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ABSTRACT

With increasing natural disaster risk and declining flood insurance take-up, homeowners in coastal areas may be at increasing risk of mortgage default. Banks have the ability to screen and price mortgages for flood risk. Banks also retain the option to securitize some of these loans. Bank lenders may have an incentive to sell their worse flood risk to the GSEs. Unlike lenders, the GSEs follow observable rules for the purchase and the pricing of securitized mortgages. This paper uses the impact of one sharp rule, the conforming loan limit, on securitization volumes. Results suggest a substantial increase in mortgage securitizations for loan amounts right below such limit after a billion-dollar natural disaster. Such increase is larger in neighborhoods when the disaster is “new news”: lenders may learn about local risk. Con- forming loans are more likely to default. A structurally estimated model of mortgage pricing and securitization suggests that bunching at the conforming loan limit is an increasing function of perceived disaster risk. A simulation of increasing disaster risk with and without the GSEs suggests that the GSEs may act as a substitute for the declining National Flood Insurance Program.

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1 Introduction

Place-based assets such as real estate are likely to be exposed to increasing risk in a world confronting ambiguous climate change. Standard financial arguments would argue that such risk, if idiosyncratic, can be diversified away. Yet a host of politically popular subsidies and institutions encourage households to invest in homes as their primary source of wealth. Lenders and government sponsored enterprises play a key role in providing the capital to allow households to bid and purchase such place-based wealth, totaling 27.5 trillion dollars in value and 10.9 trillion dollars of debt as of 2019Q1.[1] While the climate change economics literature has explored how real estate prices reflect emerging climate risk (Bakkensen & Barrage 2017, Ortega & Taṣpınar 2018, Zhang & Leonard 2018, Bernstein, Gustafson & Lewis 2019), we know little about how the mortgage industry responds.

Recent evidence suggests an increasing risk of natural disasters along the east coast: the empirical analysis of Bender, Knutson, Tuleya, Sirutis, Vecchi, Garner & Held (2010) predicts a doubling of category 4 and 5 storms by the end of the 21st century in moderate scenarios. Lin, Kopp, Horton & Donnelly (2016) suggests that, in the New York area, the return period of Hurricane Sandy's flood height[2] is estimated to decrease 4 to 5 times between 2000 and 2100.[3] Gallagher & Hartley's (2017) analysis of Hurricane Katrina suggests that insurance payments due to the federal government's National Flood Insurance Program (NFIP) led to *reductions* in debt. Yet, both the number of NFIP flood insurance policies and their total dollar amount have declined substantially since 2006 (Kousky 2018), leading to potentially greater losses for mortgage lenders. With the future of flood insurance in doubt, two key issues arise (i) whether mortgage lenders will transfer default risk due to floods to the two large securitizers Fannie Mae and Freddie Mac, and hence whether the two GSEs act as *de facto* insurers, and (ii) whether their role incentivizes households to borrow to locate in flood prone parcels.

Such natural disasters may cause losses to mortgage lenders either due to an increasing probability of household default, or, when households are insured, through an increasing probability of

[1]Source: Quarterly Financial Accounts of the United States.

[2]This is the average time between two 14-feet storm surges.

[3]Other key papers predict a similar increase in natural disaster risk over the course of the 21st century (Webster, Holland, Curry & Chang 2005, Elsner 2006, Mann & Emanuel 2006, Garner, Mann, Emanuel, Kopp, Lin, Alley, Horton, DeConto, Donnelly & Pollard 2017, Lin, Emanuel, Oppenheimer & Vanmarcke 2012, Grinsted, Moore & Jevrejeva 2013, Lin et al. 2016).

prepayment.[4] The impact of natural disasters varies substantially across neighborhoods at a local scale (Masozera, Bailey & Kerchner 2007, Vigdor 2008). Hence, the screening of mortgages for securitization may not fully take into account the risk of natural disasters attached to a particular house and a particular mortgage. As local lenders with access to better information relating to the local impact and occurrence of natural disasters may securitize mortgages that are unobservably worse risk, a '*market for lemons*' in climate risk could develop as a potential threat to the stability of financial institutions. In particular, the mispricing of disaster risk, either because of a mispricing of mortgage default or a mispricing of prepayment risk; and the correlation of such natural disaster risk across loans in a mortgage pool can together be a substantial source of aggregate risk for holders of mortgage backed securities.

This paper focuses on the impact of 15 "Billion-dollar events" on banks' securitization activity; and whether mortgages securitized in areas prone to natural disaster risk are worse risk for financial institutions that hold them in securitized mortgage pools. Billion-dollar events have caused at least a billion dollar of losses as estimated by the National Oceanic and Atmospheric Administration (Smith & Katz 2013). Two of the largest purchasers of securitized mortgages are the Government Sponsored Enterprises (GSEs) Fannie Mae and Freddie Mac: in 2008, they held or guaranteed about $5.2 trillion of home mortgage debt (Frame, Fuster, Tracy & Vickery 2015). The GSEs adopt specific sets of observable rules when screening mortgages for purchase. One such rule is based on the size of the loan: GSEs purchase conforming loans, whose loan amount does not exceed a limit set nationally. The conforming loan limit is a single limit set by the Federal Housing Finance Agency (FHFA), by Congress, and the Consumer Financial Protection Bureau (CFPB). As this national limit varies over time, this offers a unique opportunity to estimate lenders' response to shifts in their incentives to securitize mortgages. Previous literature suggests that the discontinuity in securitization costs at the limit causes a bunching in the number of originated mortgages right below the conforming loan limit (DeFusco & Paciorek 2017). Yet, it is not known whether (i) natural disaster risk leads to a shift in lenders' incentives to securitize, (ii) whether securitized loans right below the conforming loan limit are worse default or worse prepayment risk, (iii) whether securitization volumes will increase as we likely face rising disaster risk, and (iv) in the counterfactual

[4] While securitization insures the lender against the risk of default, prepayments are typically "passed through" back to the lender. The paper suggests that default risk is a significantly higher risk than prepayment risk.

scenario where the GSEs would withdraw from risky areas, whether lenders would bear the risk of default, adjust their interest rates and possibly lower their origination volumes. In particular, as local loan officers have discretion over the characteristics of the mortgages sold for securitization, the GSEs' guidelines for securitization do not rely on the on-the-ground information of loan officers and may not take into account local climate risk as accurately as the local loan officer with better knowledge of the future distribution of house prices, e.g. for houses near the bank's branch network. Lenders can securitize jumbo mortgages to other, non-GSE, securitizers called Private Label Securitizers (PLS). Yet evidence suggests that the private label securitization market is small and does not represent a significative alternative (Goodman 2016).

This paper's identification strategy combines a regression discontinuity design at the conforming loan limit with a difference-in-difference setup comparing the magnitude of the discontinuity in mortgage loan density at the limit before and after a billion dollar natural disaster. The discontinuity in density follows the intuition of McCrary's (2008) test and Keys, Mukherjee, Seru & Vig (2010) application to ad-hoc securitization rules. The difference-in-difference approach compares the change in the discontinuity in counties hit by a natural disaster, including Hurricane Sandy, Hurricane Irma, and Hurricane Katrina, with the change in the discontinuity in counties not affected by a natural disaster. The local natural disasters considered in this paper are the 15 largest "billion-dollar events" occuring between 2004 and 2012, and as presented in Smith & Katz (2013) and Weinkle, Landsea, Collins, Musulin, Crompton, Klotzbach & Pielke (2018).

The paper develops a structurally estimated model of monopolistic competition in mortgage pricing with asymmetric information about local default risk and the ability to securitize conforming loans. Such model enables two *out of sample* simulations of the impact of rising disaster risk; and of the impact of such risk in the counterfactual scenario where the GSEs would withdraw from the mortgage market. In the model, bunching and discontinuities at the conforming loan limit are increasing function of lenders' perceived price volatility and declining price trends. The model is estimated using observations at the discontinuity using Gourieroux, Monfort & Renault's (1993) method of indirect inference recently featured in Fu & Gregory (2019). Keeping household preferences and lenders' cost of capital constant, simulations of increasing price volatility and declining price trends provide the two out-of-sample predictions.

Two features of the conforming loan limit are key to the identification of the impact of securitization costs on lenders' activity. First, the conforming loan limit is time-varying. As the limits are set nationally either by the FHFA, by Congress (in 2008), and by the CFPB, they are less likely to be confounded by other regional discontinuities that would also affect the mortgage market for loans of similar amounts. Second, there are two limits starting in 2008: there is a higher limit for "high-cost", as opposed to "general" counties. As those two limits affect different *marginal* borrowers in counties whose house prices are either close or far from the limit, the estimate is more likely to capture an average effect across a large support of borrower and house characteristics.

The impact of billion dollar events on securitization activity is estimated using four different data sets: first, a national data set of all mortgage applications, originations, and securitization purchases between 1995 and 2017 inclusive collected according to the Home Mortgage Disclosure Act (HMDA); second, a loan-level payment history data set with approximately 65% of the mortgage market since 1989, including households' FICO scores, foreclosure events, delinquency, prepayment, and securitization. Third, such data can be matched to the neighborhood (Census tract) of each mortgaged house, and to the lender's identity from the Chicago Federal Reserve's Report of Income and Condition. Fourth, 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), combined with USGS elevation and land use data that identify disaster-struck coastal areas. 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 data set is the universe of banks' branch network throughout the United States. As bank branches are geolocalized, we can estimate the geographic coverage of a bank's branch network and assess which banks have a branch network that is mostly in counties hit by a billion dollar disaster.

Results suggest that after a billion-dollar event, lenders are significantly more likely to increase the share of mortgages originated and securitized below the conforming loan limit. After a billion-dollar event, the difference in denial rates for conforming loans and jumbo loans increases by 5 percentage points. This leads to a substantial increase in the volume of conforming loans post-billion dollar event. This could be driven by either a retreat to safer mortgages, if conforming loans are safer, or increasing adverse selection, if mortgages sold to the GSEs are riskier. Evidence from the national-level BlackKnight data set 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 post origination; they are more likely to be 60 or 120 delinquent; they have lower FICO scores. Banks that originate conforming loans hold typically less liquidity on their balance sheet, and 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 evidence of significant unpriced unobservable risk, suggesting a mispricing of the cost of securitization.

While analysis suggests no evidence of significant trends 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. A billion dollar event has a similar effect on securitization activity as 17% employment decline, which is about twice the standard deviation of employment growth.

Evidence suggests that such selection into the conforming segment and corresponding increase in securitization volumes is consistent with lenders learning about future flood risk from the observation of past events (the *learning hypothesis*). First, the impact of disasters on securitization volumes is greater in neighborhoods that have a historically low frequency of hurricanes. Thus a hurricane provides "new news" that may affect lenders' internal forecasts. Second, the occurence of a hurricane in one decade is correlated with the occurence of a hurricane in subsequent decades: events provide information over and above the average historical probability of hurricanes. Third, both prices and price-to-rent ratios decline, signalling declines in future rental flows.

The paper's quasi-experimental findings can be used to simulate the impact of future disaster risk on securitization volumes, with and without the GSEs' securitization activity. For this purpose, the paper develops a model of mortgage pricing with asymmetric information, household location choice, and the dynamics of mortgage default. The model is structurally estimated at the discontinuities, in the spirit of Fu & Gregory (2019). A key insight is that disaster risk (Barro 2009), which substantially affects real estate values, has a larger impact on lenders' returns than other drivers of default such as unemployment or divorce, which do not affect the payoff of foreclosure auctions. In turn, disaster risk is a key driver of bunching at the conforming loan limit. 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 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 leads to substantial shifts in households' location choices, interest rates, and origination volumes. The model's findings thus suggest that the GSEs act as an implicit substitute for the National Flood Insurance Program, and 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 at least three literatures. First, the literature on adverse selection in the mortgage securitization market. As the GSEs' securitization rules rely on a finite vector of observable loan, borrower, and collateral characteristics, lenders may not have an incentive to collect the full range of private information prior to originating loans, including collecting local information about climate risk. If mortgage lenders couldn't securitize loans and sell them, then they would have strong incentives to use their scale and their human capital to assess what risks are entailed by lending funds for 30-year fixed rate mortgages. Such market discipline is especially valuable when there is ambiguous risk and heterogeneity among buyers in their risk assessments (Bakkensen & Barrage 2017). Results of this paper suggest the ability to securitize may weaken the discipline brought about by the mortgage finance industry in fostering climate change adaptation. In contrast with Keys et al. (2010), this paper focuses on defaults implied by the strongly correlated, arguably upward-trending climate risk that is likely harder to hedge than idiosyncratic household-specific income shocks. Systematic aggregate income risk is present in the real estate literature since at least Shiller (1995). Banking regulators may need to take into account the new kind of systemic financial risk caused by local natural disasters (Carney 2015).

This paper also contributes to the literature on financial risk propagation. This paper's results suggest that participants in financial markets should likely track the contagion of climate risk. As we show that such billion dollar events affects aggregate banks' balance sheets, this paper makes a link between the literature on local natural disasters and the literature on the transmission of risks in the financial sector through banks' balance sheets. A rapidly expanding literature (Elliott, Golub & Jackson 2014, Acemoglu, Ozdaglar & Tahbaz-Salehi 2015, Heipertz, Ouazad & Rancière 2019) uses microdata on security-level holdings of assets and the supply of liabilities to estimate whether and how networks amplify financial shocks on individual banks. In this paper, we find that natural disaster risk is a shock to expected mortgage returns that increases the return to securitization. As the evidence presented in this paper indicates that the risk of such newly-originated mortgages is higher, this suggests caution for securitizers and financial institutions connected to these exposed banks.

Finally, this paper presents another consequence of increasing local natural disaster risk. As an expanding literature studies the housing market's equilibrium pricing of natural disaster risk (Bakkensen & Barrage 2017, Ortega & Taşpınar 2018, Zhang & Leonard 2018) this paper focuses on a potential *mispricing* of assets vulnerable to natural disaster risk: securitizers' guarantee fees may not be an accurate reflection of mortgage risk. While accurately-priced risk and returns are part of the typical formula for financial portfolio composition (Markowitz 1952), the mispricing of mortgage risk, carried onto securitizers' balance sheets, can be a source of unhedged and unanticipated systemic risk. The structural model presented in this paper simulates the evolution of an endogenous GSE guarantee fee that would reflect the increase in natural disaster risk. In this simulation disaster risk leads to little change in originations in risky neighborhoods. In contrast, Garmaise & Moskowitz (2009) shows that the provision of *commercial* loans declines after a disaster. This is likely due to the absence of a large goverment-guaranteed securitizer in the commercial loan market.

The paper is organized as follows. Section 2 presents a simple conceptual framework that ties expected risk to securitization volumes. Section 3 describes the three sources of data used in this paper's analysis: a loan-level data set with monthly payment history information; a billion-dollar disaster dataset paired with blockgroup-level elevation, hurricane wind speeds, and land use information; and a bank-level data set with geocoded branch networks. Section 3 also presents evidence of negative selection into securitization at the conforming loan limit. Section 4 estimates the impact of natural disasters on securitization volumes using an identification strategy that combines time-varying discontinuities with a difference-in-difference approach. Section 5 suggests that results are driven by changes in lenders' beliefs about future risks. Section 6 presents and structurally estimates a model of mortgage pricing with asymmetric information and the ability to securitize mortgages. Such model then provides the main out-of-sample simulations: (i) increasing risk, (ii) withdrawal of the GSEs, (iii) endogenous guarantee fee. Section 7 concludes.

2 Basic Mechanism and Empirical Predictions

We present here the basic mechanisms of a model of mortgage pricing with asymmetric information about default risk. The key observation is that the government sponsored enterprises' rules for securitizing loans include a strict upper bound on securitizable loan amounts, called the conforming loan limit. This affects the lender's optimal menu of mortgage interest rates and thus also affects households' self-selection into mortgage options. Such a simple model yields empirical predictions.

First, the model implies that the lender's optimal menu of mortgage payments and loan amounts will induce bunching at the conforming loan limit.[5] The bunching of loans at the conforming loan limit is positively related to the value of the securitization option. The value of the securitization is the difference between the profit of originating and securitizing and the profit of originating and holding a mortgage. Second, under mild and fairly general assumptions, *increases* in bunching reveal increases in the value of the securitization option for *lenders*, even after accounting for the endogeneity of household sorting at the limit. Third, increases in *households'* perceived disaster risk leads to demand for higher loan amounts and *less* bunching. Such three observations are formalized below.

The Lender's Menu of Mortgage Options

A lender faces a heterogeneous set of households indexed by $\theta \in [\underline{\theta}, \overline{\theta}]$ with density $f(\theta)$. Household θ's default rate $d(\theta)$ is an increasing function of the household's type. The lender offers a menu of loan sizes and mortgage payments (L, m). The profit $\pi(L, m; \theta)$ of the lender depends on the loan amount L, the mortgage payment m and the household type θ. The household derives positive utility from a larger loan size (at given payment m) and incurs a disutility $v(m, \theta)$ of mortgage payments; such disutility is decreasing in the type: households with higher expected probability of default incur less disutility of mortgage payments, $\partial v/\partial \theta < 0$. Such disutility is increasing in the mortgage payment, $\partial v/\partial m > 0$. Finally the disutility is convex in the type $\partial^2 v/\partial \theta^2 > 0$. If the household does not take up any loan, she gets utility $\underline{V}$.

The lender's objective is to find the menu $\theta \mapsto (L(\theta), m(\theta))$ that maximizes profit given each

[5] Bunching in mechanism design problems has been a subject of analysis at least since Myerson (1981).

household's participation constraint:

$$\begin{aligned}
&\max_{L(\cdot),m(\cdot)} \int_{\underline{\theta}}^{\overline{\theta}} \left[\pi(m(\theta);\theta) - L(\theta)\right] f(\theta) d\theta \\
&\text{s.t.} \quad L(\theta) - v(m(\theta);\theta) \geq L(\hat{\theta}) - v(m(\hat{\theta});\theta) \text{ for all } \hat{\theta}, \theta \\
&\qquad\;\; L(\theta) - v(m(\theta);\theta) \geq \underline{\mathrm{V}}
\end{aligned}$$

This is a formulation of the monopoly pricing problem with unobservable type (Mirrlees 1971, Maskin & Riley 1984). This leads to a simple optimal menu of mortgage payments and loan sizes where the mortgage payment for each type maximizes the surplus:

$$m(\theta) = \operatorname{argmax} \pi(m(\theta);\theta) - v(m(\theta);\theta) + \frac{1 - F(\theta)}{f(\theta)} \frac{\partial v}{\partial \theta}(m, \theta). \tag{1}$$

The first two terms are the total surplus, the sum of the lender's profit and the household's disutility. The last term provides household θ with the incentive to choose the option designed for her/him. When the profit function is smooth, households with higher default probability self-select into loans with higher mortgage installments, $dm/d\theta > 0$ as in Rothschild & Stiglitz (1976). Households with a lower propensity to default θ take smaller loan amounts to signal their higher creditworthiness, $dL/d\theta > 0$.

Bunching at the Conforming Loan Limit

The key ingredient of this paper is the discontinuity in the lender's ability to securitize a mortgage. Such discontinuity is the consequence of the GSEs' conforming loan limit.[6] For loan amounts $L \leq \tilde{L}$ the lender's profit π is the maximum of π^h, the profit of holding the mortgage, and π^s, the profit of originating and securitizing the mortgage. For loan amounts L above the conforming loan limit $\tilde{L}$, the lender's profit π is equal to π^h. At $\tilde{L}$ the profit thus experiences a discontinuity $\max\{\pi^h, \pi^s\} - \pi^h$. No discontinuity occurs in at least two cases: (i) when households are fully insured, and thus $\pi^s = \pi^h$, and (ii) when the cost of securitization, called the guarantee fee, is at high levels such that $\max\{\pi^h, \pi^s\} = \pi^h$.

