TRACING OUT CAPITAL FLOWS:

HOW FINANCIALLY INTEGRATED BANKS RESPOND TO NATURAL DISASTERS

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ABSTRACT

Multi-market banks reallocate capital when local credit demand increases after natural disasters. Following such events, credit in unaffected but connected markets declines by about 50 cents per dollar of additional lending in shocked areas, but most of the decline comes from loans in areas where banks *do not* own branches. Moreover, banks increase sales of more-liquid loans in order to lessen the impact of the demand shock on credit supply. Larger, multi-market banks appear better able than smaller ones to shield credit supplied to their core markets (those *with* branches) by aggressively cutting back lending outside those markets.

1. INTRODUCTION

This paper traces out how multi-market banks alter their credit supply decisions in response to local, exogenous shocks to credit demand stimulated by natural disasters. We find that financially integrated banks *reallocate* funds toward markets with high credit demand and away from other markets ("connected markets") in which they lend. Thus, credit seems to flow within banks toward high-return markets (where demand is high), and away from lower-return ones within banking organizations. On average, credit supplied by banks to connected markets declines by about 50 cents per dollar of increased lending in their shocked areas.

Why might shocks to loan demand affect credit supplied to connected markets by banks exposed to disasters? The short answer is that lenders must finance higher loan demand. The longer answer: banks face frictions in accessing external financing, both because issuing additional deposits and raising equity is expensive, and because selling loans to third parties is often difficult or impossible. Hence, exposed banks may have to cut lending in connected markets to have the balance sheet capacity to accommodate higher demand. Whether or not the decline lowers *overall* credit supply in connected markets depends on the presence of a second, asset-side friction. If some of the displaced lending is to borrowers over which the affected bank has a cost advantage relative to competing banks, then aggregate supply would fall. Absent such advantages, other banks could step in to replace the connected bank, or the connected bank could sell loans to third parties.

We find that the decline in lending in connected markets is concentrated outside of banks' core markets, which we define as those where the bank has a branch presence. Existing evidence suggests that a bank's physical presence in a market improves access to information about borrower quality and the value of collateral (Berger et al., 2005; Degryse and Ongena, 2005; Loutskina and Strahan, 2009; Agrawal and Hauswald, 2010; Ergungor, 2010; Cortés, 2012). Better than average access to local information can allow banks to earn rents, but also erects a barrier to loan sales and/or securitization.[1] Our findings suggest that banks protect rents that they are able to earn in their core markets (or more correctly quasi-rents, as it is costly to build a local infrastructure), by cutting lending sharply in markets where their ability to generate rents are less important (i.e. markets where they lend without a physical presence). Since other lenders can replace the lost credit in these non-core markets, where the exposed banks have no particular informational or cost advantage, aggregate effects on credit supply to connected markets are likely to be small.

We exploit natural disasters – hurricanes, earthquakes, tornadoes, floods, etc. – to generate exogenous increases in local credit demand, and test how these increases in demand affect lending in *other* markets connected to banks exposed to the shocks. Local credit demand increases in response to disasters because residents need to re-build destroyed or damaged physical capital. Local borrowers receive direct monetary support from the United States Federal Emergency Management Association (FEMA), and they supplement these funds by borrowing from banks. Banks themselves also are encouraged by their regulators to extend loans to borrowers in areas that have been hit by natural disasters. In the first portion of our analysis, we document that lending increases significantly during the months following disasters, with the maximum increase occurring about 6 months after the shock.

[1] Ashcraft (2006), Becker (2007), and Gilje (2012), for example, also show that the supply of local bank finance affects investment.

To test how credit *supply* responds to exogenous demand increases, we focus on loan originations in connected markets, those where banks lend before the disaster strikes but are not directly affected by the natural disaster itself. Thus, identification assumes that loan demand in (non-shocked) connected markets is unaffected by the natural disasters. To validate this assumption, we report a placebo test whereby markets are randomly (and thus mostly falsely) assigned as shocked. These tests reveal no change in lending to markets connected to the placebo-shocked markets, validating the premise of our strategy.

To generate our empirical model, we build a panel dataset of loan originations at the bank-county-month level. We use county to define the local credit market, and build the panel at monthly level (rather than yearly) because the timing of the natural disasters is important. Disasters strike in all months throughout the year but, as we will document, their effects on demand dissipate to nearly zero within one year's time. For lending, we use data on mortgage originations reported to regulators under the Home Mortgage Disclosure Act (HMDA). These are the only data that allow us to identify both the lending bank as well as the precise location of the loan (based on the county of the property securing the mortgage). HMDA data are sufficiently rich to allow us to estimate how changes in originations vary across different segments of the mortgage market. For example, we find that originations decline most for mortgages that can be easily securitized – those falling below the jumbo-loan threshold – which suggests that banks protect their lending originations in the most profitable segments of the credit markets. Despite this fall, rates of securitization of non-jumbo mortgages increases in connected markets, especially for smaller banks.

We show that larger banks are better able to shield lending in their core markets from demand shocks elsewhere relative to smaller banks. This difference reflects two advantages of size. First, large banks have access to national debt and equity markets that can be used to finance increased lending demand, while small banks rely heavily on deposits as their marginal source of funds. Second, large banks lend in more markets where they have no branches, and they tend to sell a much higher fraction of loans originated in these non-core markets, compared to small banks. Our results support these advantages of size, as we find that large banks reduce lending sharply in their non-core markets; in contrast, lending does not respond at all in the core markets where large banks have branches. Small banks protect their core lending markets by sharply increasing sales of their mortgage originations, but these sales are limited to the non-jumbo mortgage segment where the Government-Sponsored Enterprises (GSEs) – Fannie Mae and Freddie Mac – are active buyers. Hence, small banks do reduce lending in core markets; according to our estimates, these banks reduce lending in their core markets by 20-30 cents per dollar of exposure to the natural disaster.

These differences point to an advantage of bank size that has not been emphasized much in the literature, specifically that large banks can move capital into markets experiencing high credit demand without needing to restrict credit in their core markets. Large, multi-market and multi-product banks have numerous ways to move capital into areas with high demand. They can finance the new lending by increasing loan sales and securitization, by reducing loan origination in markets that can be served just as well by other lenders (e.g. markets where they have no branches), and/or by raising external funds in capital markets. These advantages need to be weighed against the costs of bank size related to subsidies from perceptions that they may be 'too big to fail' (Strahan, 2013).

A number of studies have used natural disasters to get exogenous variation in credit conditions. Morse (2011) finds that poor residents fare better across a number of outcomes following natural disasters in areas served by payday lenders. Chavaz (2014) shows that lenders with concentrated exposure to markets hit by the massive hurricanes in 2005 increased lending more than banks less concentrated in those areas. Consistent with this result, Cortés (2014) finds that areas with a greater relative presence of local lenders recover faster after disasters.[2] Our approach exploits all natural disasters that occurred between 2001 and 2010, and measures the effects of these well-defined events on actual lending growth. This approach allows us to build a very rich dataset with many events (and thus many degrees of freedom); by using actual lending changes in affected markets to measure the quantitative magnitude of these events, we can include major hurricanes along with smaller and more localized shocks in a single empirical framework.

Our study contributes to an emerging literature that tries to understand the role of banks in integrating portions of local credit markets where arm's length transactions (e.g. securitization) are limited by information frictions. By allowing credit to flow between markets, financial integration changes the effects of local credit-demand shocks. Ben-David, Palvia and Spatt (2014) find that deposit rates paid increase when banks face strong external loan demand. Loutskina and Strahan (2014) study the US housing boom of the 2000s and show that local booms were made larger by capital inflows fostered by both securitization and branch banking.[3] The increase in lending in booming areas such as Sun Belt states came at the expense of less-

[2] Several other recent papers have focused on discrete and massive events, such as Hurricane Katrina. Lambert, Noth and Schuwer (2012) find that banks attempt to accumulate capital following the shock. Massa and Zhang (2013) use Katrina as an exogenous force leading insurance companies exposed to losses to fire sale bonds; they find declines and later reversals in the prices of such sold bonds.

[3] Previous research has also studied how financial integration through interstate banking reform affected economic volatility and business cycle synchronization by allowing credit-supply shocks to be smoothed across geographies (Morgan, Rime, and Strahan (2004); Demyanyk, Ostergaard, and Sorenson (2007)). Financial integration at the global level have similarly been shown to help smooth shocks to the financial sector through cross-country risk sharing (e.g. Peek and Rosengren, 2000; Bekaert, Harvey and Lundblad, 2005; Kalemli-Ozcan, Papaioannou, and Peydró, 2010; Imai and Takarabe, 2011; and Cetorelli and Goldberg, 2012; Schnabl (2012).

booming areas. Consistent with this idea, Chakraborty, Goldstein, and Mackinlay (2013) find that local business lending declined when banks reallocate capital toward areas with housing booms, but that this result does not hold for large nationwide lenders. Our paper looks at the same economic mechanism using a fully disaggregated approach and with a novel strategy to identify exogenous credit demand shocks. Consistent with Chakraborty et al, we find that size helps banks insulate their connected credit markets from demand shocks.

