working paper

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Tracing Out Capital Flows: How Financially Integrated Banks Respond to Natural Disasters

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FEDERAL RESERVE BANK OF CLEVELAND

Working Paper 14-12R October 2015*

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Multimarket banks reallocate capital when local credit demand increases after natural disasters. Using property damage as an instrument for lending growth, we find credit in unaffected but connected markets declines by a little less than 50 cents per dollar of additional lending in shocked areas. However, banks shield their core markets because most of the decline comes from loans in areas where banks do not own branches. Moreover, banks increase sales of more-liquid loans and they bid up the prices of deposits in the connected markets. These actions help lessen the impact of the demand shock on credit supply.

JEL Codes: G20, G21.

Keywords: Financial Integration, Branch Banking, Securitization.

Suggested citation: Cortés, Kristle, and Philip E. Strahan, “Tracing Out Capital Flows: How Financially Integrated Banks Respond to Natural Disasters,” Federal Reserve Bank of Cleveland, working paper no. 14-12R.

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*First version September 2014.

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 ask: How do banks smooth these shocks? Our results suggest 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. The result is driven by small banks, defined as those with assets below $2 billion. For them, credit supplied to connected markets declines by a little less than 50 cents per dollar of increased lending in their shocked areas. Larger banks do not reduce credit in connected markets.

We find that the decline in lending in connected markets is concentrated outside of banks' core markets, which we define as those markets where the bank has a branch presence. Within these core markets, we find declines in lending where banks have low market share but no change in those with high market share. 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; Ergunor, 2010; Cortés, 2012; Nguyen, 2014). 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 (particularly those where they have a strong market presence), by cutting

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

lending sharply in markets where their ability to generate rents is less important (i.e. markets where they lend without a physical presence or where market share is low). 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.

To test how credit *supply* responds to exogenous demand increases elsewhere, 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 define the local credit market by "county," and use a monthly frequency because precise timing of the natural disasters is important for clarifying the effects. 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 location (county) of the property securing the mortgage).

HMDA data are sufficiently rich to allow us to estimate how changes in originations vary comparing more- and less-liquid segments of the mortgage market. Most mortgages below the jumbo-loan threshold are highly liquid because they may easily be sold to third parties due to credit guarantees sold by the Government-Sponsored Enterprises (GSEs). We can also sub-divide the HMDA data based on whether or not the originating bank intends to hold the mortgage or sell it. We find that banks exploit the ability to sell non-jumbo mortgages as a means to mitigate the impact of natural disasters on their ability to originate credit. In this segment, rates of securitization increase in connected markets after disasters, thereby mitigating the reduction of credit origination that would otherwise be necessary from constraints on banks' ability to fund those originations.

We also test the pricing implications of our model. Consistent with our result on loan quantities, we find no effect on mortgage-loan prices in markets where banks have branches. But we do find that prices for deposits in those connected markets rise. Thus, banks exposed to natural disasters bid up the price of deposits across *other* markets where they own branches to help fund the unexpectedly high loan demand in the shocked markets. Putting our results together, small banks smooth shocks following disasters across three margins: 1) they cut loan originations in non-core, connected markets; 2) they increase their securitization of the mortgages that they do continue to originate in those markets; and, 3) they increase the aggressiveness with which they bid for deposits. All three of these responses help accommodate the demand shock stemming from the disaster.

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 one 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,

[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.

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-booming areas. Consistent with this idea, Chakraborty, Goldstein, and Mackinlay (2013) find that local business lending declines 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 (2015), 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

[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 has 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).

increase comes from both new loan originations as well as additional securities holdings (Plosser, 2013). The increase in lending originations, 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 or where market share is low. Thus, banks appear to protect the rents that they can earn in core markets when they can.[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 the National Climatic Data Center's monthly storm data publications. Our sample starts with all natural disasters reported in SHELDUS that occurred in the United States between 2001 and 2010 and includes those in which the Governor declared a 'state of

[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.

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. Figure 1 shows the distribution of property damage from 2001-2010 in the affected counties. 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 a 'state of emergency' had to have been 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 in 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. We also report a robustness test to explore whether the effects are different in the tails of the property-loss distribution.

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 versions of the HMDA data do 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.

The HMDA data include loan size, whether or not a loan was approved, as well as some information on borrower characteristics. Loan size is helpful because loans above a certain cutoff may not be sold to one of the Government-Sponsored Housing Enterprises, Fannie Mae and Freddie Mac (the GSEs). These 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 by US banks that allow us to locate borrowers geographically for most lenders.[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 that are easier to finance in securitization markets respond differentially to the local credit demand shocks.

[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.

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

For pricing, we rely on *Rate Watch,* with data available to us starting in 2006. These data provide interest rate quotes by banks at the branch level for a number of loan and deposit products. As with the loan quantity regressions, we model prices with county*month fixed effects (as well as bank*county effects), thereby alleviating concerns about variation in local conditions on prices. The sample of banks varies by product type, with deposit-rate data having the most comprehensive coverage. According to *RateWatch*, most banks report data on various classes of deposits, such as CDs of varying maturities as well as savings accounts. Additional data also exist on loan products, but these are much less available. So, in our reported regressions we focus on the deposit-rate data.

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 need to rebuild damaged homes and businesses. Some of the funds for rebuilding come from FEMA directly and from insurance payments, and affected individuals supplement these funds by borrowings from banks. In fact, after many disasters regulators pressure banks to increase credit availability. 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:

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

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 2 reports the β coefficients from our estimation of (1), along with boundaries around them representing the 95 percent confidence interval for the estimates. 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 2 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 2 are based on lending in the mortgage market, which is likely not the only (or even the main) lending market affected directly 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 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 multi-market 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 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 2). We drop these 'shocked' county-months from our bank-county-month dataset in our analysis 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,

[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.

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

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

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).

Using the three-dimensional panel, 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:

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

where j indexes counties, i indexes banks, t indexes months, and k indexes lags of the exposure variable (we include 12 lags).[9] 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.[10] Note that banks operating in just one market play no direct role in estimating the β^k coefficients, since their exposure to

[9] Abnormal loan volume following natural disasters declines to zero by 12 months out, as shown in Figure 2. But we have also estimated equation (3) with 18 and 24 lags and find that these additional lags are small and not statistically significant.

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

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.[11]

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 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 and the ratio of the allowance for loan and lease losses to total assets as additional time-varying, bank-level control variables (time invariant bank-county characteristics, such as the exact distribution of its branches, get absorbed by the $\alpha_{i,j}$). The results reported below are not sensitive to whether or not we include either the bank-size measure or loan losses; most of the effects of bank characteristics are absorbed by the bank*county fixed effects. This robustness, particularly regarding loan losses, is important because we are trying to pin down how a credit demand shock propagates across markets and another possible channel could operate through bank distress.[12]

[11] We have also estimated our model without these observations and find very similar results, both in terms of the economic and the statistical significance.