[6]While π is discontinuous at $L = \tilde{L}$, the loan amount $L(\theta)$, the mortgage payment $m(\theta)$ and utility $U(\theta)$ are smooth functions of θ.

We abstract from the ability to sell to non-agency securitizers.[7] The discontinuity at $\tilde{L}$ in the seller's profit generates bunching in the density of mortgages for which $L(\theta) = \tilde{L}$, as displayed in Figure 1. Denoting $[\tilde{\theta}, \tilde{\tilde{\theta}}]$ the set of household types that are offered and choose a mortgage amount exactly equal to the conforming limit $\tilde{L}$, the lower bound of such a segment satisfies:

$$\tilde{L} = v(m(\tilde{\theta}), \tilde{\theta}) + U(\tilde{\theta}), \quad U(\tilde{\theta}) = -\int_{\underline{\theta}}^{\theta} v_\theta(m(\theta), \theta) f(\theta) d\theta, \tag{2}$$

and the upper bound satisfies:

$$\pi(m(\tilde{\tilde{\theta}}), \tilde{\tilde{\theta}}) = \pi^h(m(\tilde{\tilde{\theta}}), \tilde{\tilde{\theta}}) \tag{3}$$

and the amount of bunching is $F_\theta(\tilde{\tilde{\theta}}) - F_\theta(\tilde{\theta})$ or alternatively $f(\tilde{L})$ the point density of households choosing exactly $\tilde{L}$.

Hence bunching at the conforming loan limit reflects (i) the discontinuity in the lender's profit at such limit (equation (3)), i.e. depends positively on the difference $\pi^s - \pi^h$ of profits when securitizing and when holding the mortgage. Bunching at the conforming loan limit also reflects (ii) households' disutility of mortgage payments (equation (2)).

Proposition 1. *The amount of bunching at the conforming loan limit is positively related to the difference between the profit of securitizing mortgages and the profit of originating and holding mortgages. The amount of bunching is negatively related to borrowers' disutility of mortgage payments, and thus to average default rates.*

Bunching and Expected Default Risk

The second step is to derive the impact of an across-the-board increase in households' expected default rate on the amount of bunching at the conforming limit. Let the default rate $d(\theta, \zeta^b)$ depend on both the household's type θ and households' proxy for disaster risk ζ^b. Such increase in disaster risk has the following properties: (i) it lowers the disutility of mortgage payments as the house is paid off over a shorter period of time, hence $\partial v / \partial \zeta^b < 0$; (ii) it lowers the marginal impact of an increase in the household's propensity to default θ on the disutility of mortgage payments $\partial^2 v / \partial\theta\partial\zeta^b$. By lowering both v and U on the right-hand side of equation (2), it increases the value

[7] The market for private label securitization is a small share of the overall total (Goodman 2016).

of the threshold $\tilde{\theta}$ and leads to *less* bunching.

An increase in *lenders'* expected disaster risk ζ^ℓ has a different effect. By lowering the value of holding a mortgage, while keeping constant the value π^s of securitizing a mortgage, it leads to an increase in the upper bound $\tilde{\tilde{\theta}}$ and therefore an *increase* in bunching $F_\theta(\tilde{\tilde{\theta}}) - F_\theta(\tilde{\theta}) = f(\tilde{L})$. We get the following proposition.

Proposition 2. *An increase in lenders' expectation of disaster risk ζ^ℓ leads to an* increase *in the number of loans originated at the conforming loan limit $\tilde{L}$. Formally, $d\tilde{\tilde{\theta}}/d\zeta^\ell > 0$. An increase in borrowers' expectation of disaster risk ζ^b leads a* decline *in the number of loans originated at the conforming loan limit $\tilde{L}$.*

This proposition forms the basis of this paper's identification strategy, which estimates the impact of natural disasters on the value of the securitization option by measuring the impact of natural disasters on the size of bunching at the conforming limit:

$$\Delta f(\tilde{L}) = f(\tilde{L})\big|_{Disaster} - f(\tilde{L})\big|_{No\ disaster} \tag{4}$$

In other words, the disaster provides "new news" to either households or lenders, which shift the expected disaster risks ζ^ℓ and ζ^b potentially upwards. Bunching provides a source of information on lenders' and borrowers' updated beliefs about future disaster risk. Importantly our analysis is based on *newly* originated mortgages rather than current mortgages, reflecting forward-looking expectations of default rather than an impact on the current stock of houses and loans.

The next section presents the natural disasters, the treatment and control groups, and the mortgage application and origination data used for the econometric analysis, performed in Section 4.

3 Data Sets and Treatment Area Geography

This paper focuses on the neighborhoods of the 18 states of the Atlantic Coast and the Gulf of Mexico. We combine information from four data sources: (i) mortgage and housing market data, including information from the universe of mortgage applications and originations, payment history, FICO score, rents and house prices, (ii) natural disaster data, using the universe of Atlantic hurricanes between 1851 and 2018, (iii) sea-level rise, elevation, land use data, which enables an identification of at-risk areas, (iv) banking data, on banks' branch network and balance-sheet information.

Natural Disasters: Billion Dollar Events and the Treatment Group

The paper focuses on disasters that have caused more than 1 billion dollars in estimated damages. The estimates come from Weinkle et al.'s (2018) computations for 1900 to now; we focus on events happening between 2004 and 2012. All of these events are hurricanes, and we extract their path from the Atlantic Hurricane Data set of NOAA's National Hurricane Center[8]. The events post 2004 provide wind radiuses by speed every 6 hours, enabling the computation of the set of neighborhoods within the 64 knot hurricane wind path. This wind speed maps naturally into the Saffir Simpson hurricane intensity scale. Examples of these paths are presented for four hurricanes in Figure 4. Damages to real estate property is however unevenly distributed within the hurricane's wind path. In particular, building-level data from Hurricane Sandy reveals that coastal and low-lying areas are significantly more likely to experience damages. Using the observed damages from Hurricane Sandy, we define a set of criteria to pinpoint treated areas for all of the 15 hurricanes: first, we focus on blockgroups, the smallest Census geographic area for which the Census long form and the American Community Survey are available. Second, blockgroups are hit if (i) they are within the 64kt wind path, (ii) their minimum elevation is below 3 meters, and (iii) they are within 1.5 kilometers of the coastline, or (iv) they are within 1.5 km of wetland. Such criteria yield a set of blockgroups that correlates well with observed damages from Hurricane Sandy and Katrina.[9] Elevation comes from the USGS's digital elevation model, at 1/3 of an arc second precision (about 10 meters). Wetlands come from the 2001 National Land Cover Database.

The set of treated blockgroups is displayed on Figure 2 for hurricane Katrina and on Figure 3 for hurricane Sandy. It is also estimated for the other 13 disasters. The dark grey area is the hurricane's 64kt wind path. The blue area is the set of coastal areas or areas close to wetland. The red boundaries correspond to blockgroups whose elevation is less than 3 meters.

[8] Accessed in 2018.

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

Mortgage and Housing Market: HMDA, BlackKnight

The first data source is the universe of mortgage applications and originations from the Home Mortgage Disclosure Act, from 1995 to 2016 inclusive. The data is collected following the Community Reinvestment Act (CRA) of 1975, and includes information from between 6,700 and 8,800 reporting institutions, on between 12 and 42 million mortgage applications. The law mandates reporting by both depository and non-depository institutions. It mandates reporting by banks, credit unions, savings associations, whose total assets exceeded a threshold, set to 45 million USD in 2018,[10] 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 non-depository 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 includes the identity of the lender, loan amount, the income, race, and ethnicity 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). This paper focuses on 1-4 family housing, owner-occupied home purchase loans. The census tract of the loan enables a geographic match with the counties hit by the billion dollar events.

This first data source does not include the full range of proxies for borrowers' creditworthiness. We complement HMDA with the BlackKnight financial data files, which follow each loan's history from origination to either full payment, prepayment, foreclosure, or bankruptcy. The BlackKnight financial file follows about 65% of the market, and includes the borrower's FICO score, the structure of the mortgage ARM, FRM, Interest Only, the amortization schedule, the interest rate; and follows refinancings, securitizations, and delinquencies. In addition, BlackKnight financial data includes the home's 5-digit ZIP code, which is matched to natural disaster data.

BlackKnight financial data includes the house price and characteristics of the property. We

[10] 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.

obtain ZIP-level house price index data and rental data from Zillow, using two indices: the Zillow Home Value Index (ZHVI), a smoothed, seasonally adjusted measure of the median estimated home value;[11] and the Zillow Rent Index (ZRI): a similarly smoothed measure of the median estimated market rate rent.

The GSEs' Mandate and the Conforming Loan Limit

The Governement Sponsored Enterprises' mandate is set by the National Housing Act, Chapter 13 of the U.S. Code's Title 12 on Banks and Banking. In it, Congress establishes secondary market facilities for residential mortgages. Its stated purposes include providing "stability to the secondary market," providing "ongoing assisatnce to the secondary market for residential mortgages," as well as "manag[ing] and liquidat[ing] federally owned mortgage portfolios in an orderly manner, with a minimum of adverse effect upon the residential mortgage market and minimum loss to the Federal Government." Jaffee (2010) reports that such mandate has a very substantial influence over the mortgage market, as they cover over 50 percent of all U.S. single-family mortgages and close to 100 percent of all prime, conforming, mortgages.

This paper assesses the implications of such mandate in the case of climate risk. Section 1719 of such National Housing Act empowers the Government Sponsored Enterprises to set the standards that determine eligibility of mortgages for securitization. In particular, a set of observable loan characteristics is part of this assessment. This paper focuses on one such time-varying and county-specific observable, the conforming loan limit, set by the Federal Housing Finance Agency, by Congress, or by the Consumer Financial Protection Bureau (Weiss, Jones, Perl & Cowan 2017). Three interesting features enable an identification of the impact of such limit on 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 ratio (CLTV), while maintaining a loan amount within the upper bound of the conforming loan limit.

The observable loan characteristics that the Government Sponsored Enterprises use also pin

[11] Zillow Research, accessed October 2018.

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[12] for fixed-rate mortgages (FRM) between 0% (for applicants with a FICO score above 660 and an LTV below 60%), and 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.

The Impact of the Conforming Loan Limit: Originations and Adverse Selection

If guarantee fees were substantially above the maximum risk premium that lenders are ready to pay, securitization volumes would not affect origination volumes. Figure 6 presents evidence that the GSEs' mandate has an impact on application and on origination volumes. 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 the share of white applicants is substantially higher (between 5 and 10 ppt higher) for applicants of conforming loans. When considering only the first mortgage, Figure (c) suggests that conforming loans have lower Loan-to-Income ratio, about 0.17 lower. Figure (d) matches the HMDA application and origination file to the balance sheet of the lender, when such information is available: it includes large, FDIC guaranteed depository institutions, and does not include non-bank lenders. The figure suggests that the liquidity on lenders' asset-side is 1.1 ppt lower for originators of conforming loans. This is consistent with evidence from Loutskina & Strahan (2009) suggesting that 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 incentivize the securitization of mortgages.

The evidence presented in this figure also suggests that Private Label Securitizers (PLS) are an

[12]The BlackKnight data set used in this paper includes the loan-specific guarantee fee.

imperfect substitute for the GSEs. Indeed, while PLSs do take on the risk of non-conforming, i.e. jumbo, loans, the size of the market is smaller and fees are higher.

The discontinuity in the number of mortgages and in their characteristics can stem from a few different mechanisms; first, a household willing to purchase a house at a given price p_0 may choose a lower level of indebtedness, increasing his cash down and lowering the loan-to-value ratio. Second, the household can downscale its housing consumption to borrow an amount within the conforming loan limit. A third possibility is that the household borrows using two mortgages, one conforming mortgage that can be securitized by the lender, and a second mortgage to achieve the same combined Loan-to-Value ratio (CLTV) as a jumbo mortgage. Given an interest rate schedule, the choice of one of the three options will depend on the borrower's preferences, e.g. for (i) higher indebtedness, including the higher interest cost paid for larger mortgages, (ii) the household's preference for higher equity, (iii) and his/her expected risk of default. Thus an important goal of the analysis is to separate what is driven by the demand for debt from what is driven by the supply of credit.

Evidence of Negative Selection into Securitization

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. self-selection of safer or riskier borrowers into securitization.

Figures 7 and 8 present evidence from BlackKnight'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. Figure (a) confirms the presence of bunching in loans at the conforming loan limit in this different dataset. The granularity of the data set enables a focus on a narrower window of 95 to 105% of the conforming loan limit. Figure (b) suggests that conforming loans have *lower* credit scores. The magnitude of the discontinuity is between 14 and 30 points unconditionally, and between 5 and 3.7 (significant at 1%) when controlling for zip code and year fixed effects, within a 0.5% window around the conforming loan limit. This is reflected in the pricing of such mortgages: Figure (c) suggests that interest rates on conforming loans are *higher*, with a discontinuity of about 0.8 ppt. This suggests that lenders are pricing delinquency and default risk. Similarly, Figure (d) presents evidence that conforming loan borrowers are significantly more likely to purchase private mortgage insurance (PMI), with a discontinuity of about 3 percentage points.

While intriguing, this evidence does not a priori suggest negative selection as GSEs observe FICO scores and PMI take-up. Figure 8 builds four indicators of ex-post mortgage performance. Indeed, BlackKnight reports monthly updates on each loan covered by its network of servicers. Loans are either current, delinquent (90, 120 days), 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 visually most 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.

Appendix Table B suggests that while jumbo loans seem riskier along observable dimensions, these loans are safer along unobservable dimensions (Appendix Table C): jumbo loans are less likely to be full documentation loans, terms are longer (4.3 months), they are more likely to be adjustable rate mortgages, have higher loan-to-value ratios, and have a higher share of second mortgages. Yet, Appendix Table C suggests that they are safer along every dimension of ex-post payment history.

Overall the evidence presented in Figure 8 is consistent with negative selection of borrowers into conforming loans along unobservable dimensions: while the 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 The Impact of Disasters on Agency Securitization

4.1 Identification Strategy

Lenders' credit supply in both the conforming and the jumbo segments depends on their forecasts of households' default and prepayment behavior, as well as their forecasts of neighborhood-level house prices.[13] Flood risk affects house prices, default, and prepayment. Hence the way lenders build flood risk forecasts is a key input to their underwriting process. Forecasting models use a variety of historical observables, including the most recent history of hurricanes:

$$\text{Lender Forecasts}_{\ell ijt} = \alpha \cdot \text{Hurricane}_{jt-1} + \mathbf{x}_{\ell ijt}\boldsymbol{\gamma} + \text{Lender}^f_\ell + \text{Neighborhood}^f_j + \text{Year}^f_t + \eta_{jt} \quad (5)$$

where ℓ indexes lenders, i households, j neighborhoods, and t years. Hurricane_{jt-1} is an indicator variable for the occurence of a hurricane in the previous year. $\mathbf{x}_{ij\ell t}$ is a vector of observables that the lender uses in its forecasting process. Lender^f_ℓ is a lender fixed effect, measuring the optimism or conservative forecasting of each specific lender. Neighborhood^f_j a neighborhood fixed effect that captures non-time-varying fixed neighborhood risk. In turn, forecasts affect lending:

$$\text{Lending}_{\ell ijt} = \delta \cdot \text{Lender Forecasts}_{\ell ijt} + \mathbf{x}_{\ell ijt}\boldsymbol{\beta} + \text{Lender}^s_\ell + \text{Neighborhood}^s_j + \text{Year}^s_t + \varepsilon_{ijt} \quad (6)$$

where $\text{Lending}_{\ell ijt}$ is a range of measures of the mortgage market that includes the approval rate of applications, the interest rates of conforming and jumbo loans, . Lenders' forecasts are not typically observable, yet the reduced-form specification can be estimated:

$$\text{Lending}_{\ell ijt} = \alpha\delta \cdot \text{Hurricane}_{jt-1} + \mathbf{x}_{\ell ijt}\left[\boldsymbol{\beta} + \delta\boldsymbol{\gamma}\right] + \text{Lender}_\ell + \text{Neighb.}_j + \text{Year}_t + \underbrace{\alpha\eta_{jt} + \varepsilon_{ijt}}_{\text{Residual}_{\ell ijt}} \quad (7)$$

Identification of this reduced form is obtained under the assumption that neighborhood-level hurricane probabilities are orthogonal to time-varying lender and neighborhood unobservables conditional on lender, neighborhood, and year fixed effects. Neighborhood fixed effects capture the long-run history of hurricanes in the area (see Figure 9), and year fixed effects capture the average

[13] Such forecasts are key ingredients of models as in Campbell & Cocco (2015).

market-wide lending conditions of each year t. Formally, we identify the impact $\alpha\delta$ of a hurricane on lending under the assumption:

$$\text{Hurricane}_{jt-1} \perp \text{Residual}_{\ell ijt} \mid \text{Neighborhood}_j, \text{Lender}_\ell, \text{Year}_t \tag{8}$$

The National Oceanic and Atmospheric Administration suggests that a large share of the year-to-year variation in local hurricane risk $P(\text{Hurricane}_{jt-1} = 1 | \text{Neighborhood}_j, \text{Lender}_\ell, \text{Year}_t)$ is idiosyncratic. Indeed, "*NOAA's Seasonal outlook, issued in May, [...] 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.*[14]." Hence while lenders' and households' adaptation efforts may be based on the *long-run* history of hurricane occurence, the specific location of hurricane damages is unlikely to be forecastable once one conditions on such history. Section 4.2 provides a placebo test for this assumption.

4.2 The Impact of Natural Disasters on Lending Standards, Adverse Selection into the Conforming Segment, and Securitization Volumes

The paper identifies the impact of natural disasters on GSE securitization activity with three types of regressions. First, regressions estimating the impact of disasters on the approval rates, securitization rates, and borrower characteristics in the conforming segment relative to the jumbo segment. For instance, higher approval rates in the conforming segment relative to the jumbo segment would signal more relaxed lending standards for conforming loans. Second, regressions estimating such shifts in lending standards at each distance of the conforming limit. If the ability to securitize is driving lenders' behavior, the impact of disasters should be felt the most *exactly at* the conforming limit. Third, regressions of the impact of disasters on the volume of originations in the conforming and the jumbo segments.

The first approach combines the discontinuity estimate of Section 3 with an event-study design for each of the $d = 1, 2, \ldots, 15$ natural disasters described in Table 1, from Hurricane Charley (August 2004) to Hurricane Sandy (October 2012).

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

The year of the disaster is noted $y_0(d)$, $y_0(d) \in \{2004, 2005, 2008, 2011, 2012\}$. For each disaster, the time t relative to the disaster year is $t \equiv y - y_0(d)$. The treatment group for each disaster is the set $\mathcal{J}(d)$ of neighborhoods hit by that disaster. The criteria for inclusion in this set are described in Section 3 and combine elevation, proximity to the coastline or wetland, and belonging to the 64kt hurricane wind path. The control group $\mathcal{C}$ is made of Atlantic and Gulf of Mexico neighborhoods of that are not hit by any one of the disasters in 2004–2012. By controlling for a local neighborhood fixed effect, and for a year fixed effect, we are controlling for two key confounders: (i) the historical propensity of local hurricane risk, described in the previous section, and (ii) for the intensity of each particular hurricane season.

