 0.008 | 0.022 | 0.020 | 0.028 | 0.041** | 0.040** | 0.071*** |
| | (0.014) | (0.014) | (0.019) | (0.026) | (0.026) | (0.033) | (0.019) | (0.018) | (0.022) |
| Below $\text{Limit}_{it}$ × Treated $_{t=-3}$ | 0.015 | 0.014 | 0.016 | 0.025 | 0.025 | 0.045 | −0.002 | −0.005 | −0.016 |
| | (0.010) | (0.009) | (0.020) | (0.018) | (0.019) | (0.035) | (0.025) | (0.025) | (0.026) |
| Below $\text{Limit}_{it}$ × Treated $_{t=-2}$ | −0.002 | −0.002 | 0.003 | −0.011 | −0.010 | 0.001 | −0.017 | −0.018 | −0.027 |
| | (0.006) | (0.006) | (0.010) | (0.010) | (0.010) | (0.015) | (0.024) | (0.026) | (0.024) |
| Below $\text{Limit}_{it}$ × $\text{Treated}_{t=+0}$ | 0.003 | 0.001 | 0.006 | 0.007 | 0.005 | 0.017 | 0.006 | 0.005 | 0.013 |
| | (0.014) | (0.013) | (0.014) | (0.018) | (0.017) | (0.020) | (0.021) | (0.021) | (0.029) |
| Below $\text{Limit}_{it}$ × $\text{Treated}_{t=+1}$ | 0.025*** | 0.024*** | 0.030** | 0.024** | 0.024** | 0.044** | 0.018 | 0.017 | 0.042* |
| | (0.008) | (0.008) | (0.011) | (0.011) | (0.011) | (0.016) | (0.019) | (0.019) | (0.021) |
| Below $\text{Limit}_{it}$ × $\text{Treated}_{t=+2}$ | 0.039*** | 0.040*** | 0.063*** | 0.037** | 0.037** | 0.075*** | 0.045* | 0.046* | 0.086*** |
| | (0.011) | (0.011) | (0.015) | (0.017) | (0.017) | (0.019) | (0.024) | (0.024) | (0.027) |
| Below $\text{Limit}_{it}$ × $\text{Treated}_{t=+3}$ | 0.061*** | 0.062*** | 0.073** | 0.057** | 0.059** | 0.080** | 0.095*** | 0.097*** | 0.120** |
| | (0.016) | (0.016) | (0.030) | (0.021) | (0.021) | (0.037) | (0.029) | (0.029) | (0.043) |
| Below $\text{Limit}_{it}$ × $\text{Treated}_{t=+4}$ | 0.021 | 0.019 | 0.009 | 0.007 | 0.007 | 0.002 | 0.154** | 0.155** | 0.193*** |
| | (0.024) | (0.024) | (0.028) | (0.022) | (0.022) | (0.036) | (0.067) | (0.066) | (0.064) |
| Other Controls | $\text{Treated}_t$ for $t = -4, \ldots, +4$, Year f.e., Disaster f.e., ZIP f.e., Below $\text{Limit}_{iy} \times Year_y$, See specification (1) . | | | | | | | | |
| Observations | 1,345,012 | 1,310,397 | 803,424 | 1,345,012 | 1,310,397 | 803,424 | 1,500,360† | 1,461,539† | 900,765† |
| $R^2$ | 0.066 | 0.066 | 0.069 | 0.069 | 0.070 | 0.072 | 0.249 | 0.250 | 0.229 |
| Adjusted $R^2$ | 0.061 | 0.061 | 0.061 | 0.064 | 0.064 | 0.064 | 0.246 | 0.246 | 0.223 |
| *Note:* | *p<0.1; **p<0.05; ***p<0.01 | | | | | | | | |

*†: securitizations of originated mortgages occur for both mortgages originated in the current year and for mortgages originated in previous years. The larger number of observations (originated mortgages) in columns (7)–(9) reflects this.*

Table 3: Impact of Billion-Dollar Events on the Discontinuity in the Number of Approvals, Originations, Securitizations in the Conforming Segment vs. the Jumbo Segment