[12] We have also estimated our models adding the bank capital ratio as an additional explanatory variable. Adding this variable also has little effect on the results.

The regression in equation (3) is built from dollar-changes in lending (normalized) parceled evenly across markets, so 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 -1 and zero. 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]

While the units are convenient, the model in equation (3) has a potential endogeneity problem. The explanatory variables -12 lags of *Disaster-Lending* - are based on each bank's actual choice as to how much lending to supply following a disaster. This choice could reflect not just the incremental loan demand from the disaster, but also a bank's ability to fund that demand due to access to external funds, which could also affect the outcome in the regression (lending in other counties). To rectify this problem, we create an instrument built from the (log) property damage experienced following a disaster (as in Table 1), parceled out across banks based on their share of the shocked county's total branches (based on the prior year's branch distribution). The instrument is valid as long as a bank's branch share in a county is not correlated with its costs of external finance (conditional on bank*county effects and size), which seems plausible. Specifically, we build the following:

$$\textit{Property-Exposure}_{i,t} = (\textit{Log Property Damage-in-shocked-counties}_{j,t})*\textit{Branch Share}_{i,t}.$$

As in equation (3), we capture the relative importance of disaster exposure to each bank by normalizing the *Property-Exposure* by each bank's total lending. Thus, the reduced-form analog to equation (3) is as follows:

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

$$\Delta Lending_{i,j,t}/Total\ Lending_{i,t} = \alpha_{i,j} + \gamma_{j,t} + \Sigma\, \beta^k Property\text{-}Exposure_{i,t\text{-}k}/Total\ Lending_{i,t} + \varepsilon_{i,j,t}. \quad (4)$$

We focus most of our attention on estimates of this reduced form model for two reasons: 1) this strategy avoids endogeneity concerns; and, 2) this approach captures the full effects of bank exposure to the disasters on outcomes. That said, we do also report both the OLS and IV versions of equation (3) in our baseline model and sample to gauge the economic magnitude of shocks to loan demand with convenient units. The instrument that we use is powerful, which is easy to see by estimating the following regression linking the contemporaneous value of the shock with that of the instrument:

$$Disaster\text{-}Lending_{i,t}\ /\ Total\ Lending_{i,t} = \alpha_{i,j} + \gamma_{j,t} + Property\text{-}Exposure_{i,t}/\ Total\ Lending_{i,t} + \varepsilon_{i,j,t},$$

which yields a coefficient estimate of 10.42 with a t-statistic above 300.[14] Thus, the instrument, based on a bank's exposure to property damage, is very highly correlated with changes in the bank's mortgage originations in those shocked markets.

Table 2 reports summary statistics for the panel data used to estimate our regressions. We report the statistics separately for banks in four size bins: banks with over $100 billion in assets ("mega-banks), banks with assets between $10 and $100 billion ("large banks"), banks with assets between $2 and $10 billion in assets ("medium-sized banks"), and banks with less than $2 billion in assets ("small banks"). The distributions are based on 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.

[14] The proper first-stage regressions involved in estimating (3) include 12 regressions (one per lag) of *Disaster-Lending* on the *Property Exposure* instruments. These regressions are all very similar and not worth reporting separately. What matters for the relevance condition in an IV is the strong contemporaneous correlation between the two variables.

For the smallest banks, the dependent-variable mean ($\Delta Lending_{i,j,t}$ / $Total\ Lending_{i,t}$) equals 0.002 per month for the multi-market banks, or 0.024 per year;[15] 0.0023 (0.027 per year) for medium-sized banks; 0.0017 (0.020 per year) for large banks; and 0.0007 (0.009 per year) for the $100 billion and up mega-banks. So, other than the very largest banks, changes in loan originations exhibit a similar distribution. The mean of the key explanatory variable ($Disaster\text{-}Lending_{i,t}$), in contrast, declines with size. For the small banks, its mean is similar in magnitude to the dependent variable mean. Most of the observations take the value of zero, however, because of all bank-county-month observations in which the bank did not have any exposure to a market experiencing a natural disasters. For non-zero values, $Disaster\text{-}Lending_{i,t}$ averages 0.0069, reflecting loan changes roughly three times higher compared with non-shocked county-months. The importance of natural disasters declines as banks get larger. The mean of $Disaster\text{-}Lending_{i,t}$ declines consistently with bank size. This happens because banks operating in many markets can smooth the effect of a shock of a given size across those markets with less of an effect.

The last panel of Table 2 reports summary statistics for the deposit interest rates from *Rate Watch*. Here, we only report these statistics for the small-bank sample. As one might expect, the average rate on CDs increases with maturity, while the rate for savings deposits is the lowest at around 0.63%.

3. Results

[15] This variable is like a growth rate except that we normalize by total loan originations in the current period, rather than by county-level lending from the prior month. We do this so that the influence of outliers – a major problem with standard growth rates – is mitigated.

First, we report the reduced forms in equation (4), estimated for banks in the four asset-size category bins (Table 3). In all of our subsequent tests, we focus only on the small-bank sample. While we think that capital flows within large banking organizations are important, the reduced form results are not statistically significant for them. In part this occurs because the shocks driving credit demand variation are just too small to have a meaningful impact on the largest institutions, meaning our tests have low power for them. 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.

Second, Table 4 reports estimates of equation (3) both in OLS (using actual lending changes) and with IV (using the instrument based on property damage). We include these results to help facilitate interpretation of the findings. Relative to the reduced form the economic magnitude of the effects is easy to interpret in equation (3) because units are measured in dollar-change terms for both the outcome and the regressors (this analysis generates our headline result).

Third, we test how our reduced form results vary when we separate the sample to explore how variation across market types (core markets, those with branches v. non-core markets, those without; Tables 6 & 7) and loan types (retained v. sold and jumbo v. non-jumbo markets; Tables 8 & 9) affects responses to shocks.

Last, we report estimates of the effect of shock exposure on prices (Table 10).

<u>3.1 Reduced Form Models By Bank Size</u>

Table 3, column 1 reports the baseline reduced form model for small banks. We report the coefficients on the 12 lags of *Property-Exposure*$_{i,t}$, our measure of a bank's 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. For this sample, the sum of these coefficients is negative (-2.25) with an F-statistic of 77.61.

Column 2 of Table 3 reports the results from the placebo test, which uses the exact same structure and sample, 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.

In columns (3)-(5), we find no significant effect of exposure to natural disasters on lending in connected markets. Thus, larger banks – those above $2 billion in assets – are able to fully shield other markets from the effects of local demand shocks. In part this reflects their lower cost of external finance, but we admit that the power of our tests also weakens as banks become larger and operate across more markets. Thus, it is difficult to say with much confidence how a large bank might respond to a shock larger than one observed in our tests. In our subsequent tests, we focus only on the small bank sample.