The paper's main specification is:

$$
\begin{aligned}
Outcome_{it} = {} & \alpha \cdot \text{Below Conforming Limit}_{it} + \gamma \text{Below Conforming Limit}_{it} \times \text{Hit}_{id} \\
& + \sum_{t=-10}^{+10} \delta_t \cdot \text{Below Conforming Limit}_{it} \times \text{Hit}_{id} \times Time(t) + Time_{t=y-y_0} + Year_y \\
& + Disaster_d + Neighborhood_{j(i)} + \varepsilon_{it},
\end{aligned} \tag{9}
$$

The $Outcome_{it}$ variables are: the approval of the mortgage application, the loan-to-income ratio, whether the borrower is white, African-American, or Hispanic, the log(Income) of the applicant, the credit score, the term, the probability of foreclosure, 30, 60, 90, 120-day delinquency at any point, and voluntary payoff.

The regression is at the mortgage-level i. $j(i)$ is the ZIP code of mortgage i, Below Conforming Limit_{it} is the time and county-specific conforming loan limit (Weiss et al. 2017). By controlling for both year fixed effects and for the disaster-specific time fixed effects, we can identify the identify of the disaster separately from time trends, e.g. the nationwide real estate cycle, which may be a concern for hurricanes occuring at the peak of the housing boom or a the trough of the housing bust.

The paper's coefficients of interest are the δ_t, where controls range between $t = -10$ and $t = +10$. In particular, the δ_t for $t \geq 0$ measure how the natural disaster causes an increase or a decline in denial rates for mortgages on the left side of the conforming loan limit. The δ_t for negative values of t provide a placebo test for the equality of pre-disaster 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 ZIP codes of 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 the treatment group as defined in Section 3. The control group contributes to the identification of the baseline discontinuity $\hat{\alpha}$ as well as the identification of year fixed effects $Year_y$. The time for the control group is conventionally set to $t = -1$ while the year varies between 2000 and 2017. These year fixed effects measure the evolution of the mortgage market in these 18 states during the period of analysis. The latter part of this section discusses the robustness of the results to alternative definitions for the control group.

Impact of Disasters on the Approval Rates of Conforming Loans

Results are presented in Tables 3, 5, and in Figure 10. They involve 4.3 million loans in the HMDA files, and 1.7 million loans in the BlackKnight files, with between 8,119 and 9,627 5-digit ZIP codes. Standard errors are two-way clustered at the 5-digit ZIP and year levels.

A natural disaster leads to a 2.8 ppt decline in the denial rate in the year following the event, and up to a 8.5ppt decline 3 years after the disaster. There are effects up to 7 years inclusive after the event. Importantly in 13 out of 14 regressions, the difference prior to the event is neither statistically nor economically significant. The loan-to-income ratio of conforming loan originations declines, the fraction of white applicants increases, the fraction of Black and Hispanic applicants goes down, the income of the applicants increases.

Impact of Disasters on Adverse Selection into Securitization

When turning to ex-post mortgage performance, in Table 5, the evidence suggests that conforming loans originated *after* the disaster tend to perform worse. The probability of foreclosure is higher by 3.6 percentage points in the year following the disaster, and up to 4.9 percentage points in the third year after the disaster. The probability of 30 day delinquency at any point for conforming loans originated after the event increases by 3.6 percentage points. Similar long-term changes appear for 60 day, 90 day, 120 day delinquency. Voluntary prepayment declines as well, by 3.1 ppt in the year following the disaster.

Tables 3 and 5 together suggest that post-disaster, banks increase positive selection in observable dimensions while increasing negative selection in unobservable dimensions.

Impact of the Control Group on Results

An appropriate control group provides counterfactual observations, i.e. observations where the state of the mortgage market is comparable in both control and treatment ZIPs. In addition, the control group should not be affected by general equilibrium price spillovers. Such spillovers would occur if, for instance, declining real estate prices in disaster areas lead to an increase in the demand for housing in safer neighborhoods.

To test for such confounding effect, we exclude from the control group observations in CBSAs (μSAs and MSAs) for which there is at least one ZIP hit. This leaves 328 CBSAs in total, 53 in the treatment group, 276 in the control group (vs. 328 in the control group in the baseline sample). Results are virtually unchanged, suggesting that spillovers from the treatment to the control group are not driving the results.

Another concern may stem from the multiple treatments (the natural disaster) occuring at different points in time. Goodman-Bacon (2018) suggests that this may cause a bias in the estimation of treatment effects as neighborhoods that are treated at a different point in time are implicitly part of the control group. Yet, with only 18% of the data set 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.

A Test of the Identification Strategy: Effects Far From the Conforming Loan Limit

A second set of regressions identifies whether the estimated δ is due to observations *at* the conforming loan limit or far from the limit.

Specification (9)'s results may be driven by observations away from the conforming loan limit. In particular, given the 90%-110% window, one question is whether bunching increases exactly at the conforming loan limit. Hence, we design an additional test. We run 15 separate estimations where the Below Conforming Limit_{it} variable is replaced by an indicator for "Below p% of the Conforming Limit", 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 δ_t for 15 values $p \in [95\%, 105\%]$, which should be highest at $p = 0$ if the discontinuity at conforming limit is driving our result.

The results of these estimations are presented in Figure 10 for the approval rate (subfigures (a) and (b)) and for the securitization rates (subfigures (c) and (d)). The impacts are presented either in the year following the disaster (subfigures (a) and subfigures (c)) or in the 1st, 2nd, and 3rd years after the disaster (subfigures (b) and (d)).

The results suggest that the impact of billion disaster 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 and supports this paper's identification assumptions.

Impact on Origination Volumes

A third set of regressions regresses the log volume of originations on the set of pre- and post-indicator variables for the occurrence of a natural disaster.

$$\begin{aligned} log(Originations)_{it} = \sum_{t=-10}^{+10} \delta_t \cdot \mathrm{Hit}_{id} \times Time(t) + Time_{t=y-y_0} + Year_y \\ + Disaster_d + Neighborhood_{j(i)} + \varepsilon_{it}, \end{aligned} \tag{10}$$

where $log(Originations)_{it}$ is either the log dollar volume of originations overall in the 90-110% window, or only the log volume of originations in the conforming segment 90%-100% of the limit. Other notations are as before. The coefficients δ_t are presented in Figure 11. The results suggest a decline in the volume of mortgage originations overall, almost entirely due to the decline of originations in the jumbo segment, and the increase in mortgage originations in the conforming segment. Impacts are economically significant and lasting 5 years after the event.

5 Documenting the Mechanism: Learning About Future Risk

Section 2 suggested that the amount of bunching at the conforming loan limit depends on the lenders' perceived value of the securitization option and on households' perceived disutility of mortgage payments.

This section first suggests that natural disasters affect the market's subjective probability of natural disaster risk: prices and price-to-rent ratios decline. The section shows that hurricane risk is autocorrelated: being affected by a disaster in a given year is correlated with greater disaster risk in future years. Finally, the section suggests that the impact of disasters on mortgage markets is greater in areas historically not affected by hurricanes' wind path. These last two points provide support for the *learning hypothesis:* there is local "new news" contained in a natural disaster's path.

5.1 The Impact of Natural Disasters on Expected Price Trends

While it is typically hard to identify beliefs, empirical analysis of the price to rent ratio, in the spirit of Giglio, Maggiori & Stroebel (2014) and Giglio, Maggiori & Stroebel (2016), suggests that fluctuations in the price to rent ratio can capture changes in the market's expectation of future price trends. In this section we estimate the impact of billion dollar natural disasters on expected price trends.

We do so by estimating the impact of the post-2010 natural disasters on the price to rent ratio in a saturated specification. Fluctuations in the price to rent ratio reveals fluctuations in the market's expectations of future rents, future mortgage default, future maintenance costs, time discount factors (cost of capital), and fluctuations in taxation. The following formula abstracts from property tax, insurance payments, and assumes full depreciation of assets in case of disaster:

$$Price_{j(i)t} = \sum_{k=0}^{\infty} \frac{(1-\delta_{j(i)t+k})^k}{(1+r)^k} \left(Rent_{j(i)t+k} - Maintenance_{j(i)t+k} \right), \tag{11}$$

with $j(i)$ the ZIP code of mortgage i, and $\delta_{j(i)t+k}$ the probability of future of future disaster risk. While simple, this formula implies, with a constant rent, a constant expectation of climate risk $\mathbb{E}\delta_{j\cdot}$, and s the share of maintenance costs over rent, that the log price to rent ratio reflects future risk.

$$\log(Price/Rent)_{j(i)t} = \log\left[\frac{1-\mathbb{E}\delta_{j(i)\cdot}}{r+\mathbb{E}\delta_{j(i)\cdot}}\right] + \log(1-s) - \log(1-\tau) \tag{12}$$

The following regression estimates the impact of the natural disaster controlling for both time, year, neighborhood, and disaster fixed effects:

$$\begin{aligned} log(Price/Rent)_{j(i)} = Constant + \sum_{t=-10}^{+10} \Delta_t \text{Hit}_{id} \times Time(t) + Time_{t=y-y_0} \\ + Year_y + Disaster_d + Neighborhood_{j(i)} + \varepsilon_{j(i)t} \end{aligned} \tag{13}$$

The year fixed effects capture the economy's cost of capital r. The year fixed effects control for the nationwide's housing cycle. The neighborhood fixed effects capture unobservable differences in neighborhoods' price to rent ratios, e.g. driven by time-invariant differences in maintenance or state-level taxation differentials. Standard errors are two-way clustered at the neighborhood (zip code) and year levels.

Results are presented on Figure 12 for the price/rent ratio, rents, and prices. The time series come from Zillow's rent and house price indices, available after 2010. Yet, even on this more limited set of natural disasters, the impacts of the disaster on the price/rent ratio and prices are both economically and statistically significant post-disaster; and the placebo coefficient in the year preceding the event is not statistically significant. The price-rent ratio declines by about 3% in the year following the disaster. Using equation 12 with constant taxes and maintenance costs, and with a discount factor $r \simeq 5\%$, we can estimate a that the expected risk probability increases by about 52.5%.

While rents either do not significantly change post disaster or slightly increase (in part due to the lower supply of rental units), prices and price/rent ratios decline significantly. Given the saturated set of controls of the specification, we interpret such result as evidence of a decline in the market's expectation of future price appreciation at the ZIP level.

5.2 Learning about Local Risk from Past Disasters

The impact of a natural disaster on the amount of bunching at the conforming loan limit depends on whether a natural disaster brings "new news" that shifts the probability distribution over *future* risk. The key empirical challenge is to separate cases (a) when the probability of a natural disaster is a constant throughout the period of analysis, and the occurence of a disaster in a specific neighborhood is the realization of a shock, with no change in the future probability of a disaster from cases (b) when disasters are "new news" that bring information about future disaster risk. This section suggests that: (i) in a given geographic area, the occurence of a hurricane is correlated with the future occurrence of hurricanes, even controlling for average historical levels and (ii) that lenders' increasingly bunch their mortgage originations at the conforming limit in areas with little or no history of hurricanes, a fact consistent with belief updating.

We start with point (i). To test whether hurricanes bring such new news about the future occurence of disasters, we use the 168 years of history of geocoded hurricanes provided by the NOAA, between 1851 inclusive and 2018. For each of these events, NOAA provides the hurricane wind path and 64 knot radius as for the more recent hurricanes used as treatments. A 2018 ZIP code is in the hurricane's wind path if any point of its surface is contained in the hurricane's wind path. And we run the following regression:

$$\text{In wind path}_{jt} = \text{ZIP Code}_j + \text{Time}_t + \alpha \cdot \text{In wind path}_{jt-1} + \varepsilon_{jt} \tag{14}$$

where In wind path_{jt} is equal to 1 if a ZIP is in the hurricane's wind path during decade $t = 1, 2, \ldots, 15$; ZIP Code_j is a ZIP code fixed effect that captures the average neighborhood probability over the 168-year history, Time_t measures the average intensity of the hurricane season during the decade, and α is an autocorrelation coefficient. ε_{jt} represents idiosyncratic fluctuations. If there is no information contained in the history of hurricanes in a particular neighborhood, then $\alpha \equiv 0$, i.e. there is no autocorrelation in hurricane occurence.

Estimation of the regression requires care as the fixed effect panel estimate typically suffers from the classic Arellano & Bond (1991) dynamic panel data bias which implies that $\hat{\alpha}$ can be severely downward biased. Table 2 presents the estimation results.

Column (1) includes a set of ZIP code fixed effects, which capture 32% of the variance of the decennial probability. Column (2) includes both neighborhood and a decade fixed effect, suggesting that the neighborhood f.e. captures most of the variance of the probability. Column (3) includes a linear time trend instead of a series of decadal fixed effects, suggesting an increase in hurricane propensity over 168 years, by 0.06 percentage points per decade. Column (4) performs a similar analysis with a ZIP code fixed effect. The time trend is unchanged. Columns (5) and (6) include the lagged decennial probability (i.e. 1861–1870 for 1871-1880), where column (5) is the naive OLS coefficient and (6) is the Arellano-Bond coefficient. Bother columns present an autoregressive coefficient that is significant at 1%, implying that prior hurricane occurence is an informative predictor of future hurricane occurence: a 1 percentage point increase in prior decennial probability increases the next decade's probability by between 0.3 and 2.3 percentage points. This suggests that lenders and households learn about the specific location of future events from the windpath of past events.

We then turn to point (ii). Figure 9 presents the ZIP-level decennial probability of hurricanes between 1851 and 2017 inclusive. The Figure uses the intersection of ZIPs with hurricane wind paths. Decennial probabilities range from 0% (never in a hurricane's wind path) to a maximum of 39%, an average of 3.9 years per decade in a hurricane's wind path. We then estimate this paper's main treatment effect interacted with the historical decennial probability of hurricane occurrence. If lenders do update their beliefs about local risk from the observation of the most recent natural disaster, we should expect that a high historical probability leads to *smaller* responses of bunching to natural disasters.

This is presented in Table 5. In areas with low decennial probabilities, a natural disaster leads to a decline of the denial rate of conforming loans of 2.98% in the year following a disaster, as in the main baseline Figure 10. In contrast, the denial rate of conforming loans declines by only 1.4%, about half of the baseline effect, in areas with a historical probability in the 3rd quartile (15.6% decennial probability). There is no significant impact of natural disasters on denial rate discontinuity for areas with the highest historical probability (38.9%). Such evidence is consistent with the hypothesis that *current* natural disasters provide "new news" about *future* disaster risk.

5.3 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 ZIPs 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, year fixed effects, and estimates the impact of a natural disaster relative to the specific year t_0 of that event:

$$\mathbf{1}(\text{Default})_{it} = \sum_{k=-K}^{+K} \delta_k \cdot \mathbf{1}\left[t = (t_0(i) + k)\right] + \text{ZIP}_{j(i)} + \text{Year}_t + \text{Residual}_{it} \tag{15}$$

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.

Results are presented graphically in Figure 13. The solid lines in each graph present the coefficients δ_{-2} to δ_{+5}. The dotted lines are the 95% confidence intervals. 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 (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.

5.4 The Impact of Mandated Flood Insurance on Securitization Behavior

The availability, cost, and take-up of flood insurance affects both the option value $\pi^s - \pi^h$ of securitization. In particular, given that agency mortgage backed securities do not insure lenders against prepayment risk, full insurance would shift lenders' focus from default to prepayment risk, and substantially lower the value of securitizing mortgages.

We map the areas where flood insurance is mandated at the time of the billion dollar event, using past flood maps from the National Flood Hazard Layer. In particular, zones A, AE, A1-A30, AH, AO, AR, A99, V, VE, V1-V30 from the Flood Insurance Rate Maps are areas where homeowners are required to purchase flood insurance. We compute the share of a ZIP code that is in such a Special Flood Hazard Area (SFHA). In contrast, Zones D, X, C, X500, B, XFUT are areas where flood insurance can be purchased but is not required.

As a test of whether flood insurance mandates affect the level of bunching and the discontinuities at the conforming loan limit, we interact our treatment indicator variable with the share in the SFHA in the paper's main specification (equation 9). Results suggest no statistically significant impact of the share in an SFHA area on bunching and discontinuities. Such result may be consistent with the following recent evidence. First, average payouts were not exceeding $70,000 for the top 10 highest cost flood events (including Sandy), except for Katrina, where the average payout was close to $90,000. Second, Kousky (2018) documents a significant decline in the number and total volume of insurance policies purchased through the National Flood Insurance Program. Third, Kousky (2019) suggests that the impacts of insurance coverage on risk reduction and land use patterns may be modest. Fourth, Appendix Figure A suggests discrepancies between SFHA areas and areas experiencing actual damages. Discrepancies between the SFHA's 100-year floodplain and expected floods have been documented by Blessing, Sebastian & Brody (2017).

6 The Impact of Disaster Risk on Mortgage Securitization 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 such risk is substantially larger than what is observed in the data. We also need a model to simulate the impact of a potential withdrawal or decline of the Government Sponsored Enterprises' securitization activity.

Previous parts of the paper focused on discontinuities at the conforming loan limit to provide arguably credible causal estimates of the impact of risk perceptions on securitization. The key mechanism is that the amount of bunching depends on lenders' perception of risk: both usual forms of risk, and catastrophic risk. Catastrophic risk differs from other drivers of default risk (e.g. divorce and unemployment) as it wipes out the value of a house's equity. It thus substantially affects the outcome of foreclosure sales and ultimately lenders' return on mortgage investments. The model's estimation suggests that catastrophic risk plays a significant role in approval rates for mortgage applications, for the volume of mortgage originations, and for the securitization rate of originated mortgages.

The perception of catastrophic risk affects discontinuities at the conforming limit and an increasing catastrophic risk leads to greater discontinuities in approval rates, securitization rates, and default rates.

The structural part models (i) how lenders choose interest rates, choose which mortgages to approve and securitize, based on (ii) households' sorting across neighborhoods according to their risk of default. The model replicates the "structure-free" discontinuities estimated in Section 4.

6.1 A Structural Model of Mortgage Pricing with Asymmetric Information

There are $j = 1, 2, \ldots, J$ neighborhoods, each with a vector of amenities $\mathbf{z}_j$ of size K. Each of the $i \in [0, N]$ households chooses a neighborhood j. Such a continuum of households differs by their observable vector $\mathbf{x}$ of size and their unobservable scalar ε.

There are $\ell = 1, 2, \ldots, L$ lenders. The lender's opportunity cost of capital is noted κ_ℓ. Each lender offers a fixed rate mortgage with loan amount L_j and maturity T in each location, and chooses an interest rate $r_{\ell j}$ in each location.[15] Lenders compete in interest rates: each lender sets the interest rate $r_{\ell j}(\mathbf{x})$ in this segment $j, \mathbf{x}$ given the menu of interest rates $\mathbf{r}_{-\ell j}(\mathbf{x})$ chosen by the $L-1$ other lenders.