Our paper is most closely related to Gilje, Loutskina and Strahan (2014), who use the HMDA mortgage originations data to study how financially integrated banks respond to exogenous increases in funding availability from wealth inflows related to shale gas and oil booms. In that study, banks receiving funding windfalls expand lending *only* in markets where they have a branch presence. In this paper, we find that in response to higher demand for loans in some markets, banks cut lending in connected markets most where they have *no* branch presence.

What explains the asymmetry? Banks receiving positive liquidity windfalls optimally expand the size of their balance sheet to take advantage of a lower cost of internal funds; such an increase comes from both new loan originations as well as additional securities holdings (Plosser, 2013). The increase in lending, however, only shows up in markets where banks have an informational advantage based on the presence of a branch. Absent a source of market power in lending, such as information or monitoring advantages from a local branch presence, funding inflows are used to increase holdings of marketable securities rather than loans. In contrast, banks that experience credit demand shocks that require additional funding reduce loans most in markets where they possess little or no market power – markets without a branch presence. Thus, banks appear to protect the rents that they can earn in core markets when they can. As noted earlier, small banks have fewer funding options than larger ones and, as we show, cut lending more in their core markets.[4]

2. Data & Empirical Methods

2.1 Data

The Spatial Hazard Events and Losses Database for the United States (SHELDUS) is a county-level hazard data set covering the U.S., with different natural hazard event-types such as thunderstorms, hurricanes, floods, wildfires, and tornados. For each event, the database includes the beginning date, location (county and state), property losses, crop losses, injuries, and fatalities that affected each county. The data were derived from several existing national data sources such as National Climatic Data Center's monthly storm data publications. Our sample starts with all natural disasters reported in SHELDUS that occurred in the US states between 2001 and 2010 and includes those in which the Governor declared a 'state of emergency' with a formal request for Federal Emergency Management Agency (FEMA) funds to respond to the disaster. Thus, we include only relatively large disasters.

Table 1 reports summary statistics on the number of affected counties, total property damages, and the distribution of property damages across eight types of disasters. Overall there are 5,501 counties affected by the disasters (about 500 per year). Hurricanes, while relatively rare, each affect a large number of counties per event due to their massive scale, so we have more than 1,500 counties affected by them. Severe storms affect even more counties (over 3,000 in total) due to their high frequency, even though each one is typically limited in scope. All of the disasters in our sample are severe because since a 'state of emergency' had to have been

[4] Berrospide et al (2013) find that banks also protect their core markets from declines in lending stemming from lender distress during the housing collapse in 2007-2009.

declared, but that severity varies substantially by type. Most of the disasters mete out relatively small losses at the median, but all types mete out significant damages in the tails of the distribution. For example, tornado losses exceeded $160 million at the 99th percentile; hurricane losses exceeded $1.3 billion in tail events; even severe blizzard losses exceeded $6 million at the top end of the distribution. As we describe in detail below, we construct our variables to account for the severity of each event.

In our core models, we measure lending outcomes at the bank-county-month level, focusing on data on mortgage originations collected under the *Home Mortgage Disclosure Act* (HMDA). The annual publicly available version of the HMDA data does not include the exact date for each loan-application record, but we have access to the confidential version of these data, which do allow us to measure mortgage originations at monthly frequency. Information on timing is important in our setting because, as we show below, the effects of disasters on credit dwindle to zero by 12 months post-shock. Whether a lender is covered in HMDA depends on its size, the extent of its activity in a Central Business Statistical Area, and the weight of residential mortgage lending in its portfolio. That said, the bulk of residential mortgage lending activity is likely to be reported.[5] We map the HMDA data into bank asset size and branch location data from June of the prior year using the FDIC's *Summary of Deposits* data.

We drop large banks - those with total assets above $2 billion – from our study, leaving us with a sample of small and medium-sized banks. While we think that capital flows within

[5]Any depository institution with a home office or branch in a CBSA must report HMDA data if it has made a home purchase loan on a one-to-four unit dwelling or has refinanced a home purchase loan and if it has assets above $30 million. Any non-depository institution with at least ten percent of its loan portfolio composed of home purchase loans must also report HMDA data if it has assets exceeding $10 million. Consequently, HMDA data does not capture lending activity of small or rural originators. U.S. Census shows that about 83 percent of the population lived in metropolitan areas over our sample period.

large banking organizations are important, our preliminary empirical analysis suggests that the shocks driving credit demand variation are just too small to have a meaningful impact on the largest institutions. For example, even a shock as large as Hurricane Katrina affected only about 5% of the 2,777 counties in which Bank of America actively supplied mortgage credit in 2005. Most of the natural disasters in our data are, of course, much smaller and more localized than Katrina, and thus would have minimal effects on the credit demand faced by very large banks.

The HMDA data include loan size, whether or not a loan was approved, as well as some information on borrower characteristics. Loans above a certain size cutoff may not be sold to one of the Government-Sponsored Housing Enterprises, Fannie Mae and Freddie Mac (the GSEs). Jumbo mortgages are thus less liquid than non-jumbos (Loutskina & Strahan, 2009), so we will disaggregate our results based on this size cutoff in some of our tests. HMDA reports both the identity of the lender as well as the location of the property down to the census-tract level. These are the only comprehensive data on lending by US banks that allow us to locate borrowers geographically.[6] HMDA also contains information on the purpose of the loan (mortgage purchase loans, home-equity loans, and mortgage re-financings). We include only mortgages for home purchase in our tests. HMDA also flags whether the lender expects to sell or securitize the loan within one year of origination. We use this flag to test whether loans easier to finance in securitization markets respond differentially to the local credit demand shocks.

2.2 Natural Disasters as a Shock to Credit Demand

We use the FEMA-disaster subset of the SHELDUS data to measure exogenous changes in credit demand at the local level. Demand increases after disasters because affected residents

[6] Other loans types of loans, particularly those to small businesses who depend on banks, would be interesting to study. Detailed and comprehensive data by lender and location, however, are scarce for the small business sector.

need to rebuild damaged homes and businesses. Some of the funds for rebuilding come from FEMA directly, and affected individuals supplement these funds by borrowings from banks. In fact, banks themselves are encouraged to increase credit availability after many of these shocks by their regulators. Following the flooding in Colorado in 2013, for instance, the Federal Deposit Insurance Corporation (FDIC) issued a Financial Institutions Letter to local lenders (FIL-39-2013) with the following language: "The FDIC has announced a series of steps intended to provide regulatory relief to financial institutions and facilitate recovery in areas of Colorado affected by severe storms, flooding, landslides, and mudslides." And, "Extending repayment terms, restructuring existing loans, or easing terms for new loans, if done in a manner consistent with sound banking practices, can contribute to the health of the local community and serve the long-term interests of the lending institution."

To validate the basic premise of our identification strategy, we first test whether lending is abnormally high in the months immediately following natural disasters. We do so by constructing a panel dataset at the county-month level of (the log of) total mortgage applications (including applications to all lenders, not just those in our sample), and regress this variable on county and month fixed effects, plus a series of event-time indicator variables defined around the date of each natural disaster, as follows:

$$\textit{Log Mortgage Originations}_{j,t} = \alpha_j + \gamma_t + \Sigma\beta^k D^k_{j,t} + \varepsilon_{j,t}\,, \qquad (1)$$

where j indexes counties (α_j are county-level fixed effects), and t indexes months (γ_t are time effects). Event-time indicators ($D^k_{j,t}$) run from k = -3 (3 months before the disaster) to k = +12 (12 months after the disaster), where k = 0 represent the month in which the shock itself occurs.

Figure 1 reports the β coefficients from our estimate of (1), along with standard error boundaries representing the 95th percentile confidence interval around them. These coefficients measure abnormal mortgage originations, relative to each county's long-run average (absorbed by the α_j) and relative to the time-average across all counties (absorbed by the γ_t). Figure 1 shows no abnormally high or low levels of lending before the disaster (consistent with the disaster being exogenous and unexpected). The F-test on the pre-shock indicators equals 0.39 with a p-value of 0.76. Abnormally high levels of lending do occur after the disasters, starting in month +2, consistent with an increase in loan demand due to the shock. The F-test on the post-shock indicators equals 3.65 with a p-value of 0.0006. The increase in lending peaks about 6 months after the shock (about 3% above normal), and then dissipates by the end of 12 months.