In Table 4, we extend the model implemented on small banks in two ways. First, column (1) regresses changes in lending in connected markets on changes in *actual* lending in shocked markets *(Disaster-Lending*$_{i,t}$). That is, we estimate equation (3) above in OLS. In column (2), we report the same model but use *Property-Exposure*$_{i,t}$ as the instrument for *Disaster-Lending*$_{i,t}$. We find that lending falls by 42 to 50 cents per dollar of additional lending stimulated by the shock exposure (based on the sum of the coefficients on the twelve lags). The effect is large in both approaches economically as well as statistically, and also in both models the effect is 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, small banks are able to protect credit supply partially, but not fully, by increasing loan sales and/or raising additional deposits or other funds.

3.1.1 Large Disasters

Table 1 shows clearly that even though we have many disasters in our sample, the bulk of economic losses associated with such disasters come at the top of the loss distribution. Our model accounts for this variation by constructing exposure variables that account for shock size. That said, two concerns come to mind. First, our results may be driven solely by one or two big shocks, such as Hurricane Katrina. Second, the impact of large shocks on lending in other areas may differ from that of small shocks. For example, banks plausibly might hold back cash buffers to fund lending in areas routinely hit by shocks.

Table 5 addresses these concerns in two ways. First, we re-estimate the basic model for small banks after dropping all bank-county-months affected by Hurricane Katrina, which is by far the largest shock in our dataset (column 1).[16] Second, we estimate our model with all of the data but introduce an interaction between an indicator set to one for disasters at the 99th percentile of the property-loss distribution, multiplied by our continuous measure of exposure (columns 2 & 3, which represent a single regression estimate). This specification allows the marginal impact of disasters on lending to be greater in the tails of the loss distribution.

The same conclusions emerge from both approaches. First, our results are not driven by outlying tail-events such as Katrina (column 1); the sum of the coefficients barely changes: from -2.25 with Katrina to -2.23 without. Second, the marginal effect of shocks on connected markets is not greater for tail events (columns 2 & 3). The second conclusion comes with two caveats, however: 1) the direct effect of the indicator variable enters negatively and significantly even though the sum of the marginal effects is not significant; and, 2) we see a very strong *positive* interaction with the large-disaster indicator for the first three months after the shock; after that the interactive effects are collectively insignificant. In other words, banks seem to increase lending to connected markets immediately after disasters, perhaps because loan demand is weak and does not emerge until about 3 months after the largest disasters strike (recall Figure 2).

3.2 Core v. Non-core Markets

Next, we test how variation in credit supply depends on market characteristics. For these tests, we define core markets as those counties where a bank lent in the prior year with a branch

[16] Total property damage following Katrina was $67 billion and affected 149 counties. The second largest disaster in our dataset – Hurricane Wilma – generated losses of about $10 billion.

presence; non-core markets are defined as counties where a bank lent in the prior year but without a branch presence.

Table 6 compares core v. non-core markets by introducing the *Branch* indicator and its interaction with the disaster exposure measure. (For brevity we focus on the reduced form, but the results are similar in the OLS/IV approach.) 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 by cutting lending sharply in non-core markets. For these, the coefficient sum rises from -2.25 to -2.86 (column 1). In contrast, the marginal effect of exposure to disasters is significantly different in core markets (F-test=23.92; column 2). Moreover, the *overall* effect of exposure to disasters on lending in banks' core markets – equal to the sum of the 12 lags on both *Property-Exposure*$_{i,t}$ plus those on *Branch*Property-Exposure*$_{i,t}$ - becomes positive but is not statistically significant (= 1.06, combining the sums from columns 1 & 2). Small banks seem to protect their ability to lend in core markets from shocks; lending falls significantly in their non-core markets but not in their core markets.[17]

Table 7 analyzes the same model as in Table 6, but we now include only core markets. We subdivide these markets based on the bank's share of mortgage originations by including an interaction between *Hi Market Share*$_{i,j,t}$ and the 12 lags of the exposure variable. *Hi Market Share*$_{i,j,t}$ is set to one if the bank had above-median share of originations in the prior county-month. The results suggest that banks *do* reduce lending in core markets – markets with branches

[17] We hesitate to over interpret the time series dynamics implied by our regressors, but the interactive effects in Table 6 suggest that lending falls sharply in core markets 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.

– but *only* in those where they have a relatively small market share (column 1). The magnitude of the total effect of exposure on lending in these markets (= -2.35) is close to the overall effect estimated earlier (= -2.25; see Table 3, column 1), but it is only statistically significant at the 10% level (P-value = 0.06). Within core markets where banks have above average market share, however, we find no evidence that lending declines (=0.23, summing the 24 coefficients from columns 1 & 2). These are the markets where banks are most likely to have access to profitable lending opportunities; hence it makes sense that banks would continue to lend.

3.3 Variation across loan-types: Jumbo v. non-Jumbo Mortgage Originations

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 in the continental U.S. was $417,000 for loans secured by single-family homes.

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.[18] 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 8 and 9 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 7, we split the dependent variable ($\Delta Lending_{i,j,t}$ / $Total\ Lending_{i,t}$) into two pieces that sum to the original one:

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

$$\Delta Lending_{i,j,t} / Total\ Lending_{i,t}. \tag{5}$$

Thus, coefficients 'add up' across columns 1 and 2 of Table 8.[19] Table 9 further sub-divides the dependent variable into four components that add to the total change in lending:

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[18] 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.

[19] This adding up would hold exactly if the samples were identical between Table 3 and Table 8. 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.

$$\Delta \textit{Non-Jumbo Sold Lending}_{i,j,t} / \textit{Total Lending}_{i,t} + \Delta \textit{Non-Jumbo Retained Lending}_{i,j,t} / \textit{Total Lending}_{i,t} + \Delta \textit{Jumbo Sold Lending}_{i,j,t} / \textit{Total Lending}_{i,t} + \Delta \textit{Jumbo Retained Lending}_{i,j,t} / \textit{Total Lending}_{i,t} = \Delta \textit{Lending}_{i,j,t} / \textit{Total Lending}_{i,t}. \quad (6)$$

As shown in Table 8, 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 9, 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/sales to substitute for on-balance sheet finance required to lend in shock markets, thus mitigating (partially) the need to cut 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.[20] In the jumbo segment, the point estimate for sold loans is small and not statistically significant.

3.4 Pricing

In our last set of regressions we test whether small banks increase deposit rates in connected markets in response to disasters. Thus, we are testing for a third margin of adjustment, beyond cutting lending supply to non-core markets and increasing loans sales/securitization. The structure of the regressions is parallel to that of equation (4) - same

[20] 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).

fixed effects and explanatory variables - but we now use the reported bank-county level interest rate (in percentage points) offered on deposit accounts of various types as the outcome rather than changes in lending quantities. We have also tested for pricing effects on bank lending using the *Rate Watch* data. However, these data are only available in markets where banks operate branches. Given that we found no quantity effects (recall Table 6), it might come as no surprise that we also find no effect on loan pricing (not reported). That said, these data are much less available than the pricing data for deposits, meaning these null results have very limited power.