*This table presents the estimates of the impact of billion-dollar events on the discontinuity in mortgage numbers (approvals, originations, and securitizations) at the conforming limit, specification (2). Mortgages with amounts in the ±5% window around the conforming loan limit are considered in every year and every zip code between 1995 and 2016 inclusive. The unit of analysis here is a zip code×year. We consider zip code×tear observations with mortgages for at least 2 years before and after the event, and with a minimum of 20 loans. The conforming loan limit is determined annually and differs between high-cost and general counties. Standard errors are 2-way clustered at the zip code and year levels. The control group is the set of zip codes of Atlantic states and states of the Gulf of Mexico, from Maine to Texas.*

| | *Dependent variable:* Discontinuity in: | | | |
|---|---|---|---|---|
| | Applications | Approvals | Originations | Securitizations |
| | ±5% | ±5% | ±5% | ±5% |
| | (1) | (2) | (3) | (4) |
| $Treated_{jt=-4}$ | 0.059 | 0.059 | 0.070 | 0.085 |
| | (0.050) | (0.050) | (0.054) | (0.052) |
| $Treated_{jt=-3}$ | 0.079 | 0.079 | 0.087 | 0.074 |
| | (0.049) | (0.049) | (0.056) | (0.059) |
| $Treated_{jt=-3}$ | 0.039 | 0.039 | 0.025 | −0.0001 |
| | (0.038) | (0.038) | (0.044) | (0.039) |
| $Treated_{jt=0}$ | −0.067 | −0.067 | −0.071 | −0.050 |
| | (0.043) | (0.043) | (0.044) | (0.043) |
| $Treated_{jt=+1}$ | −0.002 | −0.002 | 0.008 | −0.008 |
| | (0.040) | (0.040) | (0.050) | (0.049) |
| $Treated_{jt=+2}$ | 0.094* | 0.094* | 0.093* | 0.068 |
| | (0.047) | (0.047) | (0.052) | (0.054) |
| $Treated_{jt=+3}$ | 0.161*** | 0.161*** | 0.151*** | 0.171*** |
| | (0.043) | (0.043) | (0.047) | (0.046) |
| $Treated_{jt=+4}$ | 0.181*** | 0.181*** | 0.185*** | 0.170*** |
| | (0.043) | (0.043) | (0.047) | (0.049) |
| Additional Controls | See Specification (2). Year f.e., Disaster f.e., ZIP f.e. | | | |
| Observations | 173,255 | 173,255 | 173,034 | 171,115 |
| $R^2$ | 0.650 | 0.650 | 0.646 | 0.628 |
| Adjusted $R^2$ | 0.647 | 0.647 | 0.643 | 0.626 |

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

Table 4: Impact of Billion-Dollar Events on Selection into the Conforming Segment

*This table estimates the impact of billion-dollar events on borrowers' credit score, loan term, and subsequent default for conforming loans vs. jumbo loans using specification (1). Descriptive statistics from McDash are presented in Appendix Table A.*

| | Credit Score | Term | Foreclosure | 30 d. del. |
|---|---|---|---|---|
| $Below\,Limit_{it} \times\ Treated_{jt=-2}$ | 2.110 | −4.268 | −0.004 | −0.003 |
| | (1.493) | (3.537) | (0.009) | (0.008) |
| $Below\,Limit_{it} \times\ Treated_{jt=0}$ | −0.117 | 2.686 | 0.009 | 0.015*** |
| | (0.912) | (2.521) | (0.008) | (0.006) |
| $Below\,Limit_{it} \times\ Treated_{jt=+1}$ | −3.371* | 4.680 | 0.036** | 0.036*** |
| | (1.962) | (3.190) | (0.018) | (0.009) |
| $Below\,Limit_{it} \times\ Treated_{jt=+2}$ | −3.745*** | 6.058** | 0.057*** | 0.033*** |
| | (1.180) | (3.070) | (0.008) | (0.009) |
| $Below\,Limit_{it} \times\ Treated_{jt=+3}$ | −3.403*** | 3.136 | 0.049*** | 0.006 |
| | (1.029) | (3.193) | (0.009) | (0.007) |
| Observations | 1,072,465 | 1,696,513 | 1,697,650 | 1,697,650 |
| R Squared | 0.176 | 0.111 | 0.246 | 0.158 |
| F Statistic | 27.915 | 21.608 | 56.772 | 32.610 |

| | 60 d. del. | 90 d. del. | 120 d. del. | Vol. Payoff |
|---|---|---|---|---|
| $Below\,Limit_{it} \times\ Treated_{jt=-2}$ | −0.001 | 0.000 | −0.000 | −0.018 |
| | (0.009) | (0.010) | (0.008) | (0.011) |
| $Below\,Limit_{it} \times\ Treated_{jt=0}$ | 0.012 | 0.010 | −0.004 | −0.012** |
| | (0.008) | (0.007) | (0.006) | (0.006) |
| $Below\,Limit_{it} \times\ Treated_{jt=+1}$ | 0.039*** | 0.032*** | 0.013 | −0.031*** |
| | (0.014) | (0.013) | (0.010) | (0.009) |
| $Below\,Limit_{it} \times\ Treated_{jt=+2}$ | 0.046*** | 0.041*** | 0.032*** | −0.026*** |
| | (0.012) | (0.010) | (0.005) | (0.008) |
| $Below\,Limit_{it} \times\ Treated_{jt=+3}$ | 0.022** | 0.024*** | 0.013** | −0.023*** |
| | (0.010) | (0.009) | (0.006) | (0.009) |
| Observations | 1,697,650 | 1,697,650 | 1,697,650 | 1,697,650 |
| R Squared | 0.198 | 0.192 | 0.175 | 0.168 |
| F Statistic | 42.833 | 41.334 | 36.952 | 35.223 |