After choosing a location-mortgage contract pair $(j, \ell) \in \{1, 2, \ldots, J\} \times \{1, 2, \ldots, L\}$, households start paying a mortgage with payment $m_{j\ell}(r_{j\ell}, T, L_j)$. They can default every year $t = 1, 2, \ldots, T$.[16]

The annual default probability $\delta(\mathbf{x}, \varepsilon, B_{jt}, p_{jt}) \in [0, 1]$ is driven both by household fundamentals $(\mathbf{x}, \varepsilon)$, by the household's mortgage balance B_{jt}, and by the house price p_{jt} in year t after origination. The latent variable $\text{Default}^*_{jt}(\mathbf{x}, \varepsilon)$ measures the household's cost-benefit analysis of defaulting, so that its annual default probability is $\delta = P(\text{Default}^*_{jt}(\mathbf{x}, \varepsilon) > 0)$.

$$\text{Default}^*_{jt}(\mathbf{x}, \varepsilon) = \alpha^{default} \log\left(B_{jt}/p_{jt}\right) + \mathbf{x}\boldsymbol{\beta}_{default} + \sigma_\varepsilon \varepsilon + \eta_{jt}(\mathbf{x}, \varepsilon) \tag{16}$$

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

$$B_{jt+1} = r_j(\mathbf{x}) B_{jt} - m_{jt}(\mathbf{x}) \tag{17}$$

The last driver of mortgage default in equation (16) 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, each lender ℓ expects that house prices follow a geometric brownian motion with constant drift α_ℓ and volatility σ_ℓ as is typical in the real estate literature (Bayer, Ellickson & Ellickson 2010). The novelty in the dynamic of prices below is that there is a probability $\pi \in [0, 1]$ of disaster risk wiping out real estate values in the neighborhood.

$$p_{t+1} = (1 - \pi) \cdot p_t \cdot (\alpha + \sigma \Delta W_t) \tag{18}$$

where α is the house price trend (in logs), σ the price volatility. ΔW_t is an i.i.d normal shock,

[15] 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.

[16] For the sake of clarity we abstract from prepayment . Prepayment can be introduced, but does not affect sorting or pricing at the conforming loan limit.

$\Delta W_t \sim N(0,1)$. Both α and σ are assumed to be common knowledge, while disaster risk π is uncertain.

If the household defaults ($\text{Default}^*_{jt}(\mathbf{x}, \varepsilon) > 0$), a foreclosure auction yields a payoff $\min\{B_{jt}, p_{jt}\}$, which is at most equal to the current mortgage balance.

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

$$\Pi_\ell(r_{\ell 1}, r_{\ell 2}, \ldots, r_{\ell J}; \mathbf{r}_{-\ell j}(\mathbf{x})) = \sum_{j=1}^{J} \Pi_{j\ell}(r_{\ell 1}, r_{\ell 2}, \ldots, r_{\ell J}; \mathbf{r}_{-\ell j}(\mathbf{x})) \tag{19}$$

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

$$\Pi_{j\ell} = \left\{ E_{j\ell}[\xi] \cdot m(r^*_{\ell J}, T, L_j) - L_j + E_{j\ell}[\phi(\delta)] \right\} \cdot P(j, \ell) + \epsilon \tag{20}$$

where ϵ is an unobservable driver of profit. The multiplier ξ of mortgage payments depends on the expected default rate, so that:

$$E_{j\ell}[\xi] \equiv E_{j\ell}\left[\sum_{t=1}^{T} \frac{\Pi_{s=1}^{t}(1 - \delta_{js}(\mathbf{x}, \varepsilon))}{1 + \kappa_\ell} \right] \tag{21}$$

with κ_ℓ the lender's opportunity cost of capital. For a specific location j and contract ℓ, the probability of default of households is:

$$E_{j\ell}[\xi] = \int \xi(\mathbf{x}, \varepsilon) f(\mathbf{x}, \varepsilon | j) d\mathbf{x} d\varepsilon \tag{22}$$

where $f(\mathbf{x}, \varepsilon | j)$ is the consequence of households' sorting and is derived in the next few paragraphs. In the lender's profit (20), the term $E_{j\ell}[\phi(\delta)]$ is the expected revenue generated by a foreclosure sale in case of default, equal to $\sum_{t=1}^{T} \Pi_{s=1}^{t}(1 - \delta_{js})/(1 + \kappa_\ell)\delta_{jt} \min\{B_{jt}, p_{jt}\}$.

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 $(\mathbf{x}, \varepsilon)$ chooses its location and contract based on local amenities $\mathbf{z}_j$ and contract features $r_{j\ell}, L_j$. It maximizes the indirect utility:

$$U_{j\ell}(\mathbf{x}, \varepsilon) = \mathbf{z}_j\gamma + \mathbf{z}_j\Omega\mathbf{x} - (\alpha + \beta\varepsilon) \cdot \log(\mathit{Total\,Cost}_j) + \eta_{j\ell} \tag{23}$$

where $\eta_{j\ell}$ is extreme-value distributed as is common in the discrete choice literature. $\mathit{Total\,Cost}_j$ is the mortgage's total cost. Here the household's sensitivity to the total cost $\log(\mathit{Total\,Cost}_j)$ depends on its unobservable default driver ε.

The probability of choosing neighborhood j and lender ℓ is noted $f(j|\mathbf{x}, \varepsilon)$ and is a simple multinomial logit that depends on the deterministic part of utility $U_{j\ell}(\mathbf{x}, \varepsilon)$, noted $V_{j\ell}(\mathbf{x}, \varepsilon)$. 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 ε in a given contract (j, ℓ) is given by using Bayes' rule:

$$f(\varepsilon|j, \ell, \mathbf{x}) = \frac{f(j, \ell|\mathbf{x}, \varepsilon) f(\mathbf{x}, \varepsilon)}{f(j, \ell)}, \tag{24}$$

which is a key ingredient in the lender's calculation of its discounting factor ξ described in equation 22. 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 ε.

The Securitization Option The introduction of the securitization option is straightforward. 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 $\varphi(\mathbf{x})$ that depends on the borrower's FICO score and the LTV.[17] 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 $E_{j\ell}[\phi]$ of a foreclosure sale.

$$\Pi^h_{j\ell} = \left\{ E_{j\ell}[\xi] \cdot m(r^*_{\ell J}, T, L_j) - L_j + E_{j\ell}[\phi(\delta)] \right\} \cdot P(j, \ell) + \epsilon^h_{j\ell} \tag{25}$$

$$\Pi^s_{j\ell} = \left\{ \xi(\varphi) \cdot m(r^*_{\ell J}, T, L_j) - L_j \right\} \cdot P(j, \ell) + \epsilon^s_{j\ell} \tag{26}$$

[17] In the model's simulation upfront fees are converted into ongoing fees following standard formulas.

As the lender picks loans for securitization after observing $(\mathbf{x}, \varepsilon)$, the lender securitizes mortgages for which the profit $\Pi^h_{j\ell}$ of originating and holding (equation (20)) is lower than the profit $\Pi^s_{j\ell}$ when originating and securitizing. Then:

$$P(\text{Approval})_{j\ell} = P\left(\max\left\{\tilde{\Pi}^h_{j\ell} + \epsilon^h_{j\ell}, \tilde{\Pi}^s_{j\ell} + \epsilon^s_{j\ell}\right\} \geq 0\right), \tag{27}$$

$$P(\text{Securitization})_{j\ell} = P\left(\tilde{\Pi}^s_{j\ell} + \epsilon^s_{j\ell} \geq \tilde{\Pi}^h_{j\ell} + \epsilon^h_{j\ell} \,\middle|\max\left\{\tilde{\Pi}^h_{j\ell} + \epsilon^h_{j\ell}, \tilde{\Pi}^s_{j\ell} + \epsilon^s_{j\ell}\right\} \geq 0\right) \tag{28}$$

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

Monopolistic Competition

Definition 3. An equilibrium is a JL-vector $\mathbf{r}$ of interest rates for each location-contract pair (j, ℓ) such that (i) each lender ℓ chooses a menu $\mathbf{r}_\ell$ of interest rates in each location j to maximize its total profit given the other lenders' menu and given households' location choices; (ii) each household $i \in [0, 1]$ chooses a location-contract pair (j, ℓ) that maximizes its 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).[18] In the empirical estimation of the model we do not estimate the full equilibrium $\mathbf{r}$ but rather find the optimal interest rate for a given lender ℓ given the menu of rates of other lenders. Assuming the economy is at an equilibrium, solving for the optimal menu of interest rates for a given lender ℓ at given menu of the other lenders $\mathbf{r}_{-\ell}$will yield the equilibrium menu of interest rates for ℓ.

Identification and at the Conforming Loan Limit We need to estimate structural parameters in three structural equations: the drivers of household default (16), the drivers of household sorting (23), and the drivers of lenders' profit of originating and holding (25) as well as originating and securitizing (26).

Mortgage default is observed for each loan amount and for each household income in the BlackKnight financial data set. The set of household characteristics borrowing in each neighbor-

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

hood is observed in Home Mortgage Disclosure Act Data. The approval rates and the securitization rates are observed in HMDA data as well. The interest rate of mortgages is observed in BlackKnight financial data.

We jointly estimate the default parameters $\left(\alpha^{default}, \boldsymbol{\beta}^{default}, \sigma_{\varepsilon}\right)$ from equation (16), the utility parameters $(\gamma, \Omega, \alpha, \beta)$ from (23), and lender ℓ's profit parameters $\left(\kappa_{\ell}, Var(\epsilon^{h}_{\cdot\ell}), Var(\epsilon^{s}_{\cdot\ell})\right)$ from (25) and (26) 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 $\boldsymbol{\theta}_{\ell} = (\boldsymbol{\theta}^{default}, \boldsymbol{\theta}^{utility}, \boldsymbol{\theta}^{profit}_{\ell})$. The four sets of predictions for lender ℓ are stacked in a vector and noted $\boldsymbol{Predictions}_{\ell}$, and the corresponding observations are noted $\boldsymbol{Observations}_{\ell}$.

The following parameters are set exogenously. The conforming loan limit is set as in Section 3. The guarantee fee is set to 40 basis points. The price trends α and volatility σ are estimated using property deeds data. 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:

$$\hat{\boldsymbol{\theta}}_{\ell} \equiv \text{argmin}\left(\boldsymbol{Predictions}_{\ell} - \boldsymbol{Observations}_{\ell}\right)' \Psi_{\ell} \left(\boldsymbol{Predictions}_{\ell} - \boldsymbol{Observations}_{\ell}\right) \tag{29}$$

where $\Psi_{\ell} = Id$ in the first step and Ψ_{ℓ} 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).

6.2 Model Fit and Simulations of Increasing Disaster Risk

Figure 14 compares the predictions of the model with the realizations for the largest lender observed in HMDA in the 2004-2016 period. The grey 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 between 90 and 110% of the conforming loan limit.

The model reproduces discontinuities in approval rates, securitization rates, default probabilities, and the share of originations. The model does not account for private label securitization activity above the conforming loan limit. Yet, it captures the higher approval rate, the higher securitization rate, the higher default rate in the conforming segment.

6.2.1 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, default rates in each neighborhood. Households' propensity to default, households' preferences, and lenders' profit parameters are kept constant, but optimal interest rates, approval rates, securitization rates are recomputed in response to the increase in π.

Figure 15 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 100-year floodplains.

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 decline is mitigated by the increase in securitization rates, moving up in the conforming segment.

This suggests that the transfer of disaster risk to the 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 option.

6.2.2 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 lenders would reduce lending volumes, increase interest rates, in the absence of the option to sell risky mortgages. Elenev, Landvoigt & Van Nieuwerburgh (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? Choose smaller loan amounts? The model predicts both aggregate shifts in default risk and local, neighborhood-level, shifts in mortgage originations, securitizations, as well as households' self-selection into the GSE-guaranteed segment.

This is what Figure 16 presents. 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)). 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 (subfigure (d)). Without the securitization option, 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)). This simulation assumes that the private label securitization market does not step in to take on the role of the GSEs.

Overall simulations suggest that the GSEs' securitization activity mitigates the impact of increasing disaster risk on the number of households purchasing a home.

7 Conclusion

Fannie Mae and Freddie Mac have an important public mission (Frame & Tracy 2018): to support liquidity in the secondary U.S. mortgage market, and thereby facilitate access to homeownership for millions of Americans. They also make possible the popular 30-year, fixed-rate mortgage. Households borrowing in 2020 using such a mortgage contract sign loans maturing in 2050. Thus, in a world of increasing disaster risk, Fannie Mae and Freddie Mac play a key role in guiding lenders and households through the climate change adaptation process.

This paper uses mortgage-level data merged with neighborhood-level natural disaster data to find that (i) after natural disasters, lenders have incentives to screen their loans for securitization, (ii) conforming loans, that are eligible for sale to Fannie Mae or Freddie Mac, are riskier than non-conforming loans at equal loan amount, (iii) after natural disasters, lenders increase their originations and securitization of conforming loans. Our out-of-sample simulations suggest that (iv) in the current status quo scenario (at constant agency guarantee fees), increasing disaster risk would not significantly affect origination volumes, at the cost of increasing securitization and default. This latter finding would not hold if the GSEs either withdrew or increased their guarantee fee: origination volumes and interest rates would then significantly respond to increasing risk.

Given that natural disasters cause correlated mortgage defaults,[19] such default may become difficult to diversify if the volume of at-risk loans increases. Hence this paper's conclusions should be of interest to stakeholders interested in monitoring the systemic climate risk held onto lenders' and GSEs' balance sheets.

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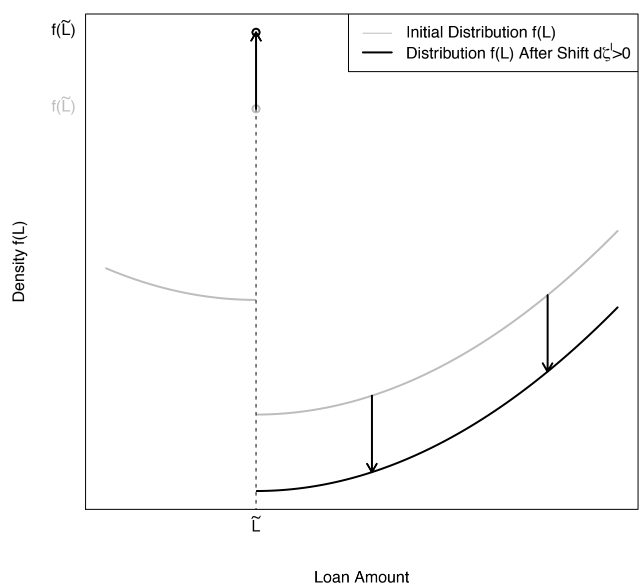
Figure 1: The Impact of Lender and Borrower's Risk Perceptions on Bunching at the Conforming Loan Limit – Theoretical Predictions from the Mechanism Design Model

These two figures present the predictions of the model of mortgage pricing with asymmetric information (Section 2) when either the lender's risk perception ζ^{ℓ} increases (subfigure (a)) or the borrower's risk perception ζ^{b} increases (subfigure (b)). Subfigure (a) suggests that bunching at the conforming limit increases, while subfigure (b) suggests that bunching at the conforming loan limit declines. Such results are described in Proposition 2.

(a) An Increase in the Lender's Perception of Risk



(b) An Increase in the Household's Perception of Risk

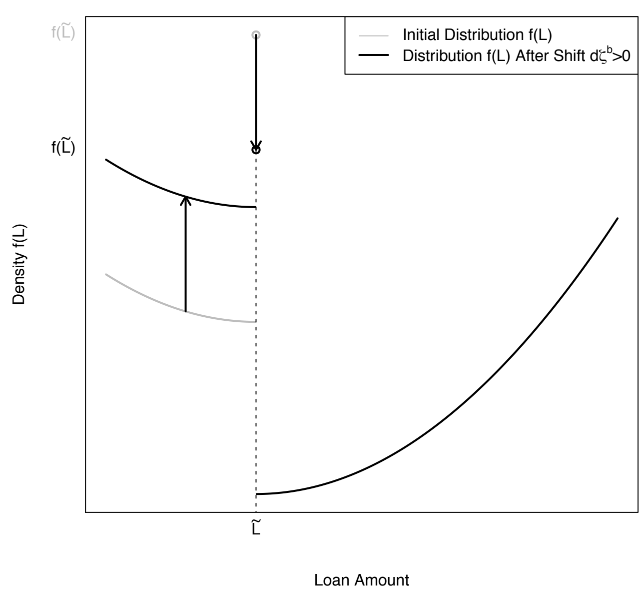


Figure 2: The treatment group for Hurricane Katrina

This figure highlights the boundaries of neighborhoods hit by Hurricane Katrina. 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 data set. 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.

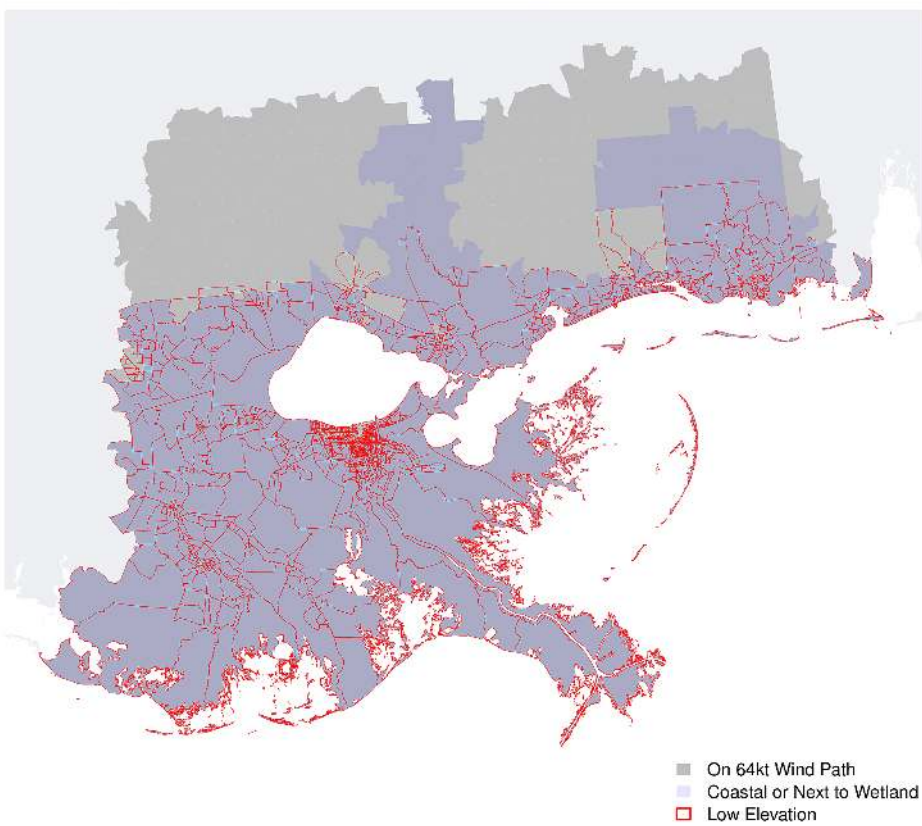


Figure 3: The treatment group for Hurricane Sandy

This figure highlights the boundaries of neighborhoods hit by 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 data set. 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.