Table 10 reports the results. Across all deposit types the sum of the coefficients on *Property Exposure*$_{i,t}$ is positive, with a significant effect for the 3-month CD category. The magnitude of these coefficients suggests that a disaster one-standard deviation above average (=0.005 – recall Table 2) would lead a bank to increase its 3-month CD rate by about 15 basis points in connected markets. This increase is about 20% of the residual variation in these rates across banks, after accounting for the fixed effects (=75 basis points). For the other categories we also estimate positive effects, although the coefficient sums are statistically weaker. This suggests that banks typically use short-term CDs to increase funds most, which probably reflects the relatively short-lived impact of the disasters on local credit demand.

4. CONCLUSIONS

In this paper we test how multi-market banks smooth credit demand shocks from natural disasters. Credit demand increases in response to local shocks created by exposure to natural disasters. Small banks respond by *increasing* credit in those areas and *taking* credit away from other markets in which they have lent. In contrast, large banks do not adjust lending in connected markets, probably because they have lower costs of external finance. Small banks mitigate the impact of reductions of credit to connected markets in three ways. First, all of the reductions occur in counties where they lend without branches; second, loan sales/securitization increase sharply, reducing the extent to which affected banks would otherwise need to cut loan originations; third, deposit rates in connected markets increase, thus helping affected banks finance additional lending held on the balance sheet. Together these three adjustments suggest that even small banks effectively smooth shocks, even absent access to national or global capital markets.

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Figure 1: Natural Disaster Property Damage Across Counties from 2001-2010

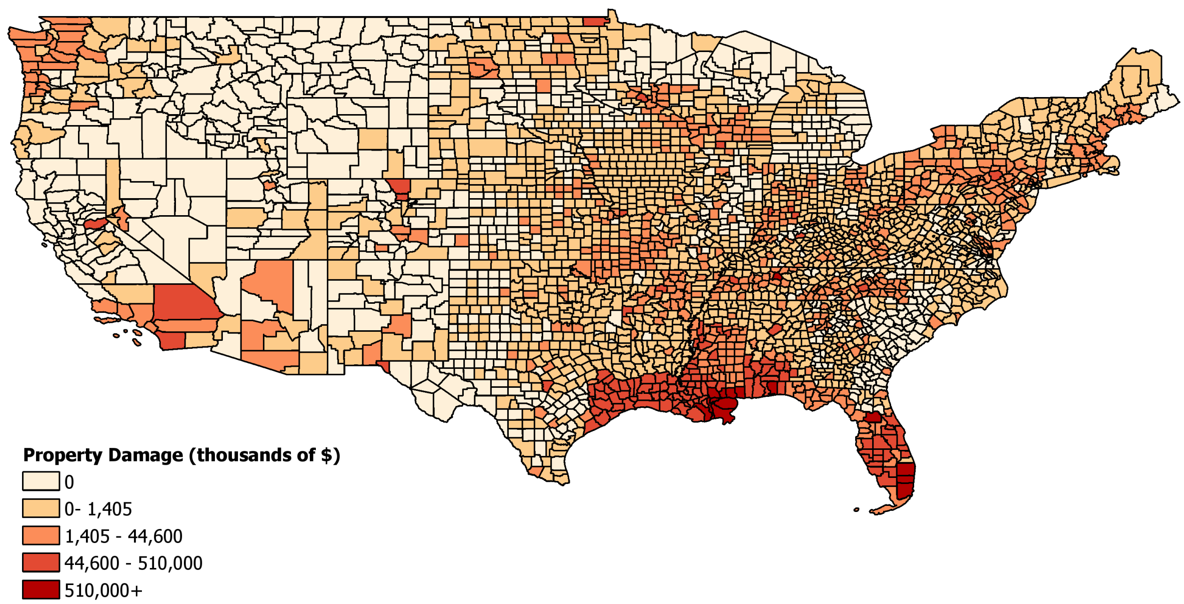

Figure 2: Log of Mortgage Originations around Natural Disasters (With 95% Confidence Intervals)

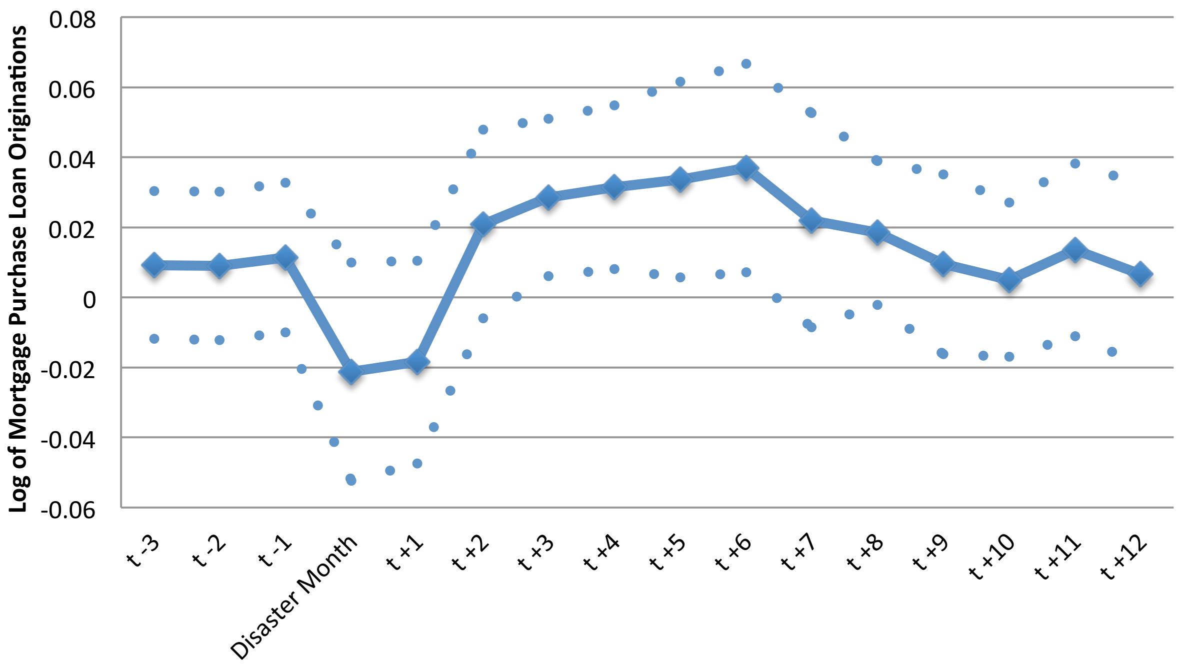

Table 1: Property Damage from Natural Disasters

This table reports data on property losses from natural disasters taken from the Spatial Hazard Events and Losses Database for the United States. These data are at the 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.