The preliminary results in Figure 1 key off lending in the mortgage market, which is likely not the only (or even the main) lending market affected by natural disasters. For example, construction loans are likely to be spurred substantially by the need of local residents to rebuild. Consistent with the idea that overall credit demand rises, Cortés (2014) uses *Call Report* data to show that small banks with at least 65% of their branches in one market increase total lending by about 25% during the year following a local natural disaster, and that most of that increase occurs in the two quarters following the shock.[7]

2.3 Modeling how Demand Shocks Affect Lending in Connected Markets

To study capital movements within banks, we build a panel dataset at the bank-county-month level, using the HMDA data on mortgage originations from 2001 to 2010. For each bank-month, we include all of the counties in which that bank originated some mortgages in the prior

[7] *Call Report* data do not report information on borrower location; hence, it is not useful for understanding lending by multi-market banks across their various markets, as we focus on below.

year. These counties are assumed to be the relevant lending markets for each bank. For example, if a bank originated mortgages in 25 counties last year, that bank would generate 300 observations this year (=12 months times 25 counties). We then flag each county in the month in which that county experienced a natural disaster, and leave that flag on during the next 12 months. Changes in lending during these 12 months are assumed to stem from extra credit demand due to the shock (recall Figure 1). We drop these 'shocked' county-months from our bank-county-month dataset because our aim is to test how the shock affects lending in connected markets.[8] The incremental lending by each bank in the shocked county-months provides a proxy for the higher demand experienced by these banks as a consequence of the natural disaster. Since banks operate across different numbers of connected (non-shocked) markets, we parcel out the increase equally across each of these markets. Analytically,

$$Shock_{i,t} = \Delta Lending\text{-}in\text{-}shocked\text{-}counties_{i,t} \,/\, N_{i,t}\,, \qquad (2)$$

where i represents banks and t represents months. The variable $\Delta Lending\text{-}in\text{-}shocked\text{-}counties_{i,t}$ equals the change in the total dollar-value of mortgage loans between month t and month $t\text{-}1$ originated by bank i, summed across all markets in which bank i operates that are flagged as shocked in month t; $N_{i,t}$ equals the number of non-shocked markets connected to bank i in month t. Notice that the shock varies at the bank-month level (as opposed to the bank-county-month level).[9]

[8] We also drop these shocked counties for an additional 12 months to be sure that credit demand there has returned to normal.

[9] We have also checked that the measure each bank's exposure to natural disaster, which is based on its actual lending changes in shocked areas, is strongly correlated with each bank's relative exposure to the property losses associated with disasters based on the location of their branch network. This alternative measure has a Spearman (rank) correlation of about 0.45 with the measure used below. We prefer our approach because, unlike the property-loss data, changes in lending (scaled by total lending) do not generate severe outliers in the right-tail of the distribution.

We estimate the effect of each bank's additional lending from the demand increase in the shocked areas on its lending originations in connected (non-shocked) markets, as follows:

$$\Delta Lending_{i,j,t} \,/\, Total\ Lending_{i,t} = \alpha_{i,j} + \gamma_{j,t} + \Sigma\, \beta^k Shock_{i,t\text{-}k} \,/\, Total\ Lending_{i,t} + \varepsilon_{i,j,t}\ , \quad (3)$$

where j indexes counties, i indexes banks, t indexes months, and k indexes lags of the exposure variable (we include 12 lags).[10] County-month effects ($\gamma_{j,t}$) sweep out potentially confounding factors affecting all lenders in a given county-month (such as unobserved local credit demand shocks, business cycle effects, trends, etc.). We also remove bank-county effects ($\alpha_{i,j}$), although we introduce interaction effects between bank characteristics and the shocks in some models. We divide both dependent and the key explanatory variables by each bank's total lending in month t as a normalization that will help reduce heteroskedasticity.[11] Note that banks operating in just one market play no direct role in estimating the β^k coefficients, since their exposure to natural disasters in non-shocked markets would always equal zero. We leave them in the model, however, because they help pin down the $\gamma_{j,t}$ and thus improve the model's power to sweep out potentially confounding credit-demand effects.

The magnitude of shocks, which differ widely depending on the severity of disasters, is captured implicitly because we measure the total change in lending experienced by a bank in all of its shocked areas. For example, a string of tornados hit 14 counties in Ohio in August 2003, and on average banks lent \$15 million more per month in the year following the disaster in the affected counties than in the six months prior to the shock. Lending changes will be large

[10] Abnormal loan volume following natural disasters declines to zero by 12 months out, as shown in Figure 1. But we have also estimated equation (3) with 18 and 24 lags and find that these additional lags are small and not statistically significant.

[11] Both the change in lending and the explanatory shock are bounded between -1 and 1 when scaled by total lending by design in order to measure succinctly the resulting contraction in lending in dollars in a response to a shock.

following large shocks (e.g. Katrina) and small following smaller ones (e.g. severe storms, blizzards, etc.).

We also include the log of bank assets as an additional time-varying, bank-level control variable (time invariant bank-county characteristics, such as the exact distribution of its branches, get absorbed by the $\alpha_{i,j}$).[12] Since the regression is built from dollar-changes in lending (normalized) parceled evenly across markets, the sum of the β coefficients from equation (3) can be interpreted as the total effect per dollar of increased lending in the shocked market on lending in the bank's connected, non-shocked markets. Thus, we expect the sum of these coefficients to lie between zero and -1. Since the key variables of interest – each bank's lags of exposure to the demand shocks – do not vary across counties, we cluster by bank in building standard errors.[13]

Table 2 reports summary statistics for the panel data used to estimate our regressions. There are 7,336,224 bank-month-county observations in the main sample from 2002-2010. We use disasters from 2001 to identify the lags for 2002 going back 12 months, so 2001 does not appear in the regression. The mean for the dependent variable equals 0.0356. The mean of the key explanatory variable $Shock_{i,t}$ equals 0.0026 (compared to just 0.0008 for the placebo specification). Recall that $Shock_{i,t}$ has a zero value for many observations: all bank-county-month observations in which the bank did not have any exposure to a market experiencing a natural disasters over the past year. For non-zero values, $Shock_{i,t}$ averages 0.0069. Since the average bank has 18 non-shocked markets at the time of a disaster, the average growth in lending

[12] Our main results are not sensitive to whether or not we include the bank-size measure; most of the effects of bank characteristics are absorbed by the bank*county fixed effects.

[13] We have also tried clustering by state and estimate standard errors smaller than those reported here.

in the shocked markets equals about 12.4% (0.0069 * 18). While not displayed in Table 2, there are 6,414 unique banks in the sample, and the median number of branches per bank is 5.

3. RESULTS

First, we report our baseline model for all bank-county-year observations, and compare those results to the placebo test (Table 3). Second, we separate the sample to explore how variation across market types (core markets, those with branches v. non-core markets, those without) and bank types (larger banks v. smaller ones) affects responses to shocks (Tables 4 & 5). Third, we go back to the pooled approach and disaggregate changes in lending (the dependent variable) based on mortgage size (jumbo v. non-jumbo) and whether or not a loan is retained or sold by the originating bank (Tables 6 & 7). Last, we combine the second and third approaches (Tables 8-10).

3.1 Baseline Model & Placebo Test

Table 3, column 1 reports the simplest model with all bank-county-years included. We report the coefficients on the 12 lags of exposure to the shock. These shocks are highly persistent by construction because we allow a given county's exposure to a disaster to last for 12 consecutive months. Individual coefficients are sometimes hard to estimate precisely (especially in later tests where we introduce interactions) due to multi-collinearity across the 12 lags. Thus, we focus most of our attention on the long-run effects (the sum of the coefficients), rather than on the individual lagged effects and the implied dynamics of those coefficients. The sum estimates the total impact on lending in connected markets per dollar of increased lending in shocked markets.

We find that lending falls by about 50 cents per dollar of additional lending stimulated by the shock exposure (i.e., the sum of the coefficients on the twelve lags = -0.504). The effect is large economically, but is also statistically significantly smaller in magnitude than -1, meaning that banks increase their overall lending in response to natural disasters. (A coefficient sum equal to -1 would imply that *all* of the extra lending in the shocked localities displaces lending in other markets.) Thus, banks are able to protect credit supply partially, but not fully, by selling securities, increasing loan sales and/or raising additional debt and equity funds.

Column 2 of Table 3 reports the results from the placebo test, which uses the exact same structure and data, but assigns markets as 'shocked' randomly. In setting up this test, we preserve the number and temporal distribution of the local natural disasters, but we assign them randomly across markets. We find no significant correlation between the (mostly falsely assigned) placebo exposure measures and actual lending in connected markets; the sum of the coefficients on the 12 lags is small and not significant, as are each of the individual coefficients on the 12 lags.

3.2 Variation across market-types and bank-types

Next, we test how variation in credit supply depends on market characteristics and bank characteristics. For these tests, we define core markets as those counties where a bank lent in the prior year with a branch presence; non-core markets are defined as counties where a bank lent in the prior year but without a branch presence. We divide lenders based on the number of counties (markets) in which they lent in the prior year, where 'small' banks are those active in fewer than 15 markets (the in-sample median) and 'large' banks are those active in more than 15 markets.[14]

[14] Results are similar if we divide the sample of banks by total assets rather than by number of markets.