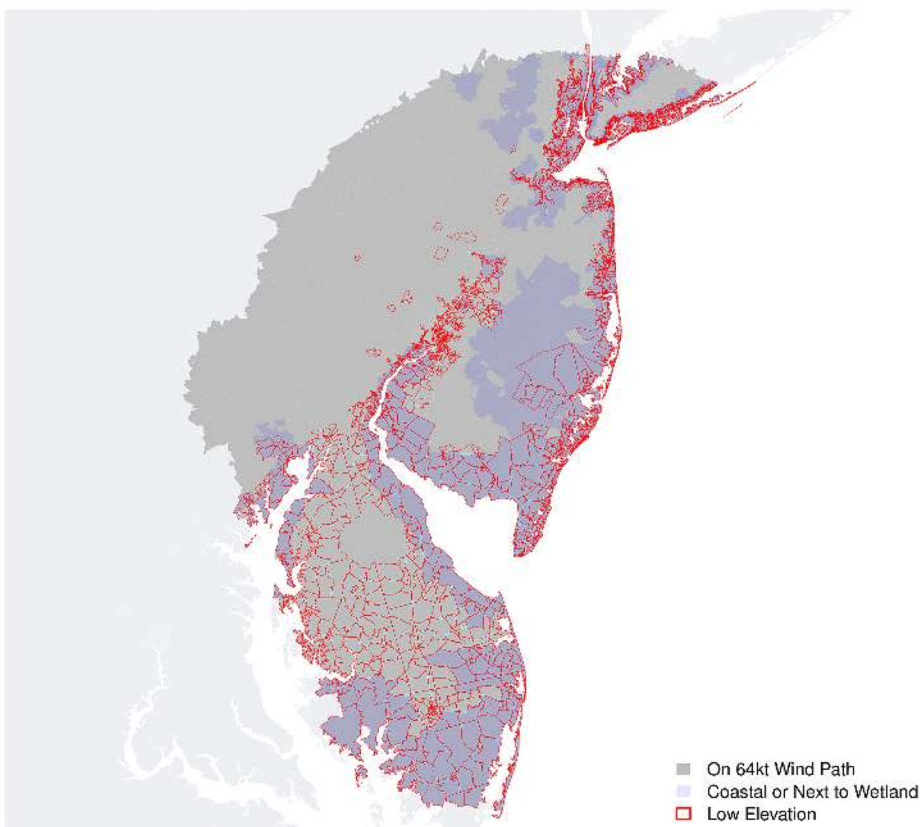
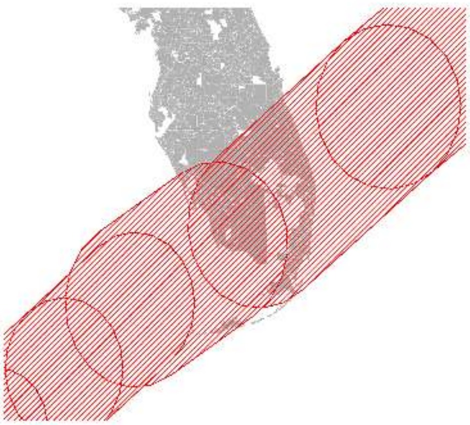


Figure 4: ZIP Codes in Hurricanes' Wind Path

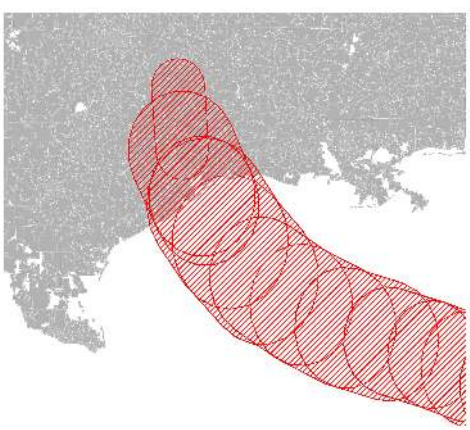
These four maps illustrate the determination of 5-digit ZIP codes (ZCTA5) in the 64 knot wind radius of a hurricane path. These are ZCTAs in grey or red in the previous figure. We present here 4 hurricanes out of the 20. The red area is the radius of 64 knot winds around each hurricane's path. Hurricane paths are measured by NOAA National Hurricane Center's Atlantic Hurricane Data Set. The grey polygons are the boundaries of ZCTAs from the 2014 edition of Census maps.

(a) Wilma 2005



(b) Katrina 2005

(c) Ike 2008

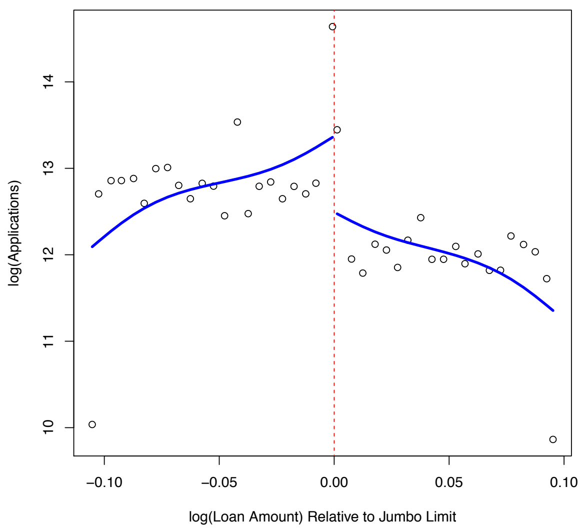


(d) Sandy 2012

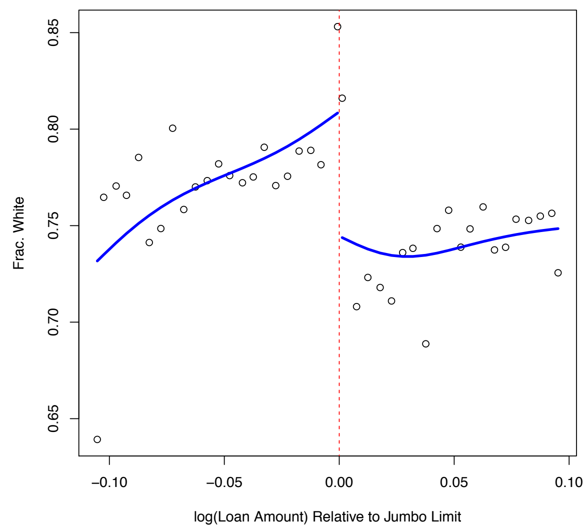
Figure 5: Baseline Discontinuities at the Conforming Loan Limit – HMDA Analysis

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.

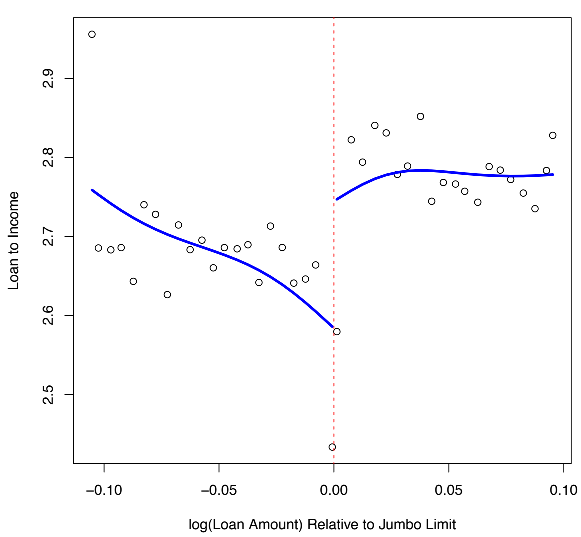
(a) Counts of Applications



(b) White Applicants



(c) Loan-to-Income Ratio



(d) Lender's Balance-Sheet Liquidity

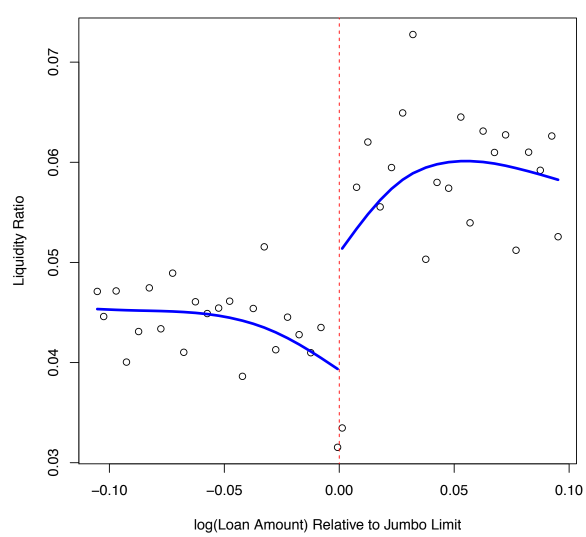
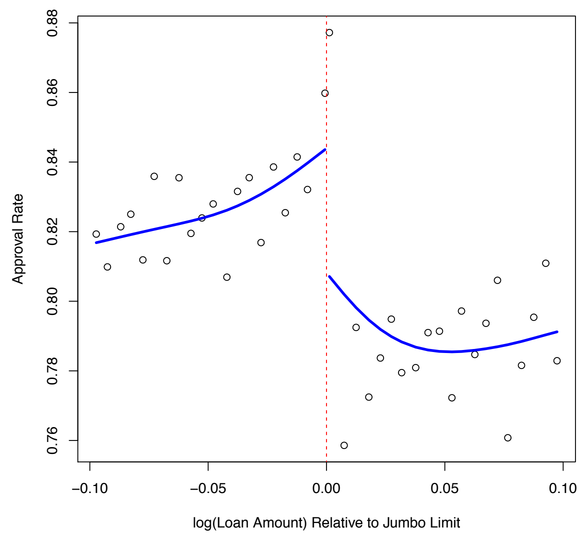


Figure 6: Baseline Discontinuities at the Conforming Loan Limit – HMDA Analysis

These figures present the estimates of the impact of the conforming loan limit on the approval rate and the securitization rate for originated mortgages. 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) Approval Rates



(b) Securitization Rates

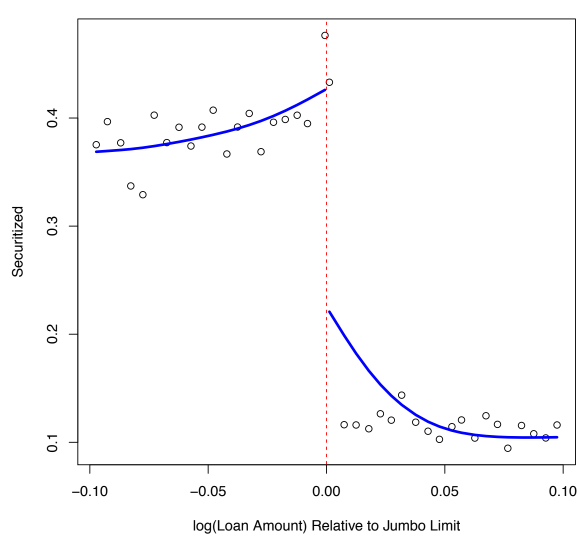
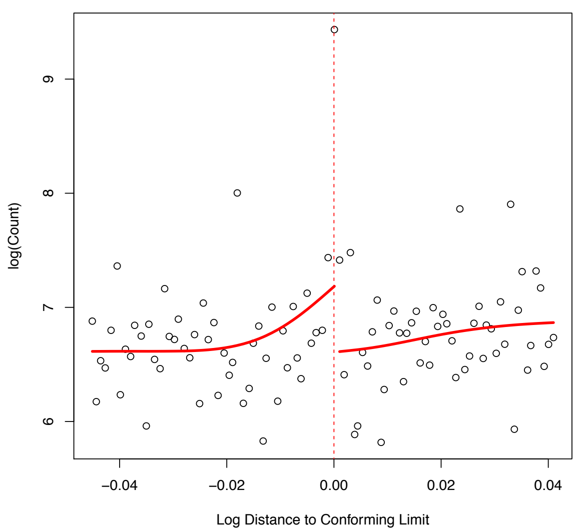


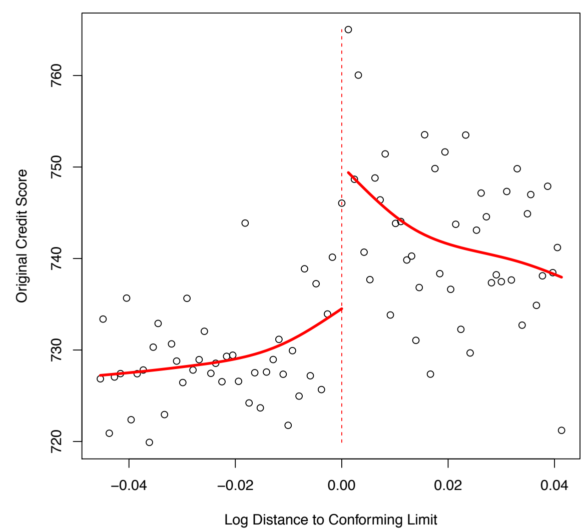
Figure 7: Baseline Discontinuities at the Conforming Loan Limit – BlackKnight Data Analysis

These figures present the estimates of the impact of the conforming loan limit on mortgage characteristics in the BlackKnight financial data set of mortgage files. The solid red 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 values are year- and county-specific.

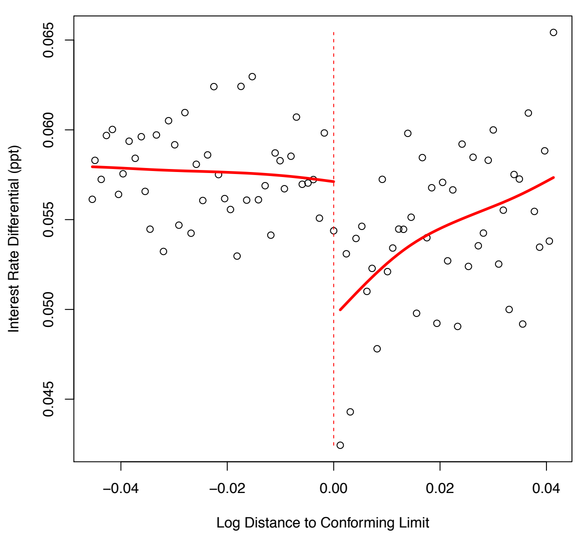
(a) Counts of Originations (First Mortgage)



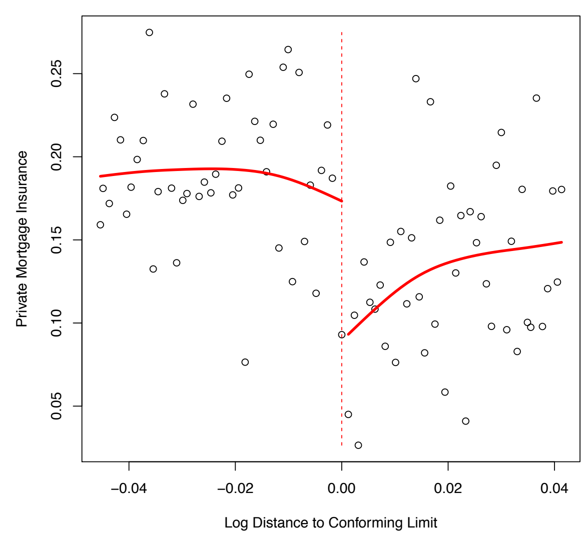
(b) Credit Score at Origination



(c) Interest Rate



(d) Private Mortgage Insurance

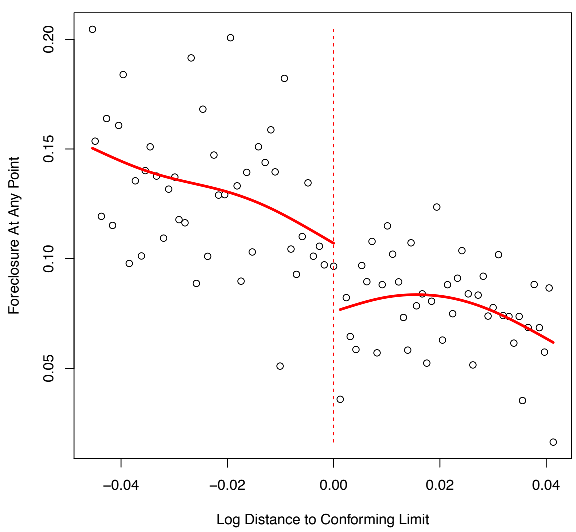


Jumbo rates are below conforming rates, consistent with the evidence presented in Oliner, Peter, Fisher, Fratantoni et al. (2019).

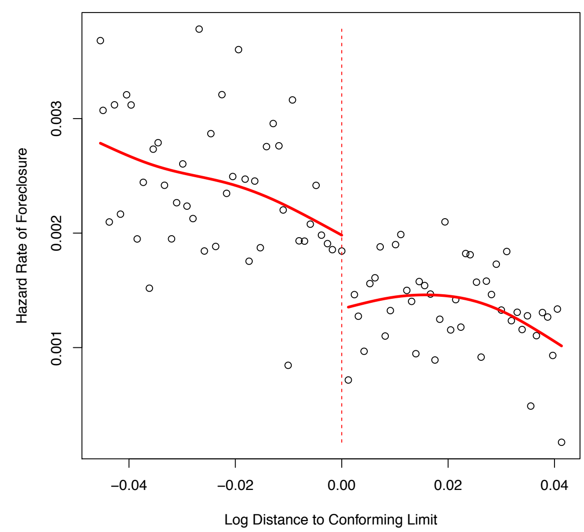
Figure 8: Default and Prepayment Around the Conforming Limit

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

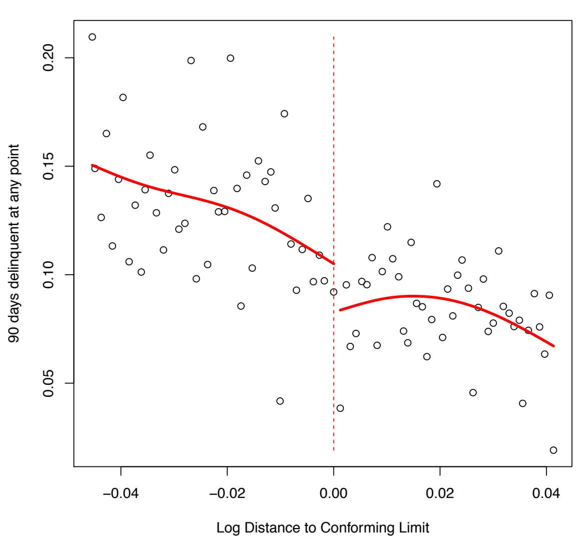
(a) Foreclosure at any point after origination



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



(c) 60 Days Delinquent At Any Point



(d) Voluntary Payoff

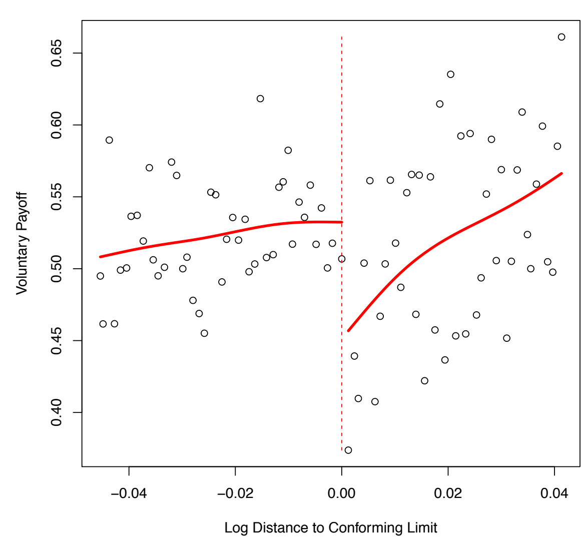
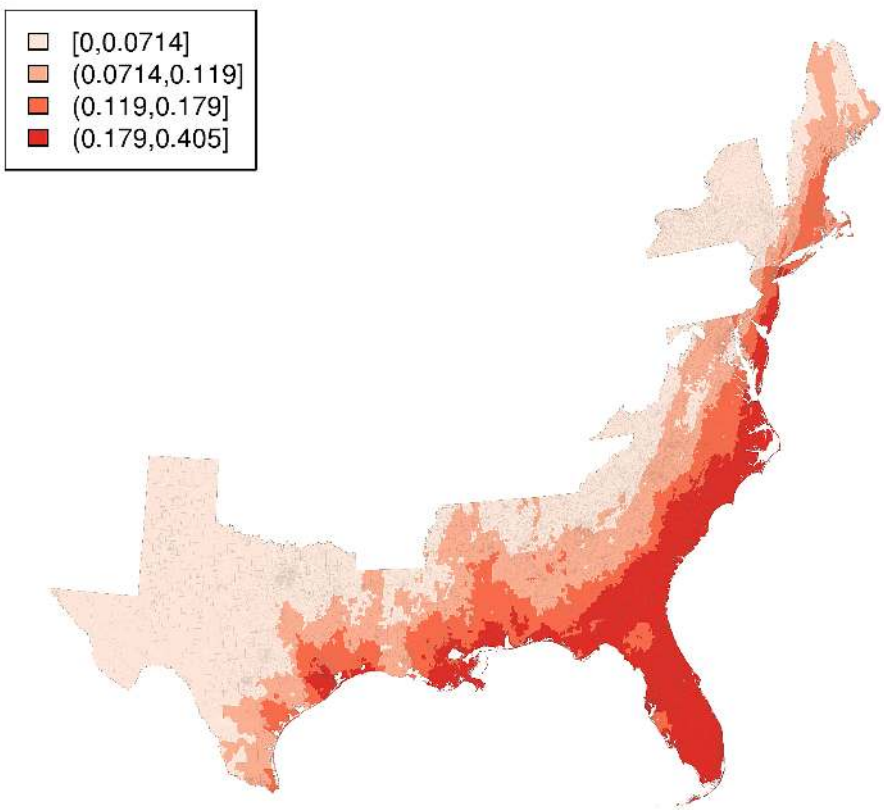


Figure 9: 168-Year Probability of Hurricane Occurence

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 neighborhood 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 neighborhood over 168 years. The hurricane path is the 64kt wind speed path.