			Property Damage Distribution				
Natural Disaster Type	Number of Affected Counties	Total Property Damage Across all Counties (Billions)	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 Lending 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 (county) 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. Property Exposure, an instrument for Disaster Lending, equals the log of property damage incurred because of a disaster, parceled out across banks based on their share of the shocked county's total branches (from the prior year's branch distribution). Both are normalized by each bank's total mortgage originations across all of its markets.

Banks with Assets <2B	**Observations**	**Mean**	**Std. Dev.**
Dependent Variable: Change in Monthly Mortgage Originations / Total Lending	7,262,965	0.0357	0.241
Dependent Variable: No "single market" banks	6,907,644	0.0020	0.105
Disaster Lending	7,262,965	0.0026	0.031
Property Exposure (instrument)	7,262,965	0.0003	0.002
Disaster Lending (zeros dropped)	2,700,383	0.0069	0.051
Property Exposure (zero values dropped)	2,386,907	0.0010	0.004
Size (Log of Assets)	7,262,965	12.88	0.984
Assets (In Thousands $s)	7,262,965	595,388	509,719
Bank Loan Losses (ratio of losses to assets)	7,262,965	0.0093	0.0224

Banks with Assets >2B & < 10B	**Observations**	**Mean**	**Std. Dev.**
Dependent Variable: Change in Monthly Mortgage Originations / Total Lending	2,681,797	0.0023	0.155
Disaster Lending	2,681,797	0.0016	0.007
Property Exposure (instrument)	2,681,797	0.0002	0.002
Disaster Lending (zeros dropped)	1,784,970	0.0024	0.008
Property Exposure (zero values dropped)	1,303,299	0.0005	0.003
Size (Log of Assets)	2,681,797	15	0.471
Assets (In Thousands $s)	2,681,797	4,815,352	2,253,651
Bank Loan Losses (ratio of losses to assets)	2,681,797	0.0106	0.0088

Banks with Assets >10B & < 100B	**Observations**	**Mean**	**Std. Dev.**
Dependent Variable: Change in Monthly Mortgage Originations / Total Lending	4,983,430	0.0017	0.130
Disaster Lending	4,983,430	0.0008	0.002
Property Exposure (instrument)	4,983,430	0.0001	0.002
Disaster Lending (zeros dropped)	4,180,651	0.0009	0.002
Property Exposure (zero values dropped)	2,971,120	0.0002	0.003
Size (Log of Assets)	4,983,430	17.15	0.641
Assets (In Thousands $s)	4,983,430	34,500,000	22,300,000
Bank Loan Losses (ratio of losses to assets)	4,983,430	0.0073	0.0056

Banks with Assets >100B	**Observations**	**Mean**	**Std. Dev.**
Dependent Variable: Change in Monthly Mortgage Originations / Total Lending	2,104,369	0.0007	0.0853
Disaster Lending	2,104,369	0.0004	0.0004
Property Exposure (instrument)	2,104,369	0.0001	0.0003
Disaster Lending (zeros dropped)	1,988,507	0.0005	0.0004
Property Exposure (zero values dropped)	2,026,069	0.0001	0.0003
Size (Log of Assets)	2,104,369	19.63	0.8322
Assets (In Thousands $s)	2,104,369	481,000,000	425,000,000
Bank Loan Losses (ratio of losses to assets)	2,104,369	0.0063	0.0029

Deposit Rates	**Observations**	**Mean**	**Std. Dev.**
3 Month CD Rate	129,953	1.8783	1.2068
6 Month CD Rate	141,797	2.3237	1.3293
12 Month CD Rate	141,923	2.6623	1.3435
24 Month CD Rate	136,238	2.8882	1.2047
60 Month CD Rate	116,277	3.4370	1.0183
Savings Account Rate	140,660	0.6269	0.4967

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

This table reports regressions of the change in mortgage originations for bank i/county j/month t on *Property Exposure* , the instrument for changes 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. 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$_{i,t}$				
	Small Banks (<$2 Billion in Assets)		Medium ($2-10 Billion)	Large ($10-100 Billion)	Mega (>$100 Billion)
	Property Exposure Based on Actually Shocked Markets	Property Exposure Based on '**Placebo**' Shocked Markets	Property Exposure Based on Actually Shocked Markets	Property Exposure Based on Actually Shocked Markets	Property Exposure Based on Actually Shocked Markets
	(1)	(2)	(3)	(4)	(5)
Property Exposure$_{i,t-1}$	0.0184	0.000760	0.140	0.583	-0.375
	(0.0579)	(0.000742)	(0.245)	(0.888)	(1.695)
Property Exposure$_{i,t-2}$	-0.0430	0.000026	0.191	1.667	-1.634
	(0.0660)	(0.000231)	(0.340)	(2.045)	(2.159)
Property Exposure$_{i,t-3}$	-0.111	-0.000164	0.0748	0.244	6.322
	(0.0732)	(0.000308)	(0.174)	(0.216)	(6.110)
Property Exposure$_{i,t-4}$	-0.202***	0.000197	-0.222	1.021	-19.75
	(0.0776)	(0.000229)	(0.255)	(2.060)	(16.03)
Property Exposure$_{i,t-5}$	-0.443***	0.000492	-0.324	-2.966	31.51
	(0.0872)	(0.000563)	(0.306)	(3.485)	(22.16)
Property Exposure$_{i,t-6}$	-0.213**	0.000026	-0.260	4.431*	-23.85**
	(0.0965)	(0.000364)	(0.203)	(2.669)	(11.50)
Property Exposure$_{i,t-7}$	-0.540***	0.000172	-0.410**	-0.521	14.89**
	(0.0940)	(0.000804)	(0.179)	(0.896)	(7.166)
Property Exposure$_{i,t-8}$	-0.190**	0.000335	-0.171	-3.123***	-7.014
	(0.0855)	(0.000304)	(0.221)	(1.137)	(8.362)
Property Exposure$_{i,t-9}$	-0.122	-0.000167	-0.340	0.444	1.138
	(0.0832)	(0.000261)	(0.268)	(1.294)	(12.45)
Property Exposure$_{i,t-10}$	-0.0905	-0.000196	-0.136	-1.399	0.353
	(0.0804)	(0.000342)	(0.393)	(1.466)	(5.336)
Property Exposure$_{i,t-11}$	-0.151**	0.000019	0.0152	1.837	2.848
	(0.0768)	(0.000249)	(0.283)	(3.324)	(4.824)
Property Exposure$_{i,t-12}$	-0.165**	0.000147	-0.00504	-2.561	-3.055**
	(0.0755)	(0.000318)	(0.331)	(2.633)	(1.330)
Log of Bank Assets	-0.0471***	-0.0386***	-0.0492***	-0.0157***	-0.00828***
	(0.00356)	(0.00341)	(0.00366)	(0.00463)	(0.00259)
Bank Loan Losses	-0.297**	-0.249**	-0.263	0.160	0.306
	(0.121)	(0.122)	(0.209)	(0.144)	(0.185)
Coefficient Sum	**-2.25**	0.00	-1.45	-0.34	1.38
F(Sum of 12 Lags)	77.610	1.110	0.950	0.000	0.070
P-Value	0.000	0.291	0.330	0.980	0.790
County by Time FE	Yes	Yes	Yes	Yes	Yes
Bank by County FE	Yes	Yes	Yes	Yes	Yes
Number of clusters (banks)	6,385	6,207	423	158	24
Observations	7,262,965	7,013,198	2,681,797	4,983,430	2,104,369
R-squared	0.219	0.205	0.293	0.244	0.162

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

Table 4: The effect of credit demand shocks on connected markets: OLS v. IV for small-bank sample (<$2 Billion)

This table reports OLS and IV regressions of the change in mortgage originations for bank i/county j/month t on *Disaster Lending* = 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. In the IV, we use *Property Exposure* as the instrument. 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. A county is included if the bank originated any mortgages in the prior year.