Table 4 compares core v. non-core markets by introducing the *Branch* indicator and its interaction with the disaster exposure measures. This model allows the amount by which lending falls with exposure to shocks to vary across market types. The effect on non-core markets equals the sum across the first 12 lags, while the effect on core-market lending equals the sum across these 12 lags plus the additional 12 interaction terms. This model shows that banks protect lending in core areas. Lending falls by about 55 cents per dollar in non-core areas but just 25 cents per dollar in core areas. Both of these coefficients sums are statistically significantly greater than zero, and they are also significantly different from each other. The direct effect of the *Branch* indicator, however, is not statistically significant because most of its effects are wiped out by the bank*county fixed effect.[15]

Table 5 puts market type and bank size together by estimating the models of Table 4 after splitting the sample: Panel A reports results for small banks and Panel B for large ones. There are twice as many small banks as there are large – 5,457 compared to 2,604 – but the observation number in the regressions is much larger in Panel B because large banks operate in more markets (by definition). These results highlight a key advantage of size. Because large banks operate in many non-core areas, they have more freedom to reduce lending in those areas to accommodate demand shocks; on average, non-core markets represent 17% of all markets in which large banks lend. As Panel B shows, in non-core markets large banks reduce lending sharply, whereas we find *no significant decline* on lending in core markets. In contrast, small banks exhibit no such difference, in large part because they tend to lend almost exclusively in markets where they have branches; in contrast to large banks, non-core markets represent just 5% of the markets in which

[15] We hesitate to over interpret the time series dynamics implied by our regressors, but the interactive effects in Table 4 suggest that lending falls sharply immediately after disasters and then rebounds thereafter. The initial sharp drop may reflect capacity constraints in labor markets if the shocked banks re-deploy bank lending officers to the shocked markets from their core markets.

small banks lend. Thus, it makes sense that the branch interaction effects are not statistically significant for this sample (insufficient variation).

3.3 Variation across loan-types

As described in Loutskina and Strahan (2009), the mortgage market has been segmented by the activities of the GSEs – Fannie Mae and Freddie Mac. The GSEs enhance liquidity by buying mortgages directly from lenders and also by selling credit protection that allows such mortgages to be securitized easily by the originator. Yet the GSEs operate under a special charter limiting the size (and credit risk) of mortgages that they may purchase or help securitize. These limitations were designed to ensure that the GSEs meet the legislative goal of promoting access to mortgage credit for low- and moderate-income households. The GSEs may thus only purchase non-jumbo mortgages, those below a given size threshold. Until the Financial Crisis, the jumbo-loan limit increased each year by the percentage change in the national average of single-family housing prices, based on a survey of major lenders by the Federal Housing Finance Board. For example, in 2006 the jumbo-loan limit was $417,000 for loans secured by single-family homes. (The limit is 50% higher in Alaska and Hawaii so we exclude them from the sample in the tests on loan type.) After 2007, the practice of tying the jumbo-loan cutoff to nationwide house-price changes was abandoned in an effort to subsidize mortgage finance and slow the decline in house prices. For example, rather than reduce the cutoff as housing prices fell, they were actually maintained or increased. Moreover, after this time the jumbo-loan cutoff was changed to reflect the level of average prices across markets. Thus, the importance of GSEs in mortgage finance increased after the Crisis.

With the actions of the GSEs, the non-jumbo mortgage markets tend to be both more competitive and more liquid than the jumbo segment. Competition tends to reduce the profitability of the non-jumbo segment, whereas liquidity tends to reduce the extent to which banks need to finance these mortgages locally.[16] For example, banks facing increased credit demand elsewhere (due to natural disasters or other reasons) may respond by increasing the extent to which non-jumbo mortgages are sold or securitized.

Tables 6 and 7 test how credit supply responds to the natural disaster exposure for different mortgage-market segments (jumbo v. non-jumbo), and whether or not lenders expect to sell or retain the mortgage. In Table 6, we split the dependent variable ($\Delta Lending_{i,j,t}$ / $Total\ Lending_{i,t}$) into two pieces that sum to the original one:

$$\Delta Non\text{-}Jumbo\ Lending_{i,j,t} / Total\ Lending_{i,t} + \Delta Jumbo\ Lending_{i,j,t} / Total\ Lending_{i,t} = \Delta Lending_{i,j,t} / Total\ Lending_{i,t}. \tag{4}$$

Thus, coefficients 'add up' across columns 1 and 2 of Table 6 to those reported in Table 3.[17] Table 7 further sub-divides the dependent variable into four components that add to the total change in lending:

$$\Delta Non\text{-}Jumbo\ Sold\ Lending_{i,j,t} / Total\ Lending_{i,t} + \Delta Non\text{-}Jumbo\ Retained\ Lending_{i,j,t} / Total\ Lending_{i,t} + \Delta Jumbo\ Sold\ Lending_{i,j,t} / Total\ Lending_{i,t} + \Delta Jumbo\ Retained\ Lending_{i,j,t} / Total\ Lending_{i,t} = \Delta Lending_{i,j,t} / Total\ Lending_{i,t}. \tag{5}$$

[16] Scharfstein and Sunderam (2013) show that markets with greater lender concentration are less competitive, leading to an increase in the difference between the price of mortgages to borrowers relative to the financing costs in the mortgage-backed securities market.

[17] This adding up would hold exactly if the samples were identical between Table 3 and Table 6. They are not because we lose some observations when we disaggregate the data into the two segments by dropping Alaska and Hawaii, where the jumbo cutoff is 50% higher than in the contiguous states.

As shown in Table 6, non-jumbo lending declines much more than jumbo lending. This difference reflects two forces both leading to the same outcome: the non-jumbo segment is quantitatively larger, so there are more dollars of lending that can be siphoned off to other markets; and, the non-jumbo segment is more competitive, so reducing a given dollar of credit in that segment is less costly to banks in terms of foregone profits.

Table 7, however, shows that more than 100% of the decline in lending in the non-jumbo segment comes from declines in retained mortgages, whereas mortgages sold actual *increases*. Thus, banks use securitization to substitute for on-balance sheet finance required to lend in shock markets, thus mitigating (partially) the decline in loan originations in connected markets. This substitution is much more feasible in the non-jumbo segment because of the actions of the GSEs, which grease the wheels of the securitization process.[18] In the jumbo segment, the point estimate for sold loans is also positive, but it is small and not statistically significant.

3.4 Variation across market-, bank-, and loan-types

In our last three Tables (8-10), we disaggregate results by bank size, loan type and market type. Table 8 reports results for changes in non-jumbo and jumbo lending (retained and sold) for small banks; Table 9 reports similar models for large banks. In Table 10, we add the *Branch* indicator and its interactions with disaster exposure to the large-bank models to account for market type. (We leave out the small-bank analogue to Table 10 because, as noted earlier, small banks lend almost exclusively in core markets; as such, the interaction terms with *Branch* indicator were not significant for the small-bank sample (recall Table 5, Panel A)).

[18] The frequency with which loans are sold falls by about 25 percentage points, comparing non-jumbo with jumbo mortgages. The drop happens discontinuously around the cutoff (Loutskina and Strahan, 2011).

For small banks (Table 8), all of the declines in mortgage originations occur in non-jumbo, retained mortgages. The coefficients suggest that lending falls in this segment by about 57 cents per dollar of increased lending in shocked markets. In contrast, the point estimate for the sold loan originations is large and positive, offsetting about 2/3s of the decline in retained mortgage originations. So, small banks substitute some of the funding needed to supply credit to shocked markets by selling more of their loan originations. This finding supports Loutskina (2011), who shows that access to securitization markets enhances loan liquidity and makes banks less sensitive to changes in funding costs from monetary policy actions. The results here imply that securitization makes banks less sensitive to changes in loan demand in external markets. In the jumbo segment, loan sales and securitization are much more costly; hence this mechanism is not available.

Patterns for large banks differ from those of smaller ones. For them, overall lending declines for both sold and retained loans in the non-jumbo segment, and also for retained mortgages in the jumbo segment (Table 9). However, when we introduce the *Branch* indicator and its interactions, which allow us to compare adjustments between core and non-core markets, we see all of the declines in lending happen in large banks' non-core markets. In their core markets, we find no significant change in mortgage originations (Table 10).

4. CONCLUSIONS

In this paper we trace out movements of capital within multi-market banks. Credit demand increases in response to local shocks created by exposure to natural disasters. Banks respond by increasing credit in those areas, and by taking credit away from other markets in which they have lent. But banks mitigate the potential reductions of credit to connected markets using the loan sales/securitization markets rather than holding originated loans, as we find that small banks increase their use of these markets to mitigate declines in overall mortgage origination. This mechanism only partially shields credit supplied by small banks in their core markets connected to the shocked markets. Larger banks, in contrast, reduce credit sharply in their non-core markets, obviating the need to reduce credit in areas where they have local market expertise.