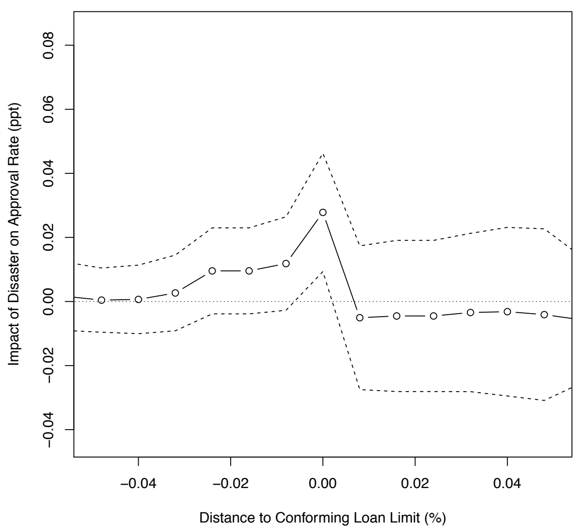


Source: NOAA's Atlantic Hurricane Data Base.

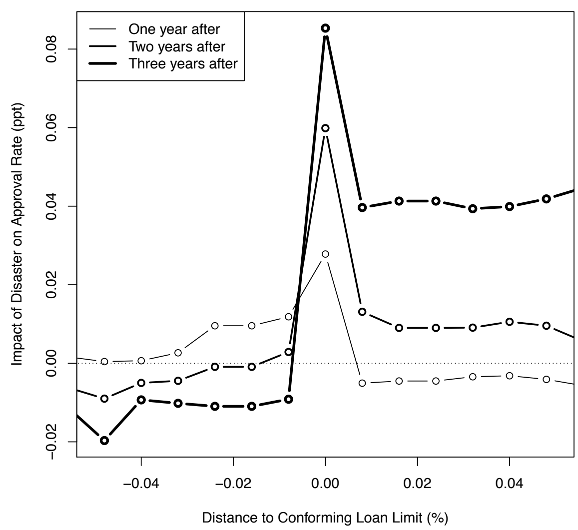
Figure 10: Impact of Billion Dollar Events on Approval and Securitization Rates at the Conforming Loan Limit

This figure describes the estimates of the impact of the 15 billion dollar events on the approval rate for loans whose loan amount is below a series of thresholds from -5% to +5% of the conforming loan limit. Each point of the curve is the coefficient of a separate regression, for thresholds ranging from -5% to +5% of the conforming loan limit. The horizontal axis is the % distance of the loan volume to the conforming loan limit. The vertical axis is the impact of the billion dollar event on the probability of approval (in percentage points) for loan volumes at each level (horizontal axis).

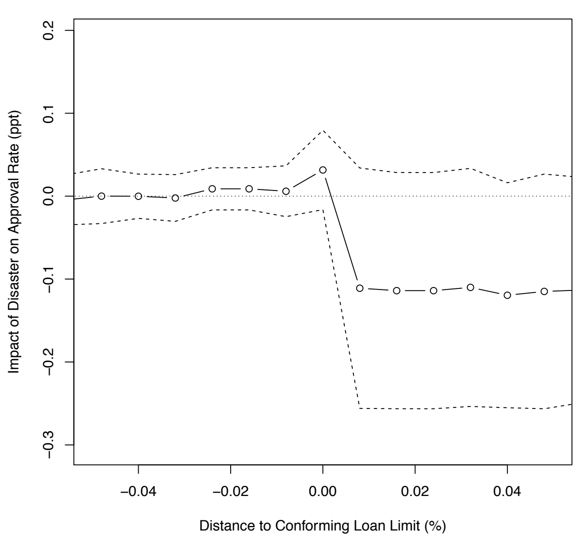
(a) Impact on Approval Rate, Year +1 after the disaster



(b) Impact on Approval Rate, Years +1 to +3



(c) Impact on Securitization Rate, Year +1 after the disaster



(d) Impact on Securitization Rate, Years +1 to +3

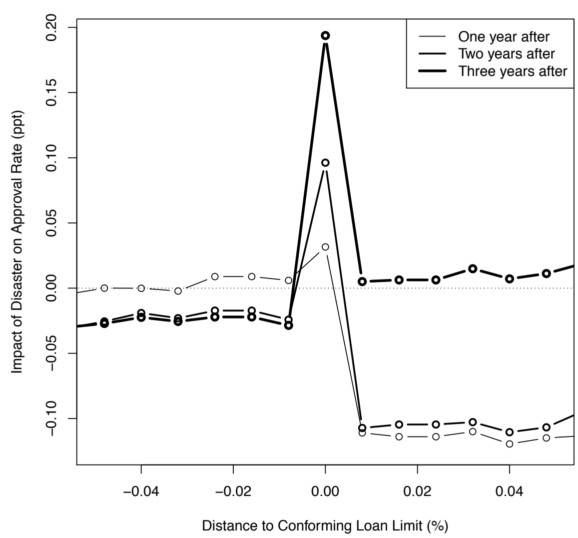
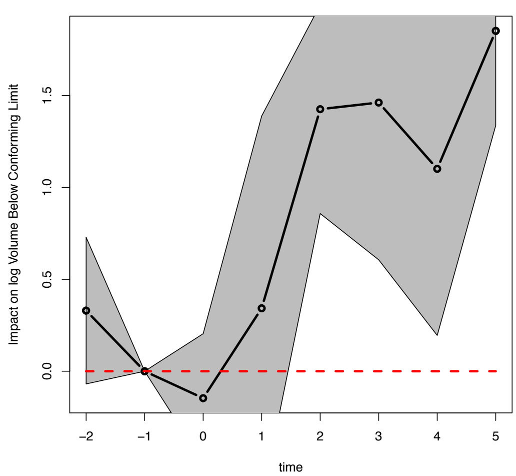


Figure 11: Impact of Billion Dollar Events on Origination and Application Volumes for Conforming Loans and Jumbo Loans

This figure describes the estimates of the impact of the billion dollar events on log loan numbers below the conforming limit (left side) and overall in the window around the limit. Results use a $\pm 2\%$ *window around the limit. Results are similar when using a* 10%, 5% *or* 1% *window around the limit. The horizontal axis is the years relative to the event. The vertical axis is the impact of the billion dollar event on logs.*

(a) Originations (Conforming Loans)



(b) Origination Volumes (Overall in Window)

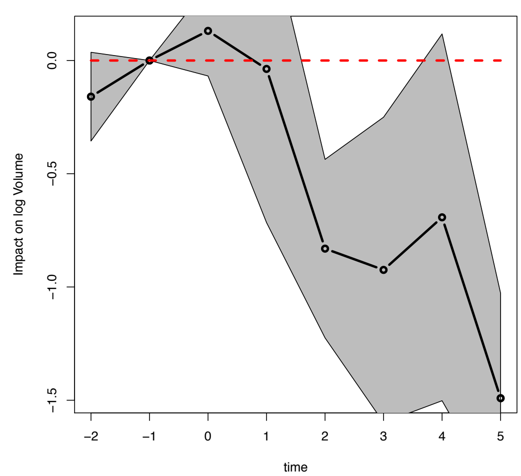
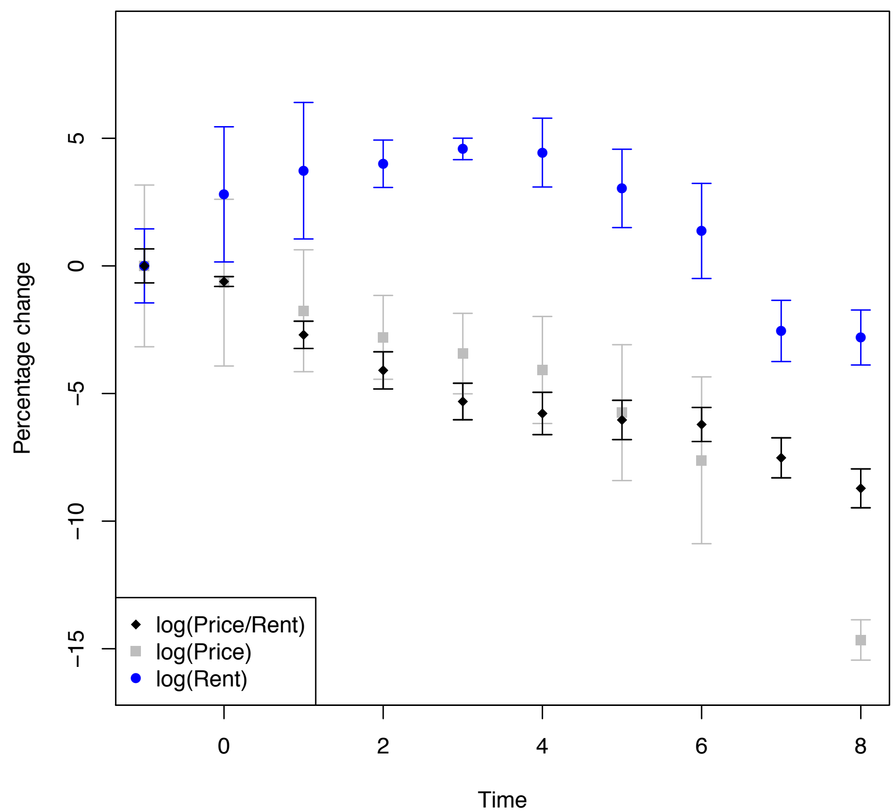


Figure 12: Impact of Billion Dollar Disasters on Prices, Rents, and the Price/Rent Ratio

This figure presents the results of a regression of log price, log rent, and log price/rent ratio on a series of pre- and post-disaster indicator variables.

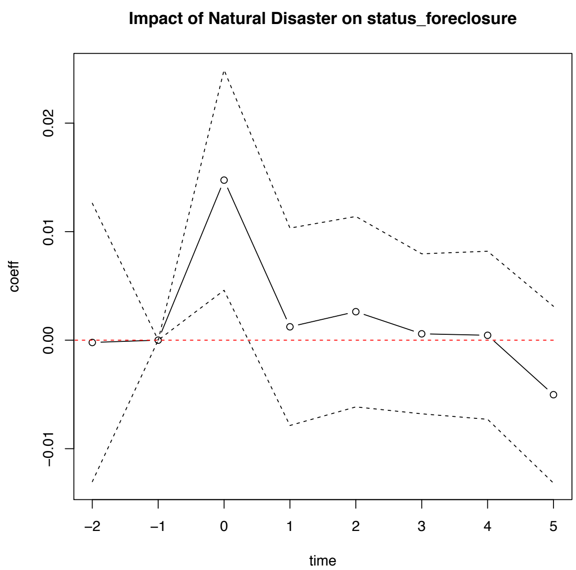


Source: Zillow House Price Index Single Family/Multifamily. Rental Price Index. Billion dollar events after 2010 (first year of data availability for Zillow's price indices) as in Table 1. Impacts on prices and price/rent ratios significant at 1% after the event. Standard errors clustered by Zip and by year.

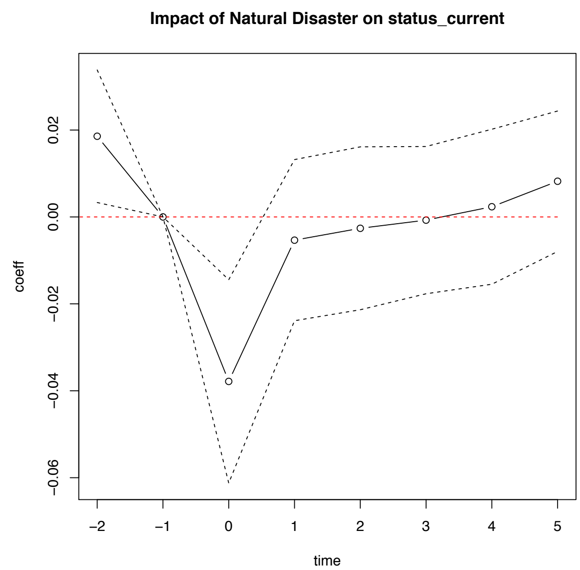
Figure 13: The Impact of Billion Dollar Events on Default and Prepayment

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

(a) Foreclosure



(b) Mortgage is Current



(c) Prepayment

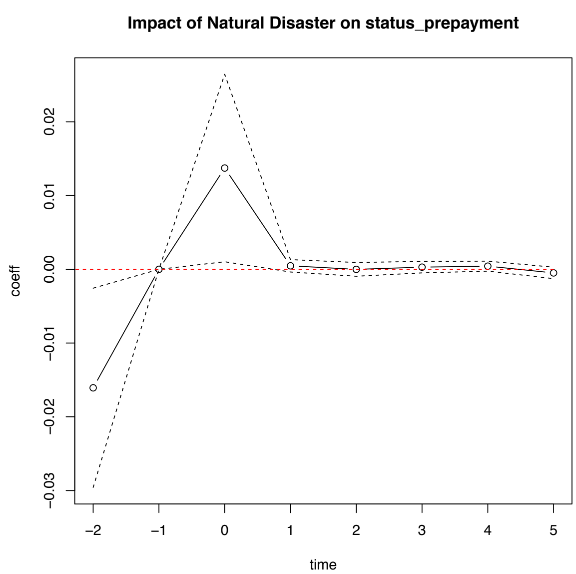
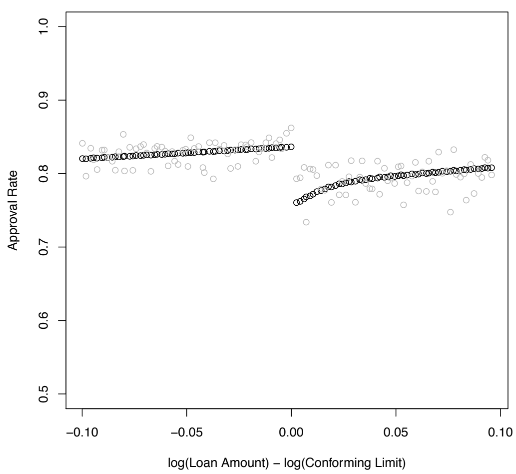


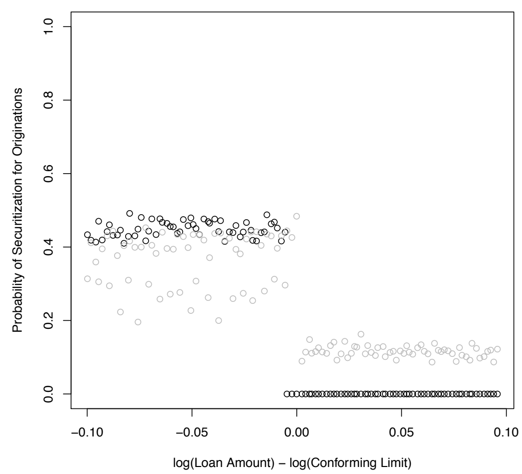
Figure 14: Model Fit: Computed Equilibrium at Estimated Parameters vs. Observations

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 BlackKnight financial data (subfigure (c)). The black points are the predictions of the estimated model.

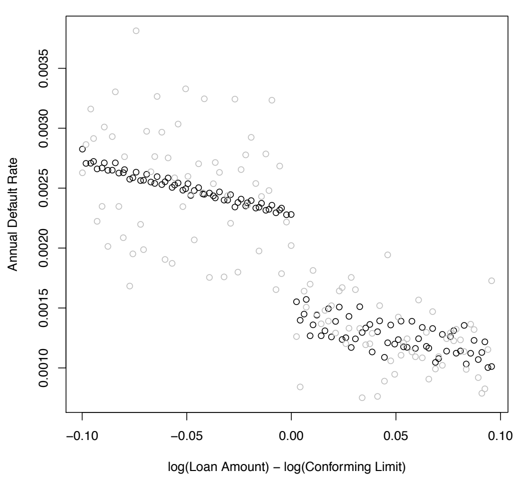
(a) Probability of Approval



(b) Probability of Securitization



(c) Default Probability (%)



(d) Share of Originations

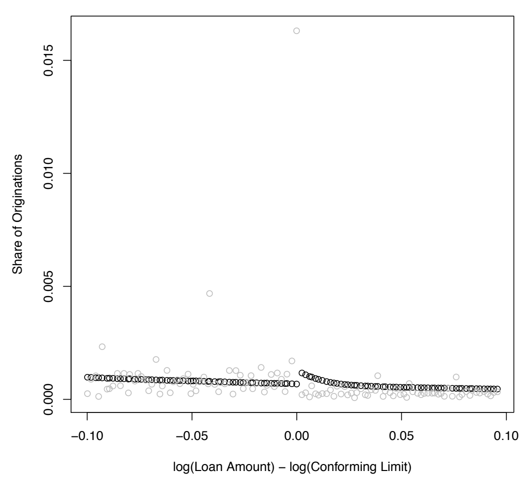
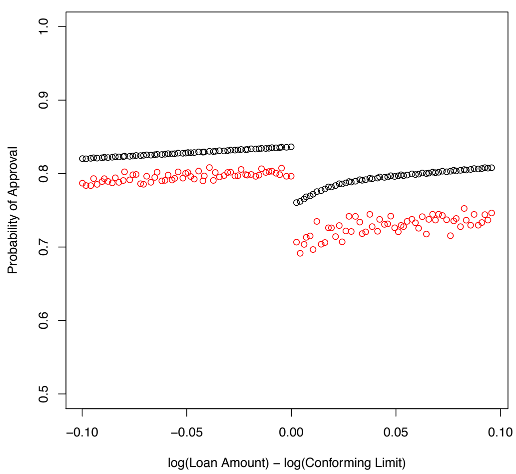


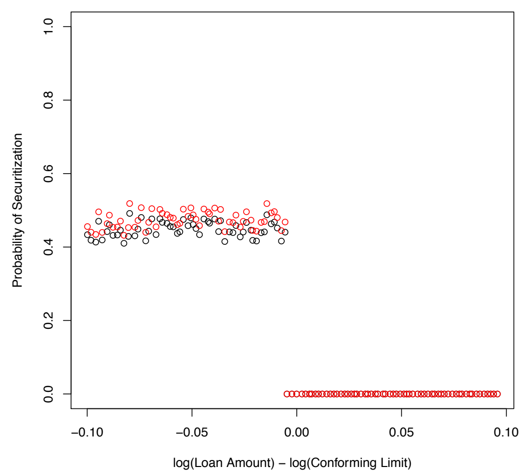
Figure 15: Impact of Increasing Disaster Risk on the Equilibrium of the Mortgage Market – with the GSEs' Securitization Activity

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 π on the equilibrium of the mortgage market. This is described in Section 6.2.1. The black points correspond to $\pi = 1\%$, and the red points are for $\pi = 1.5\%$.