	Dependent Variable : Change in Mortgage Originations$_{i,j,t}$ / Mortgage	
	OLS	**IV**
	(1)	(2)
Disaster Lending$_{i,t-1}$	-0.0364***	0.00175
	(0.00374)	(0.00547)
Disaster Lending$_{i,t-2}$	-0.0369***	-0.00488
	(0.00421)	(0.00651)
Disaster Lending$_{i,t-3}$	-0.0454***	-0.0166**
	(0.00459)	(0.00722)
Disaster Lending$_{i,t-4}$	-0.0500***	-0.0335***
	(0.00516)	(0.00791)
Disaster Lending$_{i,t-5}$	-0.0598***	-0.0620***
	(0.00562)	(0.00925)
Disaster Lending$_{i,t-6}$	-0.0563***	-0.0550***
	(0.00624)	(0.0106)
Disaster Lending$_{i,t-7}$	-0.0764***	-0.0805***
	(0.00678)	(0.0105)
Disaster Lending$_{i,t-8}$	-0.0515***	-0.0533***
	(0.00643)	(0.00951)
Disaster Lending$_{i,t-9}$	-0.0317***	-0.0372***
	(0.00617)	(0.00915)
Disaster Lending$_{i,t-10}$	-0.0244***	-0.0282***
	(0.00583)	(0.00906)
Disaster Lending$_{i,t-11}$	-0.0194***	-0.0292***
	(0.00573)	(0.00896)
Disaster Lending$_{i,t-12}$	-0.0105**	-0.0260***
	(0.00528)	(0.00817)
Log of Bank Assets	-0.0208***	-0.0469***
	(0.00317)	(0.00355)
Bank Loan Losses	-0.171**	-0.297**
	(0.0705)	(0.121)
Coefficient Sum	**-0.50**	**-0.42**
F(Sum of 12 Lags)	310.18	78.37
P-Value	0.0000	0.0000
County by Time FE	Yes	Yes
Bank by County FE	Yes	Yes
Number of clusters (banks)	6385	6,385
Observations	7,262,965	7,262,965
R-squared	0.286	0.219

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

Table 5: The effect of large credit demand shocks on connected markets: Accounting for large disasters

This table reports regressions of the change in mortgage originations for bank i/county j/month t on *Property Exposure*, the instrument for changes 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. 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$_{i,t}$			
	Markets **Without Katrina**		**Add Top 99th Percentile Interaction Terms**	
	(1)	(2)		(3)
Property Exposure$_{i,t-1}$	-0.00381	-0.0470	Top 99% * Property Exposure$_{i,t-1}$	1.257***
	(0.0590)	(0.0601)		(0.232)
Property Exposure$_{i,t-2}$	-0.0780	-0.104	Top 99% * Property Exposure$_{i,t-2}$	1.360***
	(0.0665)	(0.0675)		(0.304)
Property Exposure$_{i,t-3}$	-0.138*	-0.158**	Top 99% * Property Exposure$_{i,t-3}$	1.583***
	(0.0735)	(0.0744)		(0.429)
Property Exposure$_{i,t-4}$	-0.223***	-0.187**	Top 99% * Property Exposure$_{i,t-4}$	-0.0990
	(0.0779)	(0.0789)		(0.419)
Property Exposure$_{i,t-5}$	-0.473***	-0.460***	Top 99% * Property Exposure$_{i,t-5}$	0.814*
	(0.0880)	(0.0894)		(0.421)
Property Exposure$_{i,t-6}$	-0.237**	-0.204**	Top 99% * Property Exposure$_{i,t-6}$	0.150
	(0.0979)	(0.0995)		(0.432)
Property Exposure$_{i,t-7}$	-0.541***	-0.540***	Top 99% * Property Exposure$_{i,t-7}$	0.413
	(0.0950)	(0.0966)		(0.429)
Property Exposure$_{i,t-8}$	-0.185**	-0.171*	Top 99% * Property Exposure$_{i,t-8}$	-0.114
	(0.0872)	(0.0881)		(0.367)
Property Exposure$_{i,t-9}$	-0.0681	-0.0951	Top 99% * Property Exposure$_{i,t-9}$	-0.414
	(0.0850)	(0.0861)		(0.301)
Property Exposure$_{i,t-10}$	-0.0608	-0.0921	Top 99% * Property Exposure$_{i,t-10}$	0.142
	(0.0825)	(0.0836)		(0.272)
Property Exposure$_{i,t-11}$	-0.102	-0.159**	Top 99% * Property Exposure$_{i,t-11}$	-0.0753
	(0.0788)	(0.0791)		(0.261)
Property Exposure$_{i,t-12}$	-0.118	-0.161**	Top 99% * Property Exposure$_{i,t-12}$	-0.574**
	(0.0775)	(0.0790)		(0.273)
Log of Bank Assets	-0.0484***	-0.0460***	Top 99% Disaster	-0.00911***
	(0.00311)	(0.00355)		(0.00198)
Bank Loan Losses	-0.278**	-0.296**		
	(0.114)	(0.121)		
Coefficient Sum	**-2.23**	**-2.38**	2.06	**4.44**
F(Sum of 12 Lags)	74.630	83.06	1.71	7.68
P-Value	0.000	0.0000	0.1916	0.0056
County by Time FE	Yes		Yes	
Bank by County FE	Yes		Yes	
Number of clusters (banks)	6,385		6,385	
Observations	6,716,756		7,262,965	
R-squared	0.217		0.219	

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

Table 6: The effect of credit demand shocks on connected markets: Core v. non-core markets