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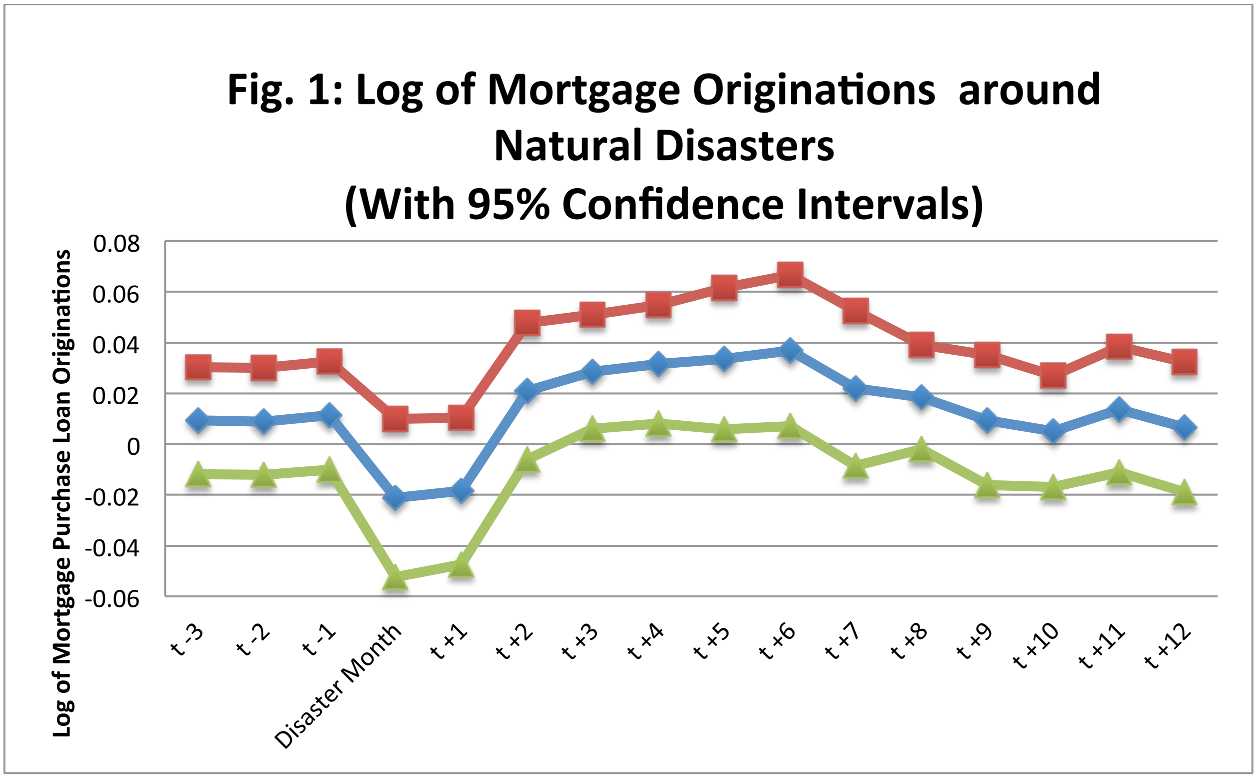
Fig. 1: Log of Mortgage Originations around Natural Disasters
(With 95% Confidence Intervals)
Log of Mortgage Purchase Loan Originations
0.08
0.06
0.04
0.02
0
-0.02
-0.04
-0.06
t -3
t -2
t -1
Disaster Month
t +1
t +2
t +3
t +4
t +5
t +6
t +7
t +8
t +9
t +10
t +11
t +12

Table 1: Property Damage from Natural Disasters

This table reports data on propery losses from natural disasters taken from the Spatial Hazard Events and Losses Database for the United States. These data are at county-level. The sample starts with all natural disasters reported in SHELDUS that occurred in the US states between 2001 and 2010 and includes those in which the Governor declared a 'state of emergency' with a formal request for Federal Emergency Management Agency (FEMA) funds to respond to the disaster.

Natural Disaster	Number of Affected Counties	Total Property Across all Counties (Billions)	Property Damage Distribution: 25th Percentile	Median	75th Percentile	95th Percentile	99th Percentile
			----------------(Millions of $s)----------------				
Coastal	68	4.82	0.1	1.0	3.2	340.0	340.0
Wildfire	280	3.43	0.0	0.1	0.4	24.0	593.0
Earthquake	16	0.08	0.0	0.0	10.6	14.6	14.6
Flooding	108	0.30	0.0	0.5	2.0	15.0	22.1
Hurricane	1,545	121	0.0	0.3	5.0	250.0	1,330.0
Severe Storm (Ice, Hail)	3,169	15	0.0	0.1	0.9	16.0	75.0
Blizzard	252	0.14	0.0	0.1	0.4	3.6	6.2
Tornado	63	0.27	0.0	0.1	0.6	15.2	130.0
All disaster types	5,501	146	0.0	0.1	1.4	44.6	510.0

Table 2: Summary Statistics Regression Variables

This table reports summary statistics for the change in monthly mortgage originations and disaster exposure used in our baseline regression models. The data are measured at the bank-county-month level, including all counties where a bank has lent in the prior year. The sample spans the years 2002 to 2010. Disaster Exposure equals the change in the total dollar-value of mortgage loans between month t and month t-1 originated by bank i, summed across all markets in which bank i operates that are flagged as having been shocked by a natural disaster in month t; we divide this by the number of non-shocked markets connected to bank i in month t. Placebo exposure is defined similarly to disaster exposure, with the difference being that shocked markets are chosen randomly. Both the change in mortgage lending and disaster exposure are normalized by each banks total mortgage originations across all of its markets.

	Observations	**Mean**	**Std. Dev.**
Change in Monthly Mortgage Originations by Total Lending	7,336,224	0.0356	0.24
Disaster Exposure	7,336,224	0.0026	0.03
Placebo Exposure	7,336,224	0.0008	0.04
Size (Log of Assets)	7,336,224	12.88	0.99
Assets (In Thousands $s)	7,336,224	601,221	515,445

Table 3: The effect of credit demand shocks on connected markets

This table reports regressions of the change mortgage originations for bank i/county j/month t on the change in lending in counties hit by natural disasters. The models include County x Month fixed effects (to absorb demand shocks) and Bank x County fixed effects (to absorb unobserved heterogeneity), with standard errors clustered by bank. The sample excludes all banks with assets above $2 billion. A county is included if the bank originated any mortgages in the prior year.

	Dependent Variable : Change in Mortgage Originations$_{i,j,t}$ / Mortgage originations$_{i,t}$	
	Disaster Exposure Based on Actually Shocked Markets	Placebo: Randomly assigned 'shocked' markets
Disaster Exposure$_{i,t-1}$	-0.0366***	0.00453
	(0.004)	(0.006)
Disaster Exposure$_{i,t-2}$	-0.0373***	-0.00416
	(0.004)	(0.007)
Disaster Exposure$_{i,t-3}$	-0.0460***	-0.00444
	(0.005)	(0.006)
Disaster Exposure$_{i,t-4}$	-0.0506***	0.0011
	(0.005)	(0.007)
Disaster Exposure$_{i,t-5}$	-0.0598***	0.00749
	(0.006)	(0.006)
Disaster Exposure$_{i,t-6}$	-0.0564***	-0.00764
	(0.006)	(0.009)
Disaster Exposure$_{i,t-7}$	-0.0767***	-0.00384
	(0.007)	(0.006)
Disaster Exposure$_{i,t-8}$	-0.0519***	-0.00449
	(0.007)	(0.009)
Disaster Exposure$_{i,t-9}$	-0.0327***	0.00125
	(0.006)	(0.005)
Disaster Exposure$_{i,t-10}$	-0.0249***	-0.00845
	(0.006)	(0.010)
Disaster Exposure$_{i,t-11}$	-0.0200***	-0.001
	(0.006)	(0.006)
Disaster Exposure$_{i,t-12}$	-0.0107**	0.000228
	(0.005)	(0.006)
Log of Bank Assets	-0.0202***	-0.0203***
	(0.003)	(0.003)
Coefficient Sum	**-0.504**	-0.019
F(1,6765487)	303.7	0.44
P-Value	0.0000	0.506
County by Time FE	Yes	Yes
Bank by County FE	Yes	Yes
Number of clusters (banks)	6,414	6,414
Observations	7,335,675	7,335,675
R-squared	0.286	0.286

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

Table 4: The effect of credit demand shocks on connected markets, Core v. Non-Core Markets

This table reports the regression of the change mortgage originations for bank i/county j/month t on the change in lending in counties hit by natural disasters, and allows the effects to vary between core markets (those with branches) and non-core markets (those without). The models include County x Month fixed effects (to absorb demand shocks) and Bank x County fixed effects (to absorb unobserved heterogeneity), with standard errors clustered by bank. The sample excludes all banks with assets above $2 billion. A county is included if the bank originated any mortgages in the prior year.