*p<0.1; **p<0.05; ***p<0.01. *For "other controls," see specification 1. They include the "Below Limit", "Below Limit× Treated", 5-Digit zip code f.e., Year and Time f.e. Standard errors are 2-way clustered at the zip code and year levels.*

Table 5: Heterogeneous Impacts of Billion-Dollar Events

*In specification (1), this table estimates the differential impact of a billion-dollar disaster in zip codes: (i) according to the historical frequency of hurricanes, the spatial distribution of such 168-year probabilities is presented in Figure C, and (ii) according to the share of a zip code in the SFHA, where insurance is mandated for agency-backed mortgages. An example of SFHAs is provided in Appendix Figure B.*

| | *Dependent variable:* | | |
|---|---|---|---|
| | Approved $\pm$10% | Originated $\pm$10% | Securitized $\pm$10% |
| | (1) | (2) | (3) |
| Below $\text{Limit}_{ijy} \times \text{Treated}_{jt=0} \times$ Historical $\text{Frequency}_j$ | −0.031 | −0.174 | −0.123 |
| | (0.124) | (0.132) | (0.152) |
| Below $\text{Limit}_{ijy} \times \text{Treated}_{jt=1} \times$ Historical $\text{Frequency}_j$ | −0.089 | −0.024 | 0.042 |
| | (0.054) | (0.108) | (0.198) |
| Below $\text{Limit}_{ijy} \times \text{Treated}_{jt=2} \times$ Historical $\text{Frequency}_j$ | −0.163 | −0.213 | 0.739** |
| | (0.099) | (0.196) | (0.270) |
| Below $\text{Limit}_{ijy} \times \text{Treated}_{jt=3} \times$ Historical $\text{Frequency}_j$ | −0.359*** | −0.507*** | 0.816*** |
| | (0.098) | (0.118) | (0.236) |
| Below $\text{Limit}_{ijy} \times \text{Treated}_{jt=4} \times$ Historical $\text{Frequency}_j$ | −0.161 | −0.363** | 0.919*** |
| | (0.173) | (0.156) | (0.135) |
| Other controls | All other controls of the main specification (1) | | |
| Observations | 823,866 | 823,866 | 673,160 |
| $R^2$ | 0.068 | 0.071 | 0.162 |
| Adjusted $R^2$ | 0.060 | 0.063 | 0.153 |

| | *Dependent variable:* | | |
|---|---|---|---|
| | Approvals $\pm$10% | Originations $\pm$10% | Securitizations $\pm$10% |
| | (1) | (2) | (3) |
| Below $\text{Limit}_{ijy} \times \text{Treated}_{jt=0} \times$ % $\text{SFHA}_j$ | −0.031 | −0.030 | −0.081 |
| | (0.020) | (0.032) | (0.051) |
| Below $\text{Limit}_{ijy} \times \text{Treated}_{jt=1} \times$ % $\text{SFHA}_j$ | −0.022** | −0.032 | −0.089 |
| | (0.009) | (0.022) | (0.060) |
| Below $\text{Limit}_{ijy} \times \text{Treated}_{jt=2} \times$ % $\text{SFHA}_j$ | −0.047* | −0.055* | −0.022 |
| | (0.023) | (0.029) | (0.051) |
| Below $\text{Limit}_{ijy} \times \text{Treated}_{jt=3} \times$ % $\text{SFHA}_j$ | −0.005 | −0.006 | −0.025 |
| | (0.022) | (0.040) | (0.059) |
| Below $\text{Limit}_{ijy} \times \text{Treated}_{jt=4} \times$ % $\text{SFHA}_j$ | −0.019 | −0.015 | 0.052 |
| | (0.036) | (0.043) | (0.038) |
| Other controls | All other controls of the main specification (1) | | |
| Observations | 826,799 | 826,799 | 675,526 |
| $R^2$ | 0.068 | 0.070 | 0.154 |
| Adjusted $R^2$ | 0.060 | 0.062 | 0.145 |

*p<0.1; **p<0.05; ***p<0.01

# Online Appendix

## A The Impact of Natural Disasters on Current Mortgages' Default and Prepayment

A key empirical question is whether natural disasters affect households' payment behavior, and whether disaster trigger either defaults or prepayments. In both cases, increases in either defaults or prepayments affect the profit of a lender that held the mortgage. Expectations of default risk should lead to greater securitization probabilities, while expectations of prepayment are less likely to affect securitization behavior as an agency MBS typically "passes through" mortgage prepayments. In other words, the agency MBS insures the lender against default risk but does not insure the lender against prepayment risk.