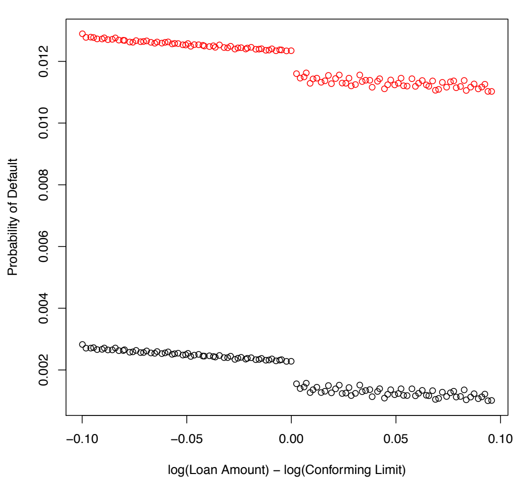
(a) Probability of Approval



(b) Probability of Securitization



(c) Default Risk



(d) Share of Originations

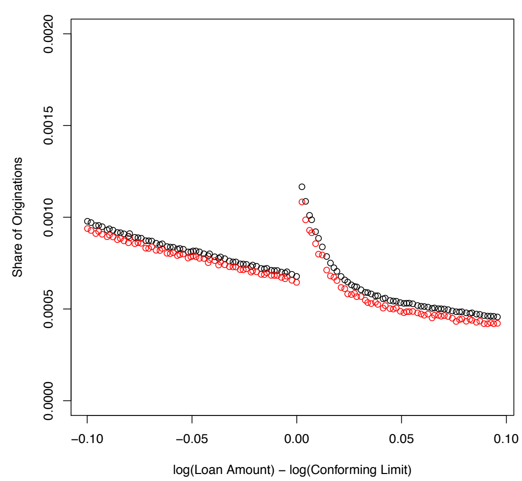
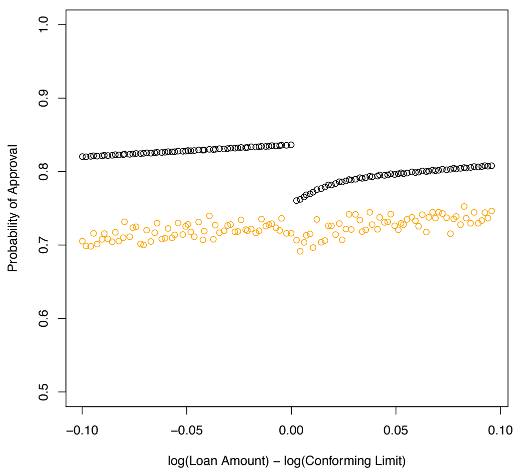


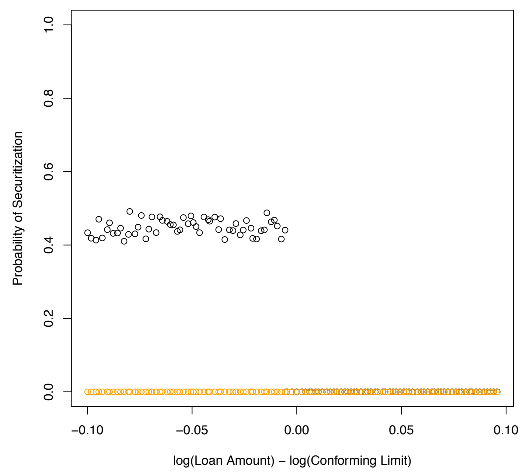
Figure 16: Increasing Risk and the Withdrawal of the GSEs

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 6.2.2.*

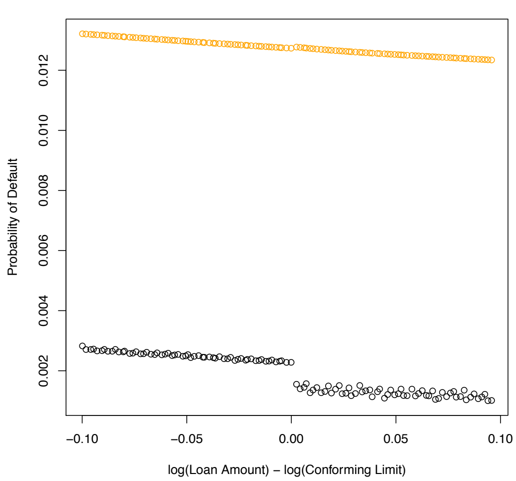
(a) Probability of Approval



(b) Probability of Securitization



(c) Default Risk



(d) Share of Originations

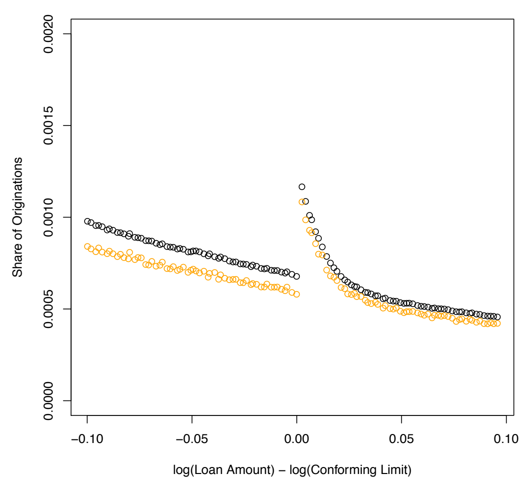


Table 1: Billion Dollar Events

This table describes the 15 'billion dollar' natural disasters occuring 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.

Year	Name	From	To	Category	States	Base Economic Damage (US $)	Normalized PL 2018	Normalized CL 2018
2005	Katrina	25-Aug	30-Aug	3	FL, LA, MS, AL	$82,200,000,000	$116,888,574,230	$118,825,443,322
2012	Sandy	30-Oct	31-Oct	1	NY	$60,280,000,000	$73,490,344,205	$72,819,173,227
2008	Ike	12-Sep	14-Sep	2	TX, LA	$25,000,000,000	$35,152,707,968	$34,686,138,787
2005	Wilma	24-Oct	24-Oct	3	FL	$20,600,000,000	$31,907,535,239	$31,922,162,521
2004	Charley	13-Aug	14-Aug	4	FL, SC	$14,000,000,000	$26,932,343,549	$27,460,765,919
2004	Ivan	12-Sep	21-Sep	3	AL, FL	$14,200,000,000	$25,893,348,510	$26,850,349,084
2004	Frances	03-Sep	09-Sep	2	FL	$9,000,000,000	$16,482,385,793	$16,476,581,358
2005	Rita	20-Sep	24-Sep	3	LA, TX	$11,254,000,000	$14,893,539,790	$14,798,423,194
2004	Jeanne	15-Sep	29-Sep	3	FL	$6,900,000,000	$13,570,831,322	$13,899,939,110
2011	Irene	26-Aug	28-Aug	1	NC	$8,600,000,000	$10,794,272,712	$10,928,324,331
2008	Gustav	31-Aug	03-Sep	2	LA	$4,300,000,000	$5,456,056,462	$5,422,320,570
2005	Dennis	04-Jul	18-Jul	3	FL, AL	$2,230,000,000	$3,542,320,160	$3,685,848,912
2005	Ophelia	09-Oct	18-Oct	1	NC	$1,600,000,000	$2,484,301,087	$2,521,769,392
2012	Isaac	21-Aug	03-Sep	1	LA	$1,940,000,000	$2,359,697,891	$2,344,120,103
2008	Dolly	20-Jul	27-Jul	1	TX	$1,050,000,000	$1,479,682,209	$1,411,245,880

PL: Pielke Landsea 2018 (PL18) methodology. CL: Collins Lowe 2018 (CL18) methodology.

Table 2: A 150-Year History of Hurricane Risk – Local Determinants, Time Trends, Idiosyncratic Risk, and Autocorrelation

The first column performs a regression of each of the 15 decennial probabilities for each of the neighborhoods on neighborhood fixed effects. It thus measures how much the "local" explains the probabilities vs. the idiosyncratic randomness. The local fixed effect explains 32% of the total variance of the probability. The second column includes in addition a fixed effect for which decade. The third column performs a regression on a linear trend, where the lhs is in decades. This predicts that over 150 years, the decennial probability of being hit has increased by 1 percentage point. The fourth column adds neighborhood fixed effects. The fifth column performs an autoregressive approach to estimate the amount of persistence, without a neighborhood fixed effect. The sixth column performs this autoregressive approach with a neighborhood fixed effect.

	(1) Decennial Probability (ppt)	(2) Decennial Probability (ppt)	(3) Decennial Probability (ppt)	(4) Decennial Probability (ppt)	(5) Decennial Probability (ppt)	(6) Decennial Probability (ppt)†
Secular Linear Trend	-	-	0.064***	0.064***	-	-
			(0.002)	(0.002)		
Lagged Probability	-	-	-	-	0.302***	2.317***
					(0.001)	(0.112)
Fixed effect	Neighborhood	Neighborhood Decade	None	Neighborhood	None	Neighborhood
Observations	1296825	1296825	1296825	1296825	1296825	1296825
Neighborhood	86455	86455	86455	86455	86455	86455
Decades	15	15	15	15	15	15
R Squared	0.32	0.33	0.01	0.32	0.09	-†

†: this specification is a dynamic panel with fixed effects. The lagged probability is instrumented by the second lag following Arellano and Bond (1991).

Table 3: Impact of Billion Dollar Events on Approvals and Mortgage Characteristics in the Conforming Segment vs. the Jumbo Segment

This table presents the estimates of the impact of billion dollar events on the discontinuity in mortgages' approval rates, applicants' and lenders' characteristics at the conforming loan limit. Mortgages with amounts between 90 and 110% of the conventional loan limit are considered in every year and every area between 1995 and 2016 inclusive. The conforming loan limit ('jumbo') 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.

	Application Approved	Loan to Income	White	Black	Hispanic	log(Income)
Below Limit × Treated × Disaster −2	+0.007	−0.029*	0.003	0.000	−0.005	0.022
	(0.008)	(0.018)	(0.005)	(0.004)	(0.004)	(0.018)
Below Limit × Treated × Disaster Year	+0.009	−0.018	0.005	−0.000	−0.007	0.004
	(0.008)	(0.021)	(0.007)	(0.003)	(0.007)	(0.010)
Below Limit × Treated × Disaster +1	+0.028***	−0.044**	0.016**	−0.003	−0.017***	0.020
	(0.009)	(0.022)	(0.008)	(0.004)	(0.004)	(0.018)
Below Limit × Treated × Disaster +2	+0.060***	−0.091***	0.045***	−0.017***	−0.028***	0.056***
	(0.012)	(0.026)	(0.007)	(0.005)	(0.006)	(0.020)
Below Limit × Treated × Disaster +3	+0.085***	−0.137***	0.045***	−0.020*	−0.018***	0.099***
	(0.023)	(0.030)	(0.015)	(0.011)	(0.006)	(0.022)
Other Controls	Below Limit, Below Limit × Treated, 5-Digit ZIP f.e., Year and Time f.e.					
Clustering	2–way 5-Digit ZIP and Year					
Observations	3,993,461	3,688,118	3,342,372	3,342,372	3,342,372	4,297,918
5-digit ZIPs	8,205	8,119	8,136	8,136	8,136	8,179
R Squared	0.045	0.118	0.231	0.203	0.235	0.180
F Statistic	22.392	59.934	121.511	103.442	124.341	113.547

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

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

This table uses BlackKnight Financial's longitudinal mortgage file to estimate the impact of billion dollar events on borrowers' credit score, loan term, and subsequent default for conforming loans vs. jumbo loans. Descriptive statistics from Blackknight financial are presented in Appendix Table A(b).

	Credit Score	Term	Foreclosure	30 d. del.	60 d. del.	90 d. del.	120 d. del.	Vol. Payoff
Below Limit × Treated × Disaster −2	−2.110	−4.268	−0.004	−0.003	−0.001	0.000	−0.000	−0.018
	(1.493)	(3.537)	(0.009)	(0.008)	(0.009)	(0.010)	(0.008)	(0.011)
Below Limit × Treated × Disaster Year	−0.117	2.686	0.009	0.015***	0.012	0.010	−0.004	−0.012**
	(0.912)	(2.521)	(0.008)	(0.006)	(0.008)	(0.007)	(0.006)	(0.006)
Below Limit × Treated × Disaster +1	−3.371*	4.680	0.036**	0.036***	0.039***	0.032***	0.013	−0.031***
	(1.962)	(3.190)	(0.018)	(0.009)	(0.014)	(0.013)	(0.010)	(0.009)
Below Limit × Treated × Disaster +2	−3.745***	6.058**	0.057***	0.033***	0.046***	0.041***	0.032***	−0.026***
	(1.180)	(3.070)	(0.008)	(0.009)	(0.012)	(0.010)	(0.005)	(0.008)
Below Limit × Treated × Disaster +3	−3.403***	3.136	0.049***	0.006	0.022**	0.024***	0.013**	−0.023***
	(1.029)	(3.193)	(0.009)	(0.007)	(0.010)	(0.009)	(0.006)	(0.009)
Other Controls	Below Limit, Below Limit × Treated, 5-Digit ZIP f.e., Year and Time f.e.							
Clustering	2–way 5-Digit ZIP and Year							
Observations	1,072,465	1,696,513	1,697,650	1,697,650	1,697,650	1,697,650	1,697,650	1,697,650
5-digit ZIPs	8,084	9,627	9,627	9,627	9,627	9,627	9,627	9,627
R Squared	0.176	0.111	0.246	0.158	0.198	0.192	0.175	0.168
F Statistic	27.915	21.608	56.772	32.610	42.833	41.334	36.952	35.223

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

Table 5: Impact of Billion Dollar Events interacted with the 168-year Hurricane History

This table estimates the differential impact of a billion-dollar disaster in ZIPs with a high historical probability of hurricanes compared to ZIPs with a low historical probability of hurricanes. The spatial distribution of such 168-year probabilities is presented in Figure 9. The second column of this table presents the interaction coefficient between each of the right-hand side variables of the first column and the 168 probability of hurricanes.

	Application Approved	× 168-year proba.
Below Limit × Treated × Disaster −2	−0.009	0.065
	(0.024)	(0.092)
Below Limit × Treated × Disaster Year	0.019	−0.078
	(0.014)	(0.057)
Below Limit × Treated × Disaster +1	0.029	−0.092
	(0.020)	(0.075)
Below Limit × Treated × Disaster +2	0.046**	−0.149*
	(0.022)	(0.088)
Below Limit × Treated × Disaster +3	0.068***	−0.273***
	(0.020)	(0.071)
Other Controls	Below Limit, Below Limit × Treated 5-Digit ZIP f.e., Year and Time f.e.	
Clustering	2–way 5-Digit ZIP and Year	
Observations	3,980,133	
5-digit ZIPs	8,216	
R Squared	0.044	
F Statistic	22.51	

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

A Natural Disasters and the Securitization Activity of Regional and National Banks

Banks' Branch Network and National Balance Sheet Data

The third data source is data on banks' reports of income and condition, collected by the Federal Financial Institutions and Examination Council (FFIEC). These data can be matched to the depository institutions that originate loans in HMDA data using a unique Replication Server System Database ID (RSSDID) and the identity of the lender's federal reporting agency. The reports of income and condition includes a range of balance sheet and income items, from which we build the following statistics: (a) the liquidity of the financial institution, defined as the ratio of cash and securities to total assets, as in Loutskina & Strahan (2009). (b) the volume of mortgages held by the financial institution. (c) the amount of recourse on mortgages sold by the institution. d) the volume of mortgage backed securities sold by the financial institution.

We match such data to the FFIEC's Summary of Deposits, Annual Survey of Branch Office Deposits. Reporting is required for all FDIC-insured financial institutions. The FFIEC collects information on the geographic location of bank branches as of June 30, the amount of deposits in each branch, the date the branch was established, and matches each branch with its corresponding national bank. The location of bank branches is then used to estimate the geographic coverage of a bank, and whether such coverage includes parts of counties hit by billion dollar event.

Which Banks React More to Billion Dollar Events?

Billion dollar events may affect the composition of the pool of lenders in disaster-struck areas. For instance, large, liquid lenders that were more likely to originate jumbo loans in the first place, may respond more to billion dollar disasters by either reducing their originations of jumbo loans, or directing consumers to loan amounts below the conforming limit. For non-bank lenders that do not typically originate large volumes of jumbo loans, the impact of billion-dollar disasters may be less noticeable.

The extent of a bank's involvement in a disaster-struck area is proxied by building two geographic measures based on their branch networks: (i) first, we measure the minimum distance of its bank branches to ZIP codes hit by billion dollar disasters; (ii) second, we compute the share of each bank's branches that are located within ZIP codes hit by the natural disaster. The first and the second measures differ: while the second measure captures the bank's specialization in the area, the first measure is a proxy for a physical presence of loan officers in areas hit by the natural disaster.

This is illustrated in the case of Hurricane Katrina in Figure B. Each point is a bank branch from the Summary of Deposits. Points are colored according to the share of bank's branch network that is located in one of the treated ZIP codes. The lower-panel table suggests that in the case of Katrina, the median bank has 3.9% of its branches in the area, and the average is 22.86%, suggesting that banks that are more geographically specialized are also banks that originate a larger number of mortgages in the area.

The panel also shows that a share of mortgages are extended by banks whose brick-and-mortar branch network is far away from the event: the mean minimum log distance is about 4.98, or 90 miles (148 kilometers). There is thus a diversity of banks supplying loans prior to the billion dollar, and this section estimates the heterogeneous response of such banks to the event.

We perform a pre- post-natural disaster regression to estimate the impact of the billion-dollar event on the composition of the supply side:

$$\begin{aligned} \textit{Lender Characteristics}_{\ell(i)} = \textit{Constant} + \sum_{t=-10}^{+10} \Delta_t \text{Hit}_{id} \times \textit{Time}(t) + \textit{Time}_{t=y-y_0} \\ + \textit{Year}_y + \textit{Disaster}_d + \textit{Neighborhood}_i + \varepsilon_{it} \end{aligned} \tag{30}$$

where d indexes disasters, $\ell(i)$ is the lender of mortgage i, t indexes time, and y indexes years. Δ_t is the impact of the event on the outcome in time $t = y - y_0(d)$ relative to disaster year. $Year_t$ a year fixed effect, and ε_{it} a residual two-way clustered at the ZIP and year levels.

The regression is performed with three types of characteristics: each of the two branch network measures, and an indicator variable for FDIC insured bank lenders (Table D). The first two regressions do not include observations of non-bank lenders. The last regression includes all observations, whether the mortgage was originated by a bank or a non-bank lender. In Table D Column (1), loans tend to be more likely to be originated by more distant banks. Column (2)'s results although non-significant in years +1 and +3, suggest a similar pattern: a lower share of branches in the area for the lenders of loans originated post-disaster. Column (3) presents evidence that the long-run share of bank lenders (as opposed to non-bank lenders) increases. Since bank lenders are more likely to originate jumbo loans prior to a disaster, we should indeed expect that they would respond more to the event, consistent with this paper's main mechanism.