This table reports regressions of the change in mortgage originations for bank i/county j/month t on *Property Exposure*, the instrument for changes in lending in counties hit by natural disasters. The model 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. 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$_{i,t}$		
	(1)		(2)
Property Exposure$_{i,t-1}$	0.0866*	Branch * Property Exposure$_{i,t-1}$	-0.399*
	(0.0506)		(0.230)
Property Exposure$_{i,t-2}$	0.00841	Branch * Property Exposure$_{i,t-2}$	-0.339
	(0.0569)		(0.255)
Property Exposure$_{i,t-3}$	0.0395	Branch * Property Exposure$_{i,t-3}$	-0.892***
	(0.0638)		(0.281)
Property Exposure$_{i,t-4}$	-0.139**	Branch * Property Exposure$_{i,t-4}$	-0.424
	(0.0678)		(0.299)
Property Exposure$_{i,t-5}$	-0.480***	Branch * Property Exposure$_{i,t-5}$	0.158
	(0.0787)		(0.318)
Property Exposure$_{i,t-6}$	-0.253***	Branch * Property Exposure$_{i,t-6}$	0.208
	(0.0918)		(0.326)
Property Exposure$_{i,t-7}$	-0.577***	Branch * Property Exposure$_{i,t-7}$	0.214
	(0.0879)		(0.349)
Property Exposure$_{i,t-8}$	-0.354***	Branch * Property Exposure$_{i,t-8}$	1.007***
	(0.0789)		(0.338)
Property Exposure$_{i,t-9}$	-0.290***	Branch * Property Exposure$_{i,t-9}$	1.119***
	(0.0769)		(0.334)
Property Exposure$_{i,t-10}$	-0.253***	Branch * Property Exposure$_{i,t-10}$	1.108***
	(0.0728)		(0.325)
Property Exposure$_{i,t-11}$	-0.334***	Branch * Property Exposure$_{i,t-11}$	1.195***
	(0.0683)		(0.323)
Property Exposure$_{i,t-12}$	-0.313***	Branch * Property Exposure$_{i,t-12}$	0.967***
	(0.0652)		(0.311)
Log of Bank Assets	-0.0471***	Branch$_{i,j,t-1}$	-0.000929
	(0.00364)		(0.00218)
Bank Loan Losses	-0.297**		
	(0.121)		
Coefficient Sum	**-2.86**	1.06	**3.92**
F(Sum of 12 Lags)	124.83	1.86	23.92
P-Value	0.0000	0.1731	0.0000
County by Time FE		Yes	
Bank by County FE		Yes	
Number of clusters (banks)		6,385	
Observations		7,262,965	
R-squared		0.219	

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

Table 7: The effect of credit demand shocks on connected markets: Core markets, by Market Share

This table reports regressions of the change in mortgage originations for bank i/county j/month t on *Property Exposure*, the instrument for changes in lending in counties hit by natural disasters. We include only counties where banks have branches. Hi-Market Share is an indicator variable = 1 for banks with above median market share from the prior county-month. The model 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. 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$_{i,t}$		
	(1)		(2)
Property Exposure$_{i,t-1}$	-0.0883	Hi-Market Share * Property Exposure$_{i,t-1}$	-0.5329
	(0.302)		(0.480)
Property Exposure$_{i,t-2}$	-0.4068	Hi-Market Share * Property Exposure$_{i,t-2}$	0.3297
	(0.332)		(0.544)
Property Exposure$_{i,t-3}$	-0.1568	Hi-Market Share * Property Exposure$_{i,t-3}$	-0.7263
	(0.344)		(0.546)
Property Exposure$_{i,t-4}$	-0.1650	Hi-Market Share * Property Exposure$_{i,t-4}$	-0.2808
	(0.381)		(0.589)
Property Exposure$_{i,t-5}$	-0.5843	Hi-Market Share * Property Exposure$_{i,t-5}$	1.145*
	(0.367)		(0.620)
Property Exposure$_{i,t-6}$	0.2145	Hi-Market Share * Property Exposure$_{i,t-6}$	-0.1366
	(0.397)		(0.665)
Property Exposure$_{i,t-7}$	-0.5328	Hi-Market Share * Property Exposure$_{i,t-7}$	0.4342
	(0.427)		(0.702)
Property Exposure$_{i,t-8}$	-0.4275	Hi-Market Share * Property Exposure$_{i,t-8}$	1.315*
	(0.404)		(0.673)
Property Exposure$_{i,t-9}$	-0.5444	Hi-Market Share * Property Exposure$_{i,t-9}$	1.0501
	(0.385)		(0.680)
Property Exposure$_{i,t-10}$	0.3702	Hi-Market Share * Property Exposure$_{i,t-10}$	-0.6154
	(0.406)		(0.679)
Property Exposure$_{i,t-11}$	-0.2595	Hi-Market Share * Property Exposure$_{i,t-11}$	0.3316
	(0.367)		(0.668)
Property Exposure$_{i,t-12}$	0.2266	Hi-Market Share * Property Exposure$_{i,t-12}$	0.2708
	(0.374)		(0.646)
Log of Bank Assets	-0.0237	Hi-Market Share$_{i,j,t-1}$	0.1813
	(0.003)		(0.003)
Bank Loan Losses	0.2267		
	(0.210)		
Coefficient Sum	**-2.35**	0.23	2.58
F(Sum of 12 Lags)	3.5	0.04	2.16
P-Value	0.0614	0.8494	0.1413
County by Time FE		Yes	
Bank by County FE		Yes	
Number of clusters (banks)		6,301	
Observations		791,726	
R-squared		0.1283	

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

Table 8: The effect of credit demand shocks on connected markets: Jumbo v. non-jumbo

This table reports regressions of the change in mortgage originations for bank i/county j/month t on *Property Exposure* , the instrument for changes 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. A county is included if the bank originated any mortgages in the prior year.

	Change in Non-Jumbo Mortgage $Originations_{i,j,t}$ / Mortgage $originations_{i,t}$	Change in Jumbo Mortgage $Originations_{i,j,t}$ / Mortgage $originations_{i,t}$
	(1)	(2)
Property $Exposure_{i,t-1}$	-0.135**	-0.00805
	(0.0532)	(0.0154)
Property $Exposure_{i,t-2}$	-0.240***	-0.0378**
	(0.0593)	(0.0169)
Property $Exposure_{i,t-3}$	-0.288***	-0.103***
	(0.0655)	(0.0173)
Property $Exposure_{i,t-4}$	-0.324***	-0.0883***
	(0.0688)	(0.0193)
Property $Exposure_{i,t-5}$	-0.473***	-0.128***
	(0.0779)	(0.0222)
Property $Exposure_{i,t-6}$	-0.295***	-0.133***
	(0.0852)	(0.0262)
Property $Exposure_{i,t-7}$	-0.582***	-0.145***
	(0.0830)	(0.0253)
Property $Exposure_{i,t-8}$	-0.234***	-0.0566**
	(0.0770)	(0.0238)
Property $Exposure_{i,t-9}$	-0.0478	-0.0871***
	(0.0748)	(0.0214)
Property $Exposure_{i,t-10}$	-0.0900	0.00883
	(0.0726)	(0.0211)
Property $Exposure_{i,t-11}$	-0.118*	-0.0246
	(0.0712)	(0.0194)
Property $Exposure_{i,t-12}$	-0.0729	0.0140
	(0.0696)	(0.0203)
Log of Bank Assets	-0.0167***	-0.00439***
	(0.00239)	(0.000733)
Bank Loan Losses	-0.123**	-0.0459**
	(0.0517)	(0.0187)
Coefficient Sum	**-2.90**	**-0.79**
F(Sum of 12 Lags)	154.88	124.95
P-Value	0.0000	0.000
County by Time FE	Yes	Yes
Bank by County FE	Yes	Yes
Number of clusters (banks)	6,247	6,247
Observations	7,066,611	7,066,611
R-squared	0.241	0.285