We estimate the impact of natural disasters on payment history by considering a dataset made of (i) the universe of individual loans in zip codes affected by the billion-dollar disasters of Table 1, regardless of the specific timing of the origination of these loans, and (ii) a 1% random sample of the universe of loans in the control group. The dataset has a total of 3.68 million loan-month observations.

The following specification controls for zip code and year fixed effects and estimates the impact of a natural disaster relative to the specific year $t_0$ of that event:

$$\mathbf{1}(\text{Default})_{it} = \sum_{k=-K}^{+K} \delta_k \cdot \mathbf{1}\left[t = (t_0(i) + k)\right] + \text{ZIP}_{j(i)} + \text{Year}_t + \text{Residual}_{it} \tag{20}$$

where $\delta_0, \delta_1, \ldots$ are the coefficients of interest, which measure the impact of the disaster on default. $t_0(i)$ is the year of the natural disaster of mortgage loan $i$. $j(i)$ is the zip code of mortgage $i$ at origination. The effect of a natural disaster is identified as disasters occur over a period a 8 years. Year and zip code fixed effects are identified by observations both in the treatment and the control groups. Residuals are two-way clustered at the zip code and year levels.

The results are presented graphically in Appendix Figure D. The solid lines in each graph present the coefficients $\delta_{-2}$ to $\delta_{+5}$. The dotted lines are the 95% confidence intervals. The results suggest that a natural disaster has a statistically significant negative impact on the probability that a loan is current, by about 4 percentage points. A natural disaster increases the probability that a loan is in foreclosure by 1.6 percentage points. In contrast, the impact on the probability of prepayment is marginally significant at 5%.

These results suggest that insurance payments and other transfers post-disaster may not mitigate the impact of natural disasters on delinquencies and foreclosures. This is consistent with recent work such as that of Kousky (2018) suggesting a decline in the number and dollar amount of properties insured through the National Flood Insurance Program. The next section assesses whether lenders tend to bunch mortgages at the conforming loan limit in areas where Fannie and Freddie require flood insurance.

# B Data Sources

The paper uses the following 13 sources of data:

1. Black Knight Financial's McDash data set with 5-digit zip code information and payment history. Typical McDash files used in other research only include the 3-digit zip code. This paper uses the complete 5-digit zip code McDash data. Figure 1 at the end of this data appendix shows that 5-digit counts are well distributed.

2. Normalized Hurricane Damage for the Continental United States 1900-2017, in Nature Sustainability. The authors provide an Excel spreadsheet.

3. Public files collected according to the Home Mortgage Disclosure Act (HMDA). Older files are obtained from the National Archives, with identifier 2456161. 2014-2016 flat files of the Loan Application Registers are available through the FFIEC's HMDA website. Recent files are provided by the Consumer Financial Protection Bureau.

4. Commercial Banks' Reports of Income and Condition, provided by the Federal Reserve of Chicago.

5. The Federal Deposit Insurance Corporation's (FDIC) Summary of Deposits provides the geolocation of bank branches for each commercial bank. This can be freely obtained at the FDIC's Branch Office Deposits data download website.

6. Census Shapefiles for ZCTA5s, blockgroups, census tracts, counties, and states, obtained through the University of Missouri's National Historical Geographic Information Survey.

7. The National Oceanic and Atmospheric Administration's (NOAA) National Hurricane Center dataset. This dataset is called the Atlantic Hurricane Database (HURDAT2) for 1851-2018.

8. The United States Geological Survey's Digital Elevation Model. This is obtained using the National Map Viewer, by zooming in on each billion-dollar event and downloading all elevation tiles. The tiles are merged, and average elevation by blockgroup is computed.

9. The United States Geological Survey's Land Cover dataset. We use the 2001 National Land Cover Dataset provided as a single Tiff file. Zonal statistics provide the share of each blockgroup in open water or wetland.

10. Hurricane Sandy's damage estimates by Blockgroup. This is provided by HUD: "A FEMA housing inspection for renters is used to assess personal property loss and for owners to assess damage to their home as well as personal property. This inspection is done to determine eligibility for FEMA Individual Assistance. For both rental and owner inspections, if the property has flood damage the inspector measures the height of the flooding. They indicate the highest floor of the flooding (for example, Basement, 1st floor, 2nd floor, etc...) and the height of the flooding in that room. In addition for the units without flooding, HUD has estimated minor/major/severe damage based on the damage inspection estimates for real property (owner) and personal property (renter). "

11. Zillow's zip-code-level Rent Index and Home Value Index. This is freely accessible here. Zillow's zip code data match well with the Census ZCTA5s.

12. FEMA's National Flood Hazard Layer of 2017, which includes Special Flood Hazard Areas. This ESRI Shapefile has been removed from FEMA's website but is freely available through the corresponding author.