	Dependent Variable : Change in Mortgage Originations$_{i,j,t}$ / Mortgage originations$_{i,t}$		
Disaster Exposure$_{i,t-1}$	-0.0264***	Branch * Disaster Exposure$_{i,t-1}$	-0.0718***
	(0.003)		(0.017)
Disaster Exposure$_{i,t-2}$	-0.0335***	Branch * Disaster Exposure$_{i,t-2}$	-0.0336*
	(0.004)		(0.018)
Disaster Exposure$_{i,t-3}$	-0.0372***	Branch * Disaster Exposure$_{i,t-3}$	-0.0650***
	(0.004)		(0.020)
Disaster Exposure$_{i,t-4}$	-0.0460***	Branch * Disaster Exposure$_{i,t-4}$	-0.0383*
	(0.005)		(0.021)
Disaster Exposure$_{i,t-5}$	-0.0608***	Branch * Disaster Exposure$_{i,t-5}$	0.00213
	(0.005)		(0.022)
Disaster Exposure$_{i,t-6}$	-0.0628***	Branch * Disaster Exposure$_{i,t-6}$	0.0395
	(0.006)		(0.024)
Disaster Exposure$_{i,t-7}$	-0.0841***	Branch * Disaster Exposure$_{i,t-7}$	0.0521**
	(0.007)		(0.026)
Disaster Exposure$_{i,t-8}$	-0.0663***	Branch * Disaster Exposure$_{i,t-8}$	0.0991***
	(0.006)		(0.026)
Disaster Exposure$_{i,t-9}$	-0.0450***	Branch * Disaster Exposure$_{i,t-9}$	0.0892***
	(0.006)		(0.026)
Disaster Exposure$_{i,t-10}$	-0.0402***	Branch * Disaster Exposure$_{i,t-10}$	0.109***
	(0.006)		(0.025)
Disaster Exposure$_{i,t-11}$	-0.0314***	Branch * Disaster Exposure$_{i,t-11}$	0.0824***
	(0.005)		(0.024)
Disaster Exposure$_{i,t-12}$	-0.0154***	Branch * Disaster Exposure$_{i,t-12}$	0.0348
	(0.005)		(0.024)
Log of Bank Assets	-0.0203***	Branch$_{i,j,t-1}$	0.00112
	(0.003)		(0.002)
	Markets w/o branches		Markets with Branches
Coefficient Sum	**-0.549**		**-0.250**
F	366.03		7.52
P-Value	0.0000		0.0061
County by Time FE		Yes	
Bank by County FE		Yes	
Number of clusters (banks)		6,414	
Observations		7,335,675	
R-squared		0.286	

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

Table 5: The effect of credit demand shocks on connected markets, Core v. Non-Core Markets: Large v. Small Banks

This table reports the regression of the change mortgage originations for bank i/county j/month t on the change in lending in counties hit by natural disasters, and allows the effects to vary between core marke (those with branches) and non-core markets (those without). The models include County x Month fixed effects (to absorb demand shocks) and Bank x County fixed effects (to absorb unobserved heterogeneity), with standard errors clustered by bank. The sample excludes all banks with assets above $2 billion. A county is included if the bank originated any mortgages in the prior year.

Dependent Variable : Change in Mortgage Originations$_{i,j,t}$ / Mortgage originations$_{i,t}$							
Panel A: **Small Banks** (15 or Fewer Lending Markets)				Panel B: **Large Banks** (More than 15 Lending Markets)			
Disaster Exposure$_{i,t-1}$	-0.0151***	Branch * Disaster Exposure$_{i,t-1}$	-0.0581***	Disaster Exposure$_{i,t-1}$	-0.0624***	Branch * Disaster Exposure$_{i,t-1}$	-0.165***
	(0.004)		(0.020)		(0.008)		(0.042)
Disaster Exposure$_{i,t-2}$	-0.0160***	Branch * Disaster Exposure$_{i,t-2}$	-0.0321	Disaster Exposure$_{i,t-2}$	-0.0628***	Branch * Disaster Exposure$_{i,t-2}$	-0.0223
	(0.005)		(0.022)		(0.009)		(0.042)
Disaster Exposure$_{i,t-3}$	-0.0172***	Branch * Disaster Exposure$_{i,t-3}$	-0.0567**	Disaster Exposure$_{i,t-3}$	-0.0720***	Branch * Disaster Exposure$_{i,t-3}$	-0.103**
	(0.005)		(0.024)		(0.010)		(0.045)
Disaster Exposure$_{i,t-4}$	-0.0204***	Branch * Disaster Exposure$_{i,t-4}$	-0.027	Disaster Exposure$_{i,t-4}$	-0.0815***	Branch * Disaster Exposure$_{i,t-4}$	-0.0721
	(0.006)		(0.026)		(0.012)		(0.047)
Disaster Exposure$_{i,t-5}$	-0.0218***	Branch * Disaster Exposure$_{i,t-5}$	-0.00099	Disaster Exposure$_{i,t-5}$	-0.142***	Branch * Disaster Exposure$_{i,t-5}$	-0.0437
	(0.007)		(0.027)		(0.013)		(0.050)
Disaster Exposure$_{i,t-6}$	-0.0207***	Branch * Disaster Exposure$_{i,t-6}$	0.0321	Disaster Exposure$_{i,t-6}$	-0.153***	Branch * Disaster Exposure$_{i,t-6}$	-0.0164
	(0.007)		(0.030)		(0.014)		(0.050)
Disaster Exposure$_{i,t-7}$	-0.0360***	Branch * Disaster Exposure$_{i,t-7}$	0.0113	Disaster Exposure$_{i,t-7}$	-0.157***	Branch * Disaster Exposure$_{i,t-7}$	0.0574
	(0.008)		(0.033)		(0.015)		(0.053)
Disaster Exposure$_{i,t-8}$	-0.0239***	Branch * Disaster Exposure$_{i,t-8}$	0.0232	Disaster Exposure$_{i,t-8}$	-0.141***	Branch * Disaster Exposure$_{i,t-8}$	0.312***
	(0.008)		(0.033)		(0.013)		(0.049)
Disaster Exposure$_{i,t-9}$	-0.0111	Branch * Disaster Exposure$_{i,t-9}$	-0.00607	Disaster Exposure$_{i,t-9}$	-0.0979***	Branch * Disaster Exposure$_{i,t-9}$	0.398***
	(0.007)		(0.032)		(0.012)		(0.050)
Disaster Exposure$_{i,t-10}$	-0.0159**	Branch * Disaster Exposure$_{i,t-10}$	0.0434	Disaster Exposure$_{i,t-10}$	-0.0684***	Branch * Disaster Exposure$_{i,t-10}$	0.291***
	(0.007)		(0.031)		(0.011)		(0.048)
Disaster Exposure$_{i,t-11}$	-0.0183**	Branch * Disaster Exposure$_{i,t-11}$	0.012	Disaster Exposure$_{i,t-11}$	-0.0322***	Branch * Disaster Exposure$_{i,t-11}$	0.348***
	(0.007)		(0.030)		(0.010)		(0.044)
Disaster Exposure$_{i,t-12}$	-0.00722	Branch * Disaster Exposure$_{i,t-12}$	-0.00994	Disaster Exposure$_{i,t-12}$	-0.0180*	Branch * Disaster Exposure$_{i,t-12}$	0.195***
	(0.006)		(0.029)		(0.010)		(0.047)
Log of Bank Assets	-0.0453***	Branch$_{i,j,t-1}$	0.00104	Log of Bank Assets	-0.0146***	Branch$_{i,j,t-1}$	0.000946
	(0.004)		(0.004)		(0.004)		(0.002)
	Markets w/o branches		Markets with Branches		Markets w/o branches		Markets with Branches
Coefficient Sum	**-0.224**		**-0.293**	**Coefficient Sum**	**-1.088**		0.091
F	41.44		5.28	F	305		0.56
P-Value	0.0000		0.022	P-Value	0.0000		0.455
County by Time FE		Yes		County by Time FE		Yes	
Bank by County FE		Yes		Bank by County FE		Yes	
Number of clusters (banks)		5,457		Number of clusters (banks)		2,604	
Observations		1,609,550		Observations		5,726,125	
R-squared		0.257		R-squared		0.397	

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

Table 6: The effect of credit demand shocks on connected markets, Jumbo v. Non-Jumbo Mortgages

This table reports the regression of the change mortgage originations for bank i/county j/month t on the change in lending in counties hit by natural disasters. The models include County x Month fixed effects (to absorb demand shocks) and Bank x County fixed effects (to absorb unobserved heterogeneity), with standard errors clustered by bank. The sample excludes all banks with assets above $2 billion. A county is included if the bank originated any mortgages in the prior year.

	Change in Non-Jumbo Mortgage $\text{Originations}_{i,j,t}$ / Mortgage $\text{originations}_{i,t}$	Change in Jumbo Mortgage $\text{Originations}_{i,j,t}$ / Mortgage $\text{originations}_{i,t}$
Disaster $\text{Exposure}_{i,t-1}$	-0.0351***	-0.00172*
	(0.003)	(0.001)
Disaster $\text{Exposure}_{i,t-2}$	-0.0323***	-0.00533***
	(0.004)	(0.001)
Disaster $\text{Exposure}_{i,t-3}$	-0.0353***	-0.00967***
	(0.004)	(0.001)
Disaster $\text{Exposure}_{i,t-4}$	-0.0408***	-0.00995***
	(0.005)	(0.001)
Disaster $\text{Exposure}_{i,t-5}$	-0.0481***	-0.0117***
	(0.005)	(0.002)
Disaster $\text{Exposure}_{i,t-6}$	-0.0446***	-0.0122***
	(0.006)	(0.002)
Disaster $\text{Exposure}_{i,t-7}$	-0.0631***	-0.0141***
	(0.006)	(0.002)
Disaster $\text{Exposure}_{i,t-8}$	-0.0406***	-0.0107***
	(0.006)	(0.002)
Disaster $\text{Exposure}_{i,t-9}$	-0.0205***	-0.0115***
	(0.006)	(0.002)
Disaster $\text{Exposure}_{i,t-10}$	-0.0180***	-0.00587***
	(0.005)	(0.002)
Disaster $\text{Exposure}_{i,t-11}$	-0.0162***	-0.00407***
	(0.005)	(0.001)
Disaster $\text{Exposure}_{i,t-12}$	-0.00998**	-0.000456
	(0.005)	(0.001)
Log of Bank Assets	-0.0161***	-0.00419***
	(0.002)	(0.001)
Coefficient Sum	**-0.405**	**-0.097**
F	275.4	159.04
P-Value	0.0000	0.000
County by Time FE	Yes	Yes
Bank by County FE	Yes	Yes
Number of clusters (banks)	6,273	6,273
Observations	7,136,703	7,136,703
R-squared	0.241	0.284

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

Table 7: The effect of credit demand shocks on connected markets: Jumbo v. Non-Jumbo and Retained v. Sold

This table reports the regression of the change mortgage originations for bank i/county j/month t on the change in lending in counties hit by natural disasters. The models include County x Month fixed effects (to absorb demand shocks) and Bank x County fixed effects (to absorb unobserved heterogeneity), with standard errors clustered by bank. The sample excludes all banks with assets above $2 billion. A county is included if the bank originated any mortgages in the prior year.