A subsequent set of analysis looks at the characteristics of lenders in the conforming segment:

$$
\begin{aligned}
\textit{Lender Characteristics}_{\ell(i)} = \alpha \cdot \text{Below Conforming Limit}_{it} + \gamma \text{Below Conforming Limit}_{it} \times \text{Hit}_{id} \\
+ \sum_{t=-10}^{+10} \delta_t \cdot \text{Below Conforming Limit}_{it} \times \text{Hit}_{id} \times \textit{Time}(t) + \textit{Time}_{t=y-y_0} + \textit{Year}_y \\
+ \textit{Disaster}_d + \textit{Neighborhood}_{j(i)} + \varepsilon_{it}, \qquad (31)
\end{aligned}
$$

The results of this analysis are presented in Table E. While the results of columns (1) and (2) (minimum distance and % of branches in disaster) are not statistically significant, the results of column (3) suggest that the share of FDIC lenders (bank lenders) increases in the conforming segment compared to the jumbo segment. These results hence suggest that bank lenders are more likely than non-bank lenders to shift their securitization behavior following a natural disaster.

B Comparing the Impact of Natural Disasters with the Impact of Income Shocks on Agency Securitization

This paper's results can be compared to the impacts of other types of predictable yet unpriced local shocks on securitization activity. Specifically, areas with a declining manufacturing sector should see more securitization activity as such predictable trends are not part of the GSEs' pricing of mortgage default rates: guaranty fees are not conditional on future income trends.

Local industrial structure can be, like natural disasters, observed and/or used in banks' predictions about future default. In contrast national securitizers cannot easily factor these observed trends in their securitization decisions. Hence, a secular decline in economic activity should lead to an increase in securitization volumes as lenders transfer mortgage default risk onto the GSEs' balance sheets.

Using the Census's County Business Patterns, we build county-level predictors of local employment shocks as in David, Dorn & Hanson (2013). Specifically, the Bartik measure B_{jt} is the inner product of the share of each industry $i = 1, 2, \ldots, N$ in county j in 1998 with the national log growth of employment in each industry i between years t and $t-1$ for $t = 1998, \ldots, 2017$. We consider 1998 as this is the first year of a consistent time series for 2-digit NAICS industries, as prior years present employment statistics in SIC industry classification. We then proceed by interacting Bartik-predicted local employment shocks on the discontinuity at the conventional loan limit, in regressions with the number of mortgages (the *bunching*) and the characteristics of the mortgages (the *sorting*) as left-hand side variables. The following specification formalizes this idea:

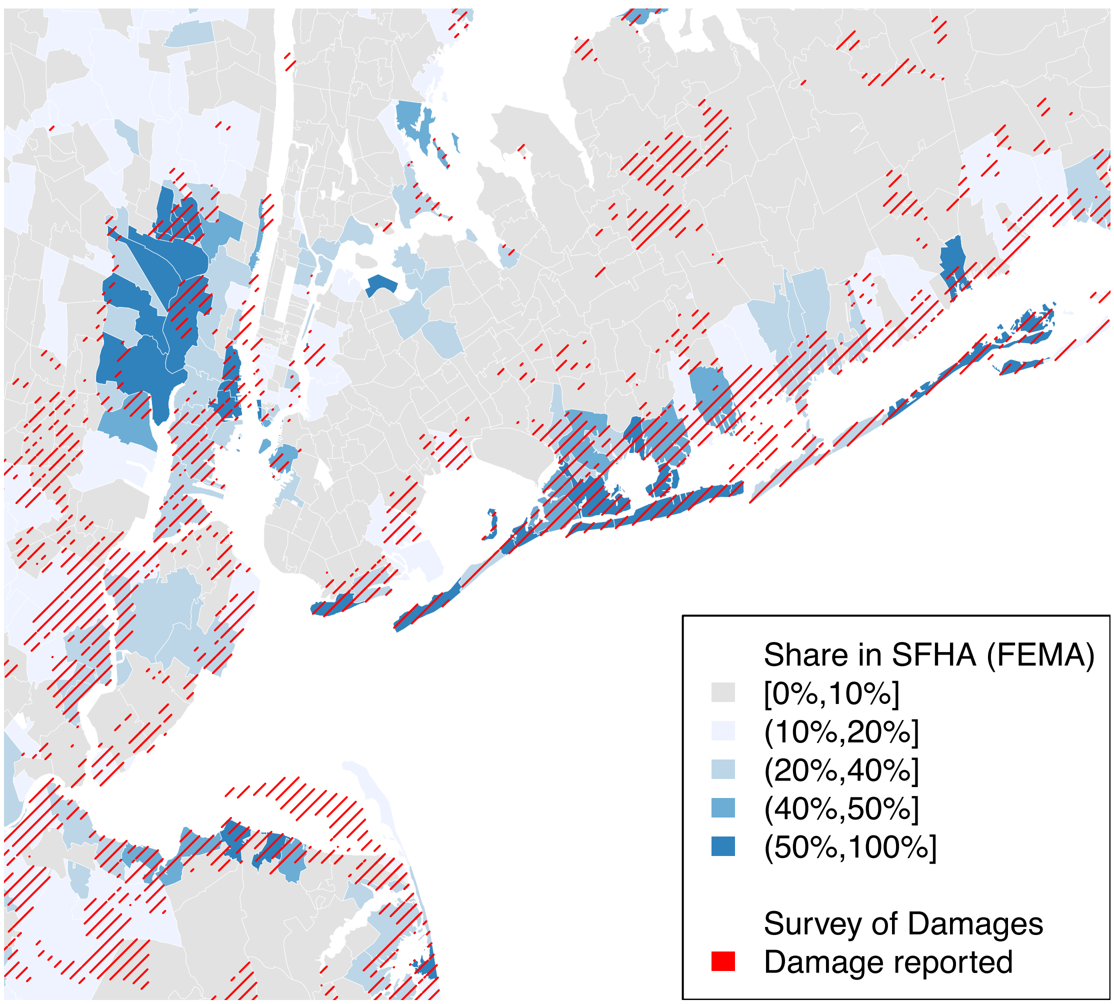
$$
\begin{aligned}
\log n_{kjt} = & \; Constant + \delta \cdot \mathbf{1}(k \geq 0) + \alpha \cdot Bartik_{jt} \\
& + \delta_b \cdot \mathbf{1}(k \geq 0) \cdot Bartik_{jt} \\
& + f(L_{kt}) \cdot \mathbf{1}(k \geq 0) + g(L_{kt}) \cdot \mathbf{1}(k < 0) + County_j + Year_t + \varepsilon_{kjt},
\end{aligned} \tag{32}
$$

and the $Bartik_{jt} = \sum_i Share\ Industry\ i_{j,1998} \cdot \Delta \log L_{it}$; and similarly with characteristics $\mathbf{x}_{it}$ as left-hand side. Bins of width 0.25 percentage points are indexed by k. As long as the local 2-digit NAICS industry share in 1998 is exogenous to local unobservable shocks in following years, the estimate $\hat{\delta}_b$ will reflect the impact of employment shocks on bunching at the conventional loan limit. $\hat{\alpha}$ is the impact of local employment shocks on origination volumes.

Results are presented in Table F. As expected a downward Bartik employment shock leads to a decline of originations across the board around the conventional loan limit. It also leads to an increase in bunching at the conventional loan limit: a billion dollar event corresponds to the effect of a $0.423/2.531 = -17\%$ employment decline.

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

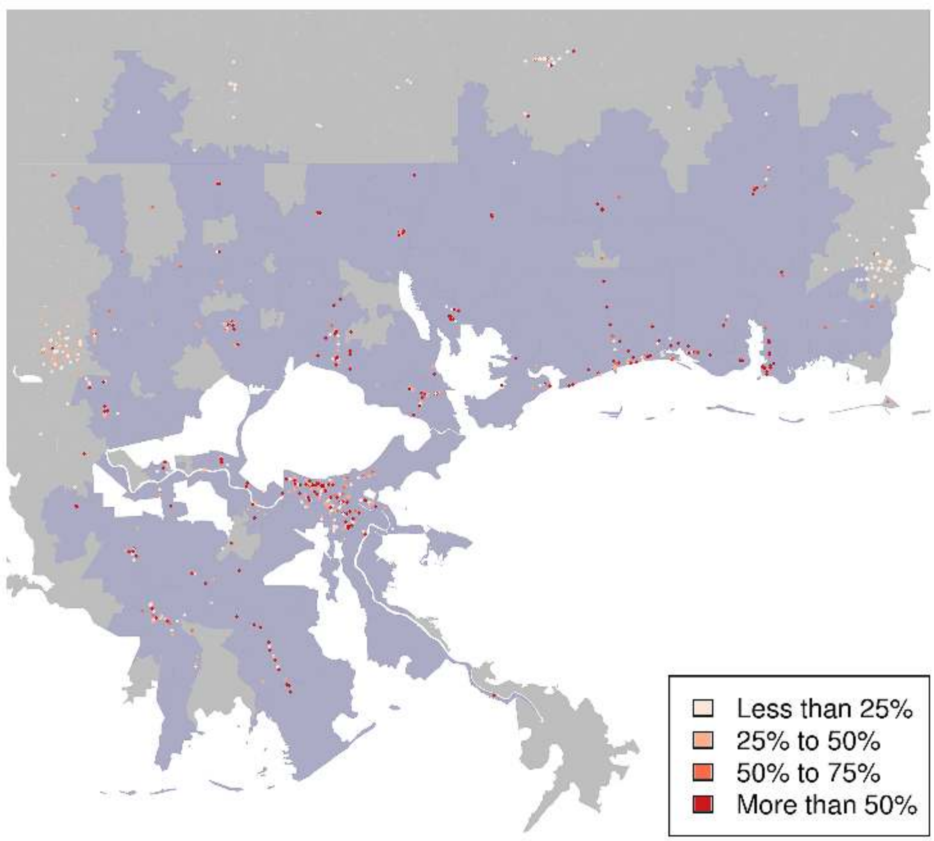
This map compares areas of the Special Flood Hazard Area maps (blue areas), where flood insurance purchase is mandated, to areas where Hurricane Sandy caused damages (red areas). The unit of mapping is the ZIP code, and the gradient of blue colors indicates the share of a ZIP code that falls within the 1% flood probability area.



Appendix Figure B: Bank Branches and Banks' Geographic Coverage of Billion Dollar Events

Each dot on this figure is a bank branch. The blue areas are 5-digit Zips hit by a billion dollar event. Bank branches are matched to their corresponding banks. Regression Table D uses two measures of a bank's geographic coverage: (i) the minimum distance of its branch network to the billion dollar event, and (ii) the share of a bank's network in zips hit. The upper panel presents a map, where the color indicates what share of a bank's branches are in the area hit by a billion dollar event, i.e. the extent to which a bank's branch network is geographically concentrated in this area. The lower panel presents descriptive statistics for the two measures. This data is built for the 15 billion dollar events described in Table 1.

(i) Share of a Bank's Network in Disaster-Struck Area: the Case of Hurricane Katrina (2005)



(ii) Descriptive statistics for the case of Hurricane Katrina

Measure	P25	Median	Mean	P75
log Minimum Distance of Branches to Area	0.00	5.20	4.98	6.55
Share of a Bank's Network in Area	0.00	3.90	22.86	31.80

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

This table describes the two main samples used in this paper: (i) the BlackKnight mortgage data set, covering up to 65% of the mortgage market, and (ii) a national universe of mortgage files, built from Home Mortgage Disclosure Act data, merged with the Federal Reserve of Chicago's Report of Income and Condition. Each of these two data sets are merged with FEMA's Billion Dollar Events, and with the average number of storms per county from NOAA. Both samples consider mortgages between 90% and 110% of the year- and county-specific conforming loan limits.

(a) Home Mortgage Disclosure Act Sample, 1995-2016

Variable	Mean	P10	P25	P50	P75	P90	Observations
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

(b) BlackKnight McDash Data Set

Variable	Mean	P10	P25	P50	P75	P90	Observations
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

Appendix Table B: Baseline Sorting Regressions – Observable Mortgage Characteristics

These regressions estimate the sorting of mortgage characteristics around the conforming loan limit, for windows of decreasing sizes around the limit. All regressions include ZCTA and year fixed effects.

	Window around conforming loan limit					
Variable	±10.0 pct	±4.0 pct	±3.0 pct	±2.0 pct	±1.0 pct	±0.5 pct
Jumbo Loan	0.871***	0.865***	0.833***	0.782***	0.680***	0.567***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.005)	(0.006)
Original Credit Score	4.723***	4.450***	4.464***	3.946***	3.727***	3.710***
	(0.374)	(0.391)	(0.449)	(0.544)	(0.755)	(0.946)
Interest Rate Differential (ppt)	0.000***	0.000***	0.000**	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Loan-to-Value Ratio	0.007***	0.010***	0.012***	0.014***	0.003*	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Combined Loan-to-Value Ratio	1.448***	1.486***	1.437***	1.007***	0.376	-0.088
	(0.169)	(0.176)	(0.206)	(0.251)	(0.353)	(0.446)
Second Mortgage	0.018***	0.018***	0.017***	0.012***	0.007	0.003
	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)	(0.006)
Full Documentation	-0.021***	-0.021***	-0.021***	-0.023***	-0.030***	-0.033***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.007)	(0.009)
Debt to Income Ratio	0.070	0.093	0.060	0.248	0.434*	0.312
	(0.133)	(0.139)	(0.157)	(0.189)	(0.262)	(0.340)
log(Property Value)	0.076***	0.065***	0.040***	0.015***	0.010***	0.007*
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.004)
Mortgage Term	4.311***	4.520***	4.612***	4.581***	3.711***	3.291***
	(0.308)	(0.321)	(0.369)	(0.462)	(0.651)	(0.878)
Fixed Rate Mortgage	-0.023***	-0.024***	-0.025***	-0.032***	-0.038***	-0.040***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.006)	(0.008)
Private Mortgage Insurance	-0.030***	-0.029***	-0.030***	-0.032***	-0.043***	-0.048***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)	(0.005)

*p<0.1; **p<0.05; ***p<0.01. Standard errors clustered at the ZCTA-year level.

Appendix Table C: Baseline Sorting Regressions – Defaults

These regressions estimate the impact of the conforming loan limit on the mortgage's payment history for windows of decreasing sizes around the limit. All regressions include ZCTA and year fixed effects.

	Window around conforming loan limit					
Variable	±10.0 pct	±4.0 pct	±3.0 pct	±2.0 pct	±1.0 pct	±0.5 pct
Foreclosure at any point	-0.020***	-0.019***	-0.018***	-0.016***	-0.017***	-0.014***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)
30 days delinquent at any point	-0.009***	-0.008***	-0.007**	-0.004	-0.005	-0.004
	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)	(0.005)
60 days delinquent at any point	-0.016***	-0.015***	-0.013***	-0.009***	-0.012***	-0.010**
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)
90 days delinquent at any point	-0.014***	-0.013***	-0.012***	-0.008***	-0.010***	-0.007*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)
120 days delinquent at any point	-0.004**	-0.003**	-0.003*	-0.001	-0.000	-0.004
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)
Voluntary Payoff	0.053***	0.052***	0.043***	0.034***	0.026***	0.011
	(0.003)	(0.003)	(0.003)	(0.004)	(0.006)	(0.007)

*p<0.1; **p<0.05; ***p<0.01. Standard errors clustered at the ZCTA-year level.

Appendix Table D: Impact of Billion Dollar Events on Banks' Mortgage Credit Supply – Overall (Conforming and non-Conforming Loans)

This set of tables estimates the impact of billion dollar events on (i) the median distance of lenders' branch network to the location of the disaster, (ii) the supply of credit by lenders whose branch network is located in the disaster area, (iii) the supply of credit by banks regulated by the Federal Deposit Insurance Corporation (FDIC), (iv) the origination of conforming loans by such FDIC-insured banks.

	(1) log(Median Distance)	(2) % of Branches in Disaster	(3) FDIC Insured Lender†
Treated × Disaster −2	−0.858	−0.009	−0.021
	(0.768)	(0.010)	(0.015)
Treated × Disaster Year	+1.762**	−0.002	+0.003
	(0.814)	(0.009)	(0.013)
Treated × Disaster +1	+1.913***	−0.007	+0.001
	(0.756)	(0.008)	(0.012)
Treated × Disaster +2	+1.388*	−0.014**	+0.1198
	(0.755)	(0.007)	(0.019)
Treated × Disaster +3	+1.391*	−0.011	+0.0415*
	(0.729)	(0.009)	(0.021)
Other Controls	Treated, 5-Digit ZIP f.e., Year and Time f.e.		
Clustering	2–way 5-Digit ZIP and Year		
Observations	1,527,061†	1,527,061†	2,547,648†
5-digit ZIPs	7,721	7,721	8,213
R Squared	0.411	0.241	0.133
F Statistic	136.438	62.072	91.150

†*: columns (1) and (2) focus on the set of loans originated by bank lenders. Column (3) includes observations from all bank and non-bank lenders. The sample is identical to the sample of the paper's baseline regressions: loans in the 90%-110% window around the conforming loan limit.*

Appendix Table E: The Response of Banks to the Billion Dollar Events – Conforming Loans vs Jumbo Loans

In contrast with the previous table, which estimated the impact of billion dollar events on the characteristics of originators irrespective of the conforming or jumbo segments, this table focuses on the characteristics of lenders in the conforming segment vs. the jumbo segment.

	(1) log(Median Distance)	(2) % of Branches in Disaster	(3) FDIC Insured Lender†
Below Limit × Treated × Disaster −2	+0.903	+0.007	+0.007
	(0.550)	(0.008)	(0.012)
Below Limit × Treated × Disaster Year	+0.420	+0.005	−0.003
	(0.364)	(0.005)	(0.010)
Below Limit × Treated × Disaster +1	+0.090	+0.0029	+0.014
	(0.439)	(0.008)	(0.016)
Below Limit × Treated × Disaster +2	−0.228	−0.012	+0.062***
	(0.331)	(0.007)	(0.016)
Below Limit × Treated × Disaster +3	+0.353	−0.030	+0.078***
	(0.398)	(0.027)	(0.026)
Other Controls	Below Limit, Below Limit × Treated 5-Digit ZIP f.e., Year and Time f.e.		
Clustering	2–way 5-Digit ZIP and Year		
Observations	1,527,061†	1,527,061†	2,547,648†
5-digit ZIPs	7,721	7,721	8,213
R Squared	0.413	0.309	0.133
F Statistic	136.72	50.07	90.91

Appendix Table F: Impact of Bartik Shocks on the Bunching at the Conforming Loan Limit

This table estimates the impact of labor demand shocks on the bunching at the conforming loan limit. Labor demand shocks are predicted using a Bartik (1991) type predictor of employment growth $Bartik_{jt} = \sum_i Share\ Industry\ i_{j,1998} \cdot \Delta \log L_{it}$ *where* $Share\ Industry\ i_{j,1998}$ *is the share of industry i in the employment of county j in 1998, and* $\Delta \log L_{it}$ *is the national log employment growth in industry i.*

	Dependent variable (Counts):			
	(1)	(2)	(3)	(4)
	log(Applications)	log(Originations)	log(Denials)	log(Securitizations)
Employment Growth Bartik Predictor	0.993***	1.065***	-0.395	2.091***
	(0.407)	(0.379)	(0.266)	(0.391)
Above Conforming Limit	-0.666***	-0.560***	-0.291***	-0.567***
	(0.009)	(0.009)	(0.006)	(0.008)
× Employment Growth Bartik Predictor	1.943***	2.531***	0.519***	-0.124
	(0.323)	(0.327)	(0.203)	(0.271)
Other Controls	Polynomial in $\log(Loan) - \log(Conforming\ Loan\ Limit)$			
R Squared	0.63	0.56	0.45	0.53
Observations	859679	859679	859679	859679
F Statistic	472.49	356.14	224.45	309.83

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