13. The U.S. Census' County Business Patterns.

## C Crosswalks

In addition we built the following crosswalks (available through the corresponding author):

- Relationship files between ZCTA5s and Counties.
- Relationship files from HMDA Tracts to ZCTA5s.
- Relationship files from 2000 Blockgroups to ZCTA5s.
- Relationship files from ZCTA5s to CBSAs.
- Relationship files between 2000 and 2010 Blockgroups.

Each of these relationship files was built using GDAL's ogr2ogr intersection tool, with a North America Albers Equal Area Conic Coordinate Reference System (CRS). Such projected CRS allows the computation of areas and distances. When needed, counts were apportioned on the basis of the squared meter surface area of the intersections of two overlapping geographic areas. Means were computed using weighted means, where the weights are the surface areas of the intersections. Similar statistics obtained when using housing counts as weights.

HMDA uses census tracts of the 1990 census for all years prior to 2003 in our data. HMDA uses census tracts of the 2000 census for its 2004 to 2012 editions. HMDA uses census tracts of the 2010 census for its 2013-2016 editions. The success rate of the match between HMDA tracts and Census data is about 95%.

- Relationship files from HMDA's Respondentid to the Report of Income and Condition's RSSDID.

This is built using HMDA's Transmittal Sheet. This crosswalk is only available for bank lenders.

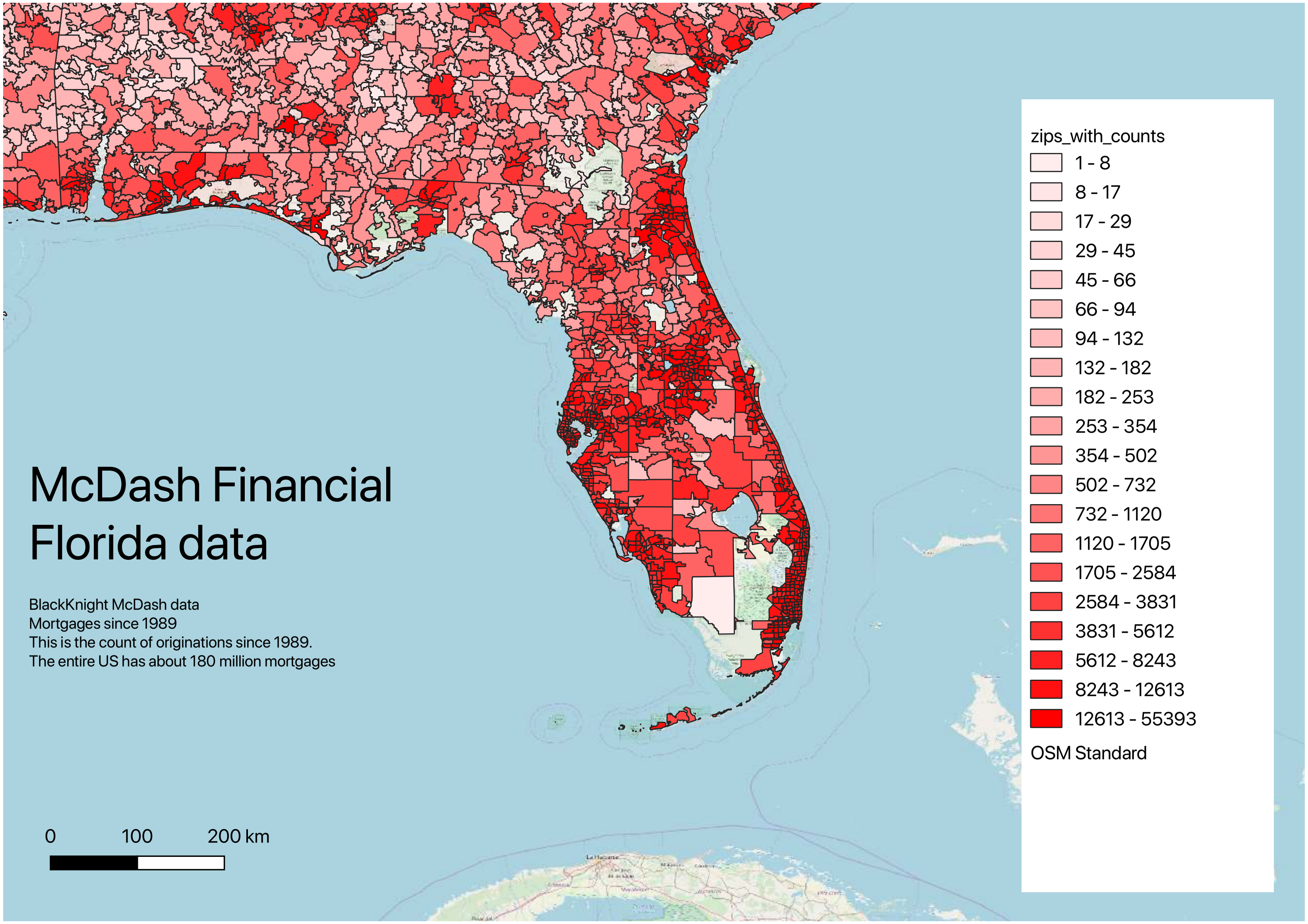
## D Software

- The classifier for damage is built using the *tree* function in the tree package developed by Prof. Brian Ripley of Oxford University.