	Change in Non-Jumbo Sold Mortgage Originations$_{i,j,t}$ / Mortgage originations$_{i,t}$	Change in Non-Jumbo Retained Mortgage Originations$_{i,j,t}$ / Mortgage originations$_{i,t}$	Change in Jumbo Mortgage Sold Originations$_{i,j,t}$ / Mortgage originations$_{i,t}$	Change in Jumbo Retained Mortgage Originations$_{i,j,t}$ / Mortgage originations$_{i,t}$
Disaster Exposure$_{i,t-1}$	0.0199***	-0.0550***	-0.00456***	0.00284**
	(0.00375)	(0.00322)	(0.00106)	(0.00138)
Disaster Exposure$_{i,t-2}$	0.0167***	-0.0490***	-0.00532***	-9.96e-06
	(0.00422)	(0.00378)	(0.00133)	(0.00160)
Disaster Exposure$_{i,t-3}$	0.0105**	-0.0459***	-0.00492***	-0.00474***
	(0.00441)	(0.00388)	(0.00150)	(0.00183)
Disaster Exposure$_{i,t-4}$	-0.0105**	-0.0303***	-0.00483**	-0.00511**
	(0.00504)	(0.00432)	(0.00190)	(0.00224)
Disaster Exposure$_{i,t-5}$	0.0129**	-0.0610***	-0.00703***	-0.00464*
	(0.00544)	(0.00474)	(0.00203)	(0.00244)
Disaster Exposure$_{i,t-6}$	0.0122**	-0.0568***	-0.00444**	-0.00772***
	(0.00594)	(0.00508)	(0.00216)	(0.00257)
Disaster Exposure$_{i,t-7}$	-0.00146	-0.0616***	-0.00747***	-0.00660**
	(0.00607)	(0.00533)	(0.00250)	(0.00296)
Disaster Exposure$_{i,t-8}$	-0.00541	-0.0352***	0.00352	-0.0142***
	(0.00567)	(0.00517)	(0.00216)	(0.00270)
Disaster Exposure$_{i,t-9}$	-0.00299	-0.0176***	0.00963***	-0.0211***
	(0.00577)	(0.00508)	(0.00203)	(0.00251)
Disaster Exposure$_{i,t-10}$	0.00463	-0.0226***	0.0131***	-0.0190***
	(0.00534)	(0.00490)	(0.00192)	(0.00240)
Disaster Exposure$_{i,t-11}$	0.00458	-0.0207***	0.0117***	-0.0158***
	(0.00519)	(0.00457)	(0.00174)	(0.00214)
Disaster Exposure$_{i,t-12}$	0.0193***	-0.0293***	0.0113***	-0.0117***
	(0.00473)	(0.00449)	(0.00153)	(0.00197)
Log of Bank Assets	-0.00708***	-0.00903***	-0.00360***	-0.000588
	(0.00136)	(0.00145)	(0.000969)	(0.000872)
Coefficient Sum	**0.080**	**-0.485**	0.011	**-0.108**
F	8.82	373.71	1.24	90.68
P-Value	0.0030	0.0000	0.265	0.0000
County by Time FE	Yes	Yes	Yes	Yes
Bank by County FE	Yes	Yes	Yes	Yes
Number of clusters (banks)	6,273	6,273	6,273	6,273
Observations	7,136,703	7,136,703	7,136,703	7,136,703
R-squared	0.24	0.128	0.139	0.154

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

Table 8: The effect of credit demand shocks on connected markets for <u>Small Banks</u>: Jumbo v. Non-Jumbo and Retained v. Sold

This table reports the regression of the change mortgage originations for bank i/county j/month t on the change in lending in counties hit by natural disasters for banks operating in fewer than 15 local markets. The models include County x Month fixed effects (to absorb demand shocks) and Bank x County fixed effects (to absorb unobserved heterogeneity), with standard errors clustered by bank. The sample excludes all banks with assets above $2 billion. A county is included if the bank originated any mortgages in the prior year.

	Change in Non-Jumbo Sold Mortgage Originations$_{i,j,t}$ / Mortgage originations$_{i,t}$	Change in Non-Jumbo Retained Mortgage Originations$_{i,j,t}$ / Mortgage originations$_{i,t}$	Change in Jumbo Mortgage Sold Originations$_{i,j,t}$ / Mortgage originations$_{i,t}$	Change in Jumbo Retained Mortgage Originations$_{i,j,t}$ / Mortgage originations$_{i,t}$
Disaster Exposure$_{i,t-1}$	0.0305***	-0.0575***	-0.00229**	0.00437***
	(0.005)	(0.004)	(0.001)	(0.002)
Disaster Exposure$_{i,t-2}$	0.0302***	-0.0509***	-0.00195	0.0014
	(0.005)	(0.005)	(0.001)	(0.002)
Disaster Exposure$_{i,t-3}$	0.0296***	-0.0501***	-0.00251	-0.00214
	(0.006)	(0.005)	(0.002)	(0.002)
Disaster Exposure$_{i,t-4}$	0.00644	-0.0277***	0.000634	-0.00403
	(0.007)	(0.006)	(0.002)	(0.003)
Disaster Exposure$_{i,t-5}$	0.0401***	-0.0597***	-0.00354	0.00142
	(0.007)	(0.007)	(0.002)	(0.003)
Disaster Exposure$_{i,t-6}$	0.0445***	-0.0589***	-0.000952	-0.000344
	(0.008)	(0.007)	(0.002)	(0.003)
Disaster Exposure$_{i,t-7}$	0.0307***	-0.0618***	-0.00754***	0.0043
	(0.008)	(0.008)	(0.003)	(0.004)
Disaster Exposure$_{i,t-8}$	0.0267***	-0.0446***	-0.000728	-0.0000423
	(0.008)	(0.007)	(0.003)	(0.003)
Disaster Exposure$_{i,t-9}$	0.0260***	-0.0302***	0.00391*	-0.0102***
	(0.008)	(0.007)	(0.002)	(0.003)
Disaster Exposure$_{i,t-10}$	0.0323***	-0.0379***	0.00639***	-0.00873***
	(0.007)	(0.007)	(0.002)	(0.003)
Disaster Exposure$_{i,t-11}$	0.0240***	-0.0395***	0.00363**	-0.00542**
	(0.007)	(0.006)	(0.001)	(0.002)
Disaster Exposure$_{i,t-12}$	0.0362***	-0.0470***	0.00462***	-0.00277
	(0.006)	(0.006)	(0.001)	(0.002)
Log of Bank Assets	-0.0120***	-0.0282***	-0.0123***	0.00798***
	(0.002)	(0.002)	(0.001)	(0.001)
Coefficient Sum	**0.357**	**-0.566**	0.000	-0.022
F	75.71	210.43	0	2.46
P-Value	0.0001	0.0000	0.9755	0.1168
County by Time FE	Yes	Yes	Yes	Yes
Bank by County FE	Yes	Yes	Yes	Yes
Number of clusters (banks)	5,313	5,313	5,313	5,313
Observations	1,568,928	1,568,928	1,568,928	1,568,928
R-squared	0.216	0.195	0.296	0.201

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

Table 9: The effect of credit demand shocks on connected markets for Large Banks: Jumbo v. Non-Jumbo and Retained v. Sold

This table reports the regression of the change mortgage originations for bank i/county j/month t on the change in lending in counties hit by natural disasters for banks operating in more than 15 local markets. The models include County x Month fixed effects (to absorb demand shocks) and Bank x County fixed effects (to absorb unobserved heterogeneity), with standard errors clustered by bank. The sample excludes all banks with assets above $2 billion. A county is included if the bank originated any mortgages in the prior year.