- The share of each blockgroup in open water or wetland is computed using gdalwarp and rasterstats developed by Frank Warmerdam of Planet Labs (formerly University of Waterloo), Silke Reimer.
- Regressions use the lfe R package developed by Simen Gaure (Ragnar Frisch Centre for Economic Research), Grant McDermott (University of Oregon), Karl Dunkle Werner (Berkeley's Department of Agricultural and Resource Economics), Matthieu Stigler (post-doctoral Fellow at Stanford's Center for Food Security and the Environment), Daniel Lüdecke (University Medical Center Hamburg).
- McDash data were processed using PostgreSQL 9.6, JetBrains' DataGrip.

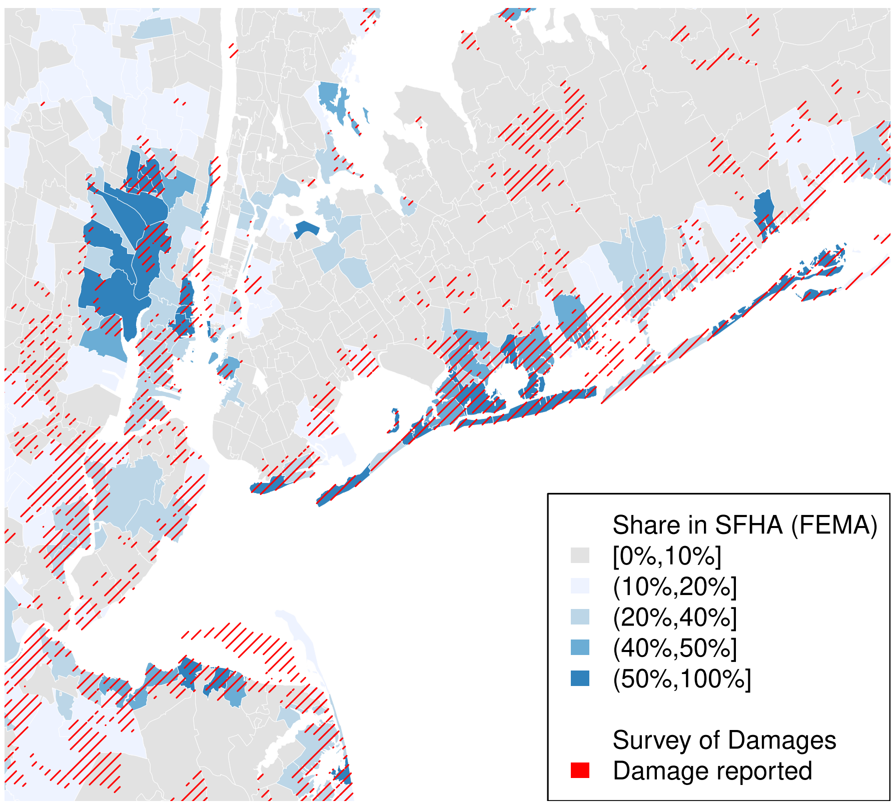
Appendix Figure A: Data Appendix - Counts by 5 digit zip code

*This map zooms in on Florida to show the distribution of counts of mortgages across 5-digit zip codes. Typical McDash data includes only the 3-digit zip code. The data used in this paper has the granularity required to assess the local impact of hurricanes on mortgage originations.*



Appendix Figure B: Comparing FEMA's Special Flood Hazard Areas and Damages – An Example for Hurricane Sandy

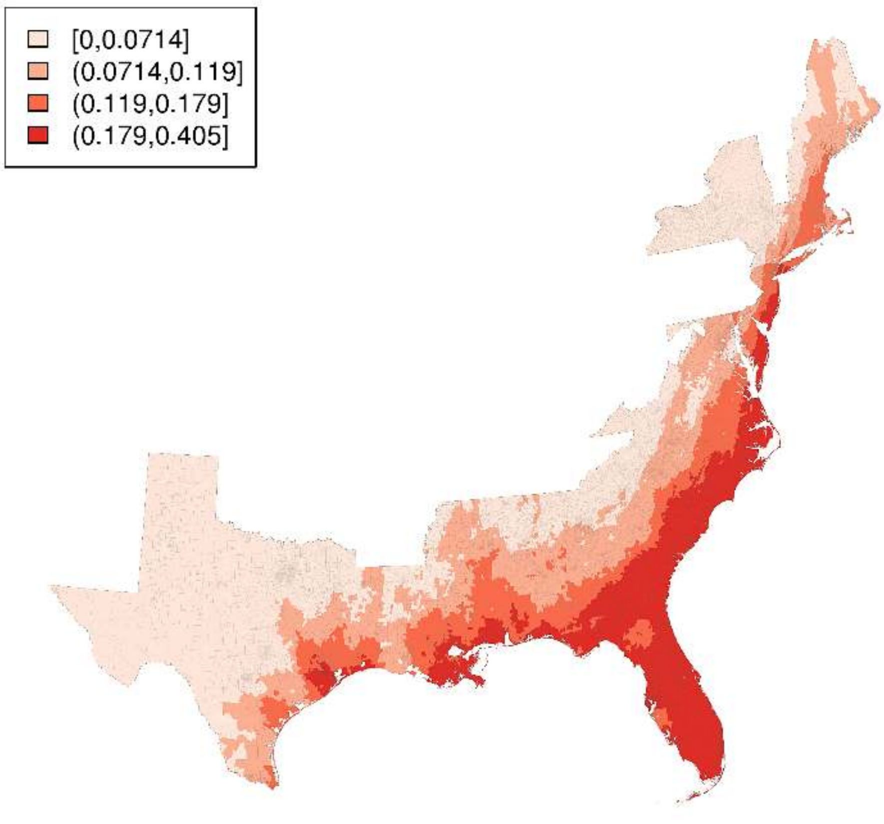
*For parts of the metropolitan of New York, this map compares (a) areas of the Special Flood Hazard Area maps (blue areas), where flood insurance purchases are mandated for agency-backed mortgages†, with (b) areas where Hurricane Sandy caused damage (red areas) according to Department of Housing and Urban Development's (HUD) inspection data and released by FEMA in its IA Registrant Inspection Data‡. The unit of mapping is the zip code tabulation area (ZCTA5), and the gradient of blue colors indicates the share of a zip code that falls within the 1% flood probability area ("100-year floodplain"). The paper uses such data for all zip code tabulation areas of the Atlantic states and states of the Gulf of Mexico.*




†*: Fannie Mae's Selling Guide, Section B7-3-07, Flood Insurance Coverage Requirements.* ‡*: Sandy Damage Estimates Based on FEMA IA Registrant Inspection Data, released by data.gov.*

Appendix Figure C: 168-Year Probability of Hurricane Occurrence

*This map presents, for each of the 86,455 blockgroups of the states of the Atlantic coast and the Gulf of Mexico, the number of hurricane paths intersecting the blockgroup divided by 167 years. The time period is 1851-2017. For instance, a probability of 0.10 implies that there were between 16 and 17 hurricanes going through the blockgroup over 168 years. The hurricane path is the 64 kt wind speed path. 64kt corresponds to a category 1 hurricane in the Saffir-Simpson scale.*

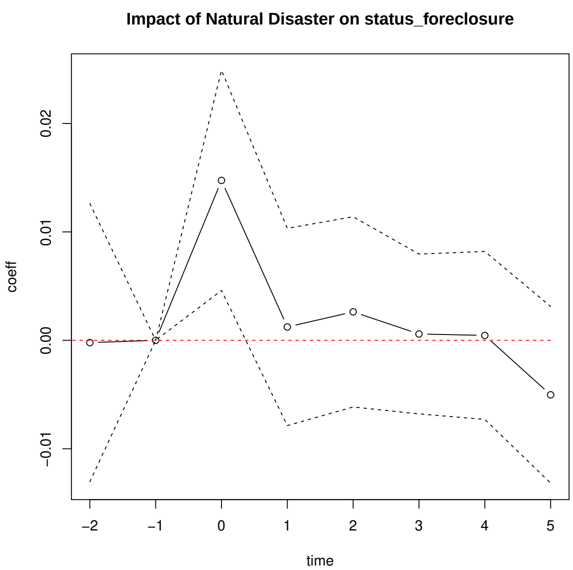



*Source: NOAA's Atlantic Hurricane Data Base.*

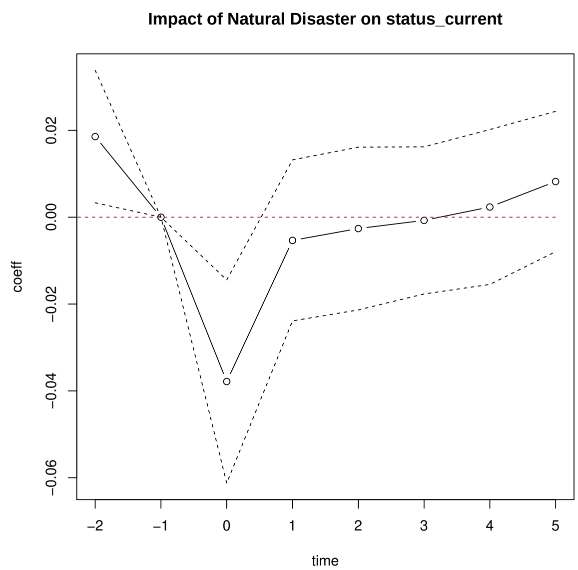
Appendix Figure D: The Impact of Billion-Dollar Events on the Default and Prepayment of Mortgages