	Change in Non-Jumbo Sold Mortgage Originations$_{i,j,t}$ / Mortgage originations$_{i,t}$	Change in Non-Jumbo Retained Mortgage Originations$_{i,j,t}$ / Mortgage originations$_{i,t}$	Change in Jumbo Mortgage Sold Originations$_{i,j,t}$ / Mortgage originations$_{i,t}$	Change in Jumbo Retained Mortgage Originations$_{i,j,t}$ / Mortgage originations$_{i,t}$
Disaster Exposure$_{i,t-1}$	-0.0212***	-0.0451***	-0.00724*	-0.00275
	(0.007)	(0.007)	(0.004)	(0.004)
Disaster Exposure$_{i,t-2}$	-0.00923	-0.0372***	-0.00337	-0.0132***
	(0.007)	(0.007)	(0.004)	(0.004)
Disaster Exposure$_{i,t-3}$	-0.0356***	-0.0297***	-0.00201	-0.0141***
	(0.007)	(0.007)	(0.004)	(0.005)
Disaster Exposure$_{i,t-4}$	-0.0440***	-0.0238***	-0.00889*	-0.00956*
	(0.008)	(0.007)	(0.005)	(0.005)
Disaster Exposure$_{i,t-5}$	-0.0530***	-0.0567***	-0.0142***	-0.0205***
	(0.008)	(0.008)	(0.005)	(0.005)
Disaster Exposure$_{i,t-6}$	-0.0653***	-0.0489***	-0.00617	-0.0315***
	(0.009)	(0.008)	(0.006)	(0.006)
Disaster Exposure$_{i,t-7}$	-0.0556***	-0.0613***	-0.0113*	-0.0210***
	(0.009)	(0.008)	(0.006)	(0.007)
Disaster Exposure$_{i,t-8}$	-0.0520***	-0.0277***	-0.00013	-0.0296***
	(0.008)	(0.007)	(0.005)	(0.005)
Disaster Exposure$_{i,t-9}$	-0.0349***	-0.00903	0.0129**	-0.0276***
	(0.007)	(0.007)	(0.005)	(0.005)
Disaster Exposure$_{i,t-10}$	-0.0302***	-0.00179	0.0153***	-0.0239***
	(0.007)	(0.007)	(0.005)	(0.005)
Disaster Exposure$_{i,t-11}$	-0.00865	0.0113	0.0216***	-0.0235***
	(0.007)	(0.007)	(0.005)	(0.005)
Disaster Exposure$_{i,t-12}$	-0.00246	0.00533	0.0186***	-0.0213***
	(0.008)	(0.007)	(0.004)	(0.005)
Log of Bank Assets	-0.00578***	-0.00498***	-0.00187*	-0.00198*
	(0.002)	(0.001)	(0.001)	(0.001)
Coefficient Sum	**-0.412**	**-0.325**	0.015	**-0.239**
F	128.2	124	0.48	101.43
P-Value	0.0000	0.0000	0.4902	0.0000
County by Time FE	Yes	Yes	Yes	Yes
Bank by County FE	Yes	Yes	Yes	Yes
Number of clusters (banks)	2,599	2,599	2,599	2,599
Observations	5,567,775	5,567,775	5,567,775	5,567,775
R-squared	0.337	0.216	0.142	0.237

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

Table 10: The effect of credit demand shocks on connected markets forLarge Banks: Jumbo v. Non-Jumbo and Retained v. Sold, with Branch Interactions

This table reports the regression of the change mortgage originations for bank i/county j/month t on the change in lending in counties hit by natural disasters for banks operating in more than 15 local markets. The models include County x Month fixed effects (to absorb demand shocks) and Bank x County fixed effects (to absorb unobserved heterogeneity), with standard errors clustered by bank. The sample excludes all banks with assets above $2 billion. A county is included if the bank originated any mortgages in the prior year.

	Change in Non-Jumbo Sold Mortgage Originations$_{i,j,t}$ / Mortgage originations$_{i,t}$	Change in Non-Jumbo Retained Mortgage Originations$_{i,j,t}$ / Mortgage originations$_{i,t}$	Change in Jumbo Mortgage Sold Originations$_{i,j,t}$ / Mortgage originations$_{i,t}$	Change in Jumbo Retained Mortgage Originations$_{i,j,t}$ / Mortgage originations$_{i,t}$
Disaster Exposure$_{i,t-1}$	-0.0164**	-0.0329***	-0.00783*	-0.00231
	(0.007)	(0.006)	(0.004)	(0.004)
Disaster Exposure$_{i,t-2}$	-0.0138*	-0.0296***	-0.00322	-0.0157***
	(0.007)	(0.006)	(0.004)	(0.004)
Disaster Exposure$_{i,t-3}$	-0.0314***	-0.0245***	-0.00178	-0.0142***
	(0.007)	(0.006)	(0.005)	(0.005)
Disaster Exposure$_{i,t-4}$	-0.0386***	-0.0247***	-0.00769	-0.00984*
	(0.008)	(0.006)	(0.005)	(0.006)
Disaster Exposure$_{i,t-5}$	-0.0501***	-0.0569***	-0.0154***	-0.0197***
	(0.008)	(0.007)	(0.005)	(0.006)
Disaster Exposure$_{i,t-6}$	-0.0635***	-0.0519***	-0.006	-0.0299***
	(0.009)	(0.007)	(0.006)	(0.007)
Disaster Exposure$_{i,t-7}$	-0.0627***	-0.0593***	-0.0118*	-0.0222***
	(0.009)	(0.008)	(0.007)	(0.007)
Disaster Exposure$_{i,t-8}$	-0.0655***	-0.0406***	-0.00178	-0.0326***
	(0.008)	(0.007)	(0.005)	(0.006)
Disaster Exposure$_{i,t-9}$	-0.0544***	-0.0200***	0.0127**	-0.0360***
	(0.007)	(0.007)	(0.005)	(0.006)
Disaster Exposure$_{i,t-10}$	-0.0430***	-0.0104	0.0155***	-0.0285***
	(0.007)	(0.007)	(0.005)	(0.005)
Disaster Exposure$_{i,t-11}$	-0.0244***	0.00154	0.0212***	-0.0298***
	(0.008)	(0.007)	(0.005)	(0.005)
Disaster Exposure$_{i,t-12}$	-0.00877	0.000665	0.0174***	-0.0258***
	(0.008)	(0.007)	(0.005)	(0.005)
Branch * Disaster Exposure$_{i,t-1}$	-0.044	-0.126***	0.00592	-0.000789
	(0.033)	(0.042)	(0.006)	(0.011)
Branch * Disaster Exposure$_{i,t-2}$	0.0393	-0.0867**	-0.0011	0.0255**
	(0.027)	(0.035)	(0.007)	(0.011)
Branch * Disaster Exposure$_{i,t-3}$	-0.0456*	-0.0603*	-0.00237	0.00259
	(0.024)	(0.034)	(0.007)	(0.012)
Branch * Disaster Exposure$_{i,t-4}$	-0.0605**	-0.00367	-0.0113	0.00168
	(0.027)	(0.036)	(0.008)	(0.014)
Branch * Disaster Exposure$_{i,t-5}$	-0.0353	-0.00577	0.0107	-0.00882
	(0.028)	(0.034)	(0.008)	(0.014)
Branch * Disaster Exposure$_{i,t-6}$	-0.0216	0.0231	-0.00142	-0.0161
	(0.029)	(0.035)	(0.009)	(0.015)
Branch * Disaster Exposure$_{i,t-7}$	0.0640**	-0.0153	0.00438	0.0096
	(0.027)	(0.037)	(0.009)	(0.015)
Branch * Disaster Exposure$_{i,t-8}$	0.135***	0.126***	0.0157*	0.0309**
	(0.027)	(0.036)	(0.008)	(0.014)
Branch * Disaster Exposure$_{i,t-9}$	0.200***	0.114***	0.00243	0.0857***
	(0.025)	(0.036)	(0.008)	(0.013)
Branch * Disaster Exposure$_{i,t-10}$	0.144***	0.0923**	-0.00096	0.0541***
	(0.025)	(0.037)	(0.007)	(0.013)
Branch * Disaster Exposure$_{i,t-11}$	0.169***	0.0995***	0.00476	0.0692***
	(0.025)	(0.034)	(0.007)	(0.012)
Branch * Disaster Exposure$_{i,t-12}$	0.0724**	0.046	0.0121	0.0512***
	(0.034)	(0.037)	(0.008)	(0.012)
Branch	-0.000736	-0.00113	0.00110**	0.00181***
	(0.001)	(0.001)	(0.001)	(0.001)
Log of Assets	-0.00582***	-0.00496***	-0.00191*	-0.00207*
	(0.002)	(0.001)	(0.001)	(0.001)
Coefficient Sum (no branches)	**-0.473**	**-0.349**	0.011	**-0.267**
F	151.4	148.28	0.612	115.58
P-Value	0.0000	0.0000	0.6118	0.0000
Coefficient Sum (branches)	0.144	-0.145	0.050	0.038
F	2.49	2.26	3.56	0.85
P-Value	0.1140	0.1330	0.059	0.3570
County by Time FE	Yes	Yes	Yes	Yes
Bank by County FE	Yes	Yes	Yes	Yes
Number of clusters (banks)	2,599	2,599	2,599	2,599
Observations	5,567,775	5,567,775	5,567,775	5,567,775
R-squared	0.337	0.216	0.142	0.237

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