*These figures present the coefficients of a regression of payment history dummies on a set of pre- and post- natural disaster indicator variables. Regressions control for both zip code and year fixed effects.*

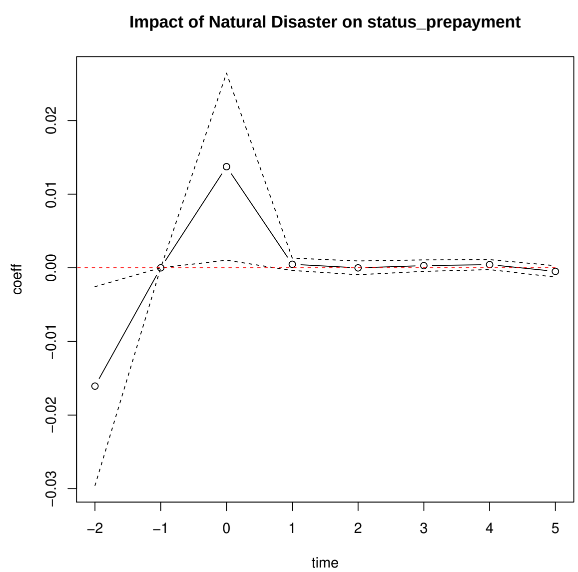
(a) Foreclosure




(b) Mortgage is Current




(c) Prepayment



Appendix Table A: Descriptive Statistics for the HMDA and McDash Samples

*This table describes the two main samples used in this paper: (i) the dataset of mortgage applications collected according to the Home Mortgage Disclosure Act (12 USC Banks and Banking, ch29, §§ 2801-2811, and § 461), and provided by the Federal Financial Institutions and Examination Council, merged with the Federal Reserve of Chicago's Report of Condition and Income using the reporter panel; and (ii) Black Knight Financial's McDash mortgage dataset, covering about 65% of the mortgage market, with 5-digit zip code identifiers. Each of these two datasets are merged with the treatment area geography described in Section 2.1. Both samples consider mortgages between 80% and 120% of the year- and county-specific conforming loan limits. The window is tightened to 95-105% in some specifications.*

| Variable | Mean | P10 | P25 | P50 | P75 | P90 | Observations |
|---|---|---|---|---|---|---|---|
| *Home Mortgage Disclosure Act* | | | | | | | |
| Application Denied | 0.152 | 0.000 | 0.000 | 0.000 | 0.000 | 1.000 | 10,835,083 |
| Loan Originated | 0.512 | 0.000 | 0.000 | 1.000 | 1.000 | 1.000 | 13,446,510 |
| log(Applicant Income) | 11.767 | 7.032 | 9.061 | 13.181 | 14.532 | 14.532 | 990,712 |
| Loan to Income | 2.654 | 1.508 | 1.976 | 2.606 | 3.308 | 3.889 | 9,892,849 |
| Asian Applicant | 0.099 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 9,084,807 |
| Black Applicant | 0.040 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 9,084,807 |
| Hispanic Applicant | 0.070 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 9,084,807 |
| White Applicant | 0.781 | 0.000 | 1.000 | 1.000 | 1.000 | 1.000 | 9,084,807 |
| Lender's Liquidity Ratio | 0.044 | 0.001 | 0.008 | 0.032 | 0.032 | 0.129 | 1,139,292 |
| Lender's Securitizability | 0.710 | 0.601 | 0.638 | 0.638 | 0.795 | 0.883 | 1,133,724 |
| Credit Union | 0.017 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 13,446,510 |
| Reg. by Federal Reserve | 0.110 | 0.000 | 0.000 | 0.000 | 0.000 | 1.000 | 13,446,510 |
| *McDash* | | | | | | | |
| Below Conforming Limit | 0.620 | 0.000 | 0.000 | 1.000 | 1.000 | 1.000 | 1,746,112 |
| Credit Score | 712.481 | 625.000 | 671.000 | 721.000 | 767.000 | 790.000 | 1,086,311 |
| Term | 345.996 | 300.000 | 360.000 | 360.000 | 360.000 | 360.000 | 1,744,975 |