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

Table 9: The effect of credit demand shocks on connected markets: Jumbo v. non-jumbo and retained v. sold

This table reports regressions of the change in mortgage originations for bank i/county j/month t on *Property Exposure* , the instrument for changes 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. 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 $originations_{i,t}$
	(1)	(2)	(3)	(4)
Property $Exposure_{i,t-1}$	0.509***	-0.644***	-0.0711***	0.0631***
	(0.0553)	(0.0483)	(0.0177)	(0.0222)
Property $Exposure_{i,t-2}$	0.324***	-0.564***	-0.0508**	0.0130
	(0.0572)	(0.0522)	(0.0208)	(0.0249)
Property $Exposure_{i,t-3}$	0.263***	-0.551***	-0.0129	-0.0897***
	(0.0632)	(0.0554)	(0.0242)	(0.0279)
Property $Exposure_{i,t-4}$	-0.0180	-0.306***	0.0679**	-0.156***
	(0.0693)	(0.0605)	(0.0292)	(0.0337)
Property $Exposure_{i,t-5}$	0.403***	-0.877***	-0.00640	-0.121***
	(0.0752)	(0.0676)	(0.0309)	(0.0357)
Property $Exposure_{i,t-6}$	0.574***	-0.869***	-0.0368	-0.0961**
	(0.0816)	(0.0742)	(0.0360)	(0.0427)
Property $Exposure_{i,t-7}$	0.306***	-0.888***	-0.0867**	-0.0583
	(0.0774)	(0.0735)	(0.0345)	(0.0414)
Property $Exposure_{i,t-8}$	0.261***	-0.495***	0.0265	-0.0831**
	(0.0703)	(0.0716)	(0.0305)	(0.0366)
Property $Exposure_{i,t-9}$	0.444***	-0.492***	-0.0167	-0.0704**
	(0.0718)	(0.0643)	(0.0270)	(0.0316)
Property $Exposure_{i,t-10}$	0.544***	-0.634***	0.0164	-0.00757
	(0.0671)	(0.0652)	(0.0265)	(0.0317)
Property $Exposure_{i,t-11}$	0.423***	-0.541***	-0.0150	-0.00963
	(0.0692)	(0.0618)	(0.0226)	(0.0283)
Property $Exposure_{i,t-12}$	0.449***	-0.522***	0.0514**	-0.0374
	(0.0678)	(0.0658)	(0.0254)	(0.0310)
Log of Bank Assets	-0.00735***	-0.00934***	-0.00363***	-0.000764
	(0.00133)	(0.00139)	(0.000939)	(0.000854)
Bank Loan Losses	-0.0768**	-0.0463**	-0.0118	-0.0341*
	(0.0340)	(0.0209)	(0.0123)	(0.0179)
Coefficient Sum	**4.48**	**-7.38**	-0.13	**-0.65**
F(Sum of 12 Lags)	267.58	668.00	0.99	18.56
P-Value	0.0000	0.0000	0.3194	0.0000
County by Time FE	Yes	Yes	Yes	Yes
Bank by County FE	Yes	Yes	Yes	Yes
Number of clusters (banks)	6,247	6,247	6,247	6,247
Observations	7,066,611	7,066,611	7,066,611	7,066,611
R-squared	0.240	0.128	0.139	0.154

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

Table 10: The effect of credit demand shocks on deposit pricing in connected markets

This table reports regressions of the interest rate paid by banks to raise deposits for bank i/county j/month t on *Property Exposure* , the instrument for changes 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. A county is included if the bank originated any mortgages in the prior year.

	3-Month CDs	6-Month CDs	12-Month CDs	24-Month CDs	60-Month CDs	Savings Accounts
	(1)	(2)	(3)	(4)	(5)	(6)
Property Exposure$_{i,t-1}$	2.758**	2.094*	1.012	1.240	0.872	0.621
	(1.084)	(1.175)	(1.226)	(1.063)	(1.096)	(0.397)
Property Exposure$_{i,t-2}$	1.888*	1.276	0.234	0.732	0.834	0.158
	(1.131)	(1.229)	(1.244)	(1.110)	(1.076)	(0.347)
Property Exposure$_{i,t-3}$	1.319	1.009	0.419	1.091	1.364	0.319
	(1.154)	(1.254)	(1.277)	(1.153)	(1.060)	(0.375)
Property Exposure$_{i,t-4}$	2.394**	1.976	1.744	1.980*	2.418**	0.533
	(1.141)	(1.277)	(1.283)	(1.160)	(1.165)	(0.369)
Property Exposure$_{i,t-5}$	2.427**	2.145	2.107	2.639**	1.853	0.566
	(1.207)	(1.377)	(1.389)	(1.252)	(1.255)	(0.409)
Property Exposure$_{i,t-6}$	2.803**	2.211	2.048	2.210*	1.279	0.658
	(1.305)	(1.482)	(1.490)	(1.327)	(1.250)	(0.456)
Property Exposure$_{i,t-7}$	3.054**	2.343	1.721	1.789	-0.0428	0.623
	(1.551)	(1.671)	(1.673)	(1.497)	(1.420)	(0.616)
Property Exposure$_{i,t-8}$	3.023**	1.990	1.226	1.365	-0.776	-0.237
	(1.513)	(1.631)	(1.645)	(1.482)	(1.389)	(0.493)
Property Exposure$_{i,t-9}$	3.828**	3.168*	2.432	2.348	-0.0689	0.359
	(1.525)	(1.644)	(1.687)	(1.456)	(1.377)	(0.546)
Property Exposure$_{i,t-10}$	2.414	1.921	1.158	1.587	-0.515	-0.144
	(1.622)	(1.711)	(1.747)	(1.528)	(1.462)	(0.504)
Property Exposure$_{i,t-11}$	2.313	1.566	1.026	1.693	0.723	0.0397
	(1.731)	(1.828)	(1.853)	(1.616)	(1.600)	(0.584)
Property Exposure$_{i,t-12}$	0.0338	-1.369	-1.907	-0.953	-0.520	-0.955*
	(1.791)	(1.980)	(2.035)	(1.823)	(1.820)	(0.549)
Log of Bank Assets	-2.697***	-3.113***	-3.236***	-2.881***	-2.349***	-0.696***
	(0.204)	(0.239)	(0.249)	(0.226)	(0.199)	(0.0525)
Bank Loan Losses	-86.18***	-69.87***	-69.67***	-60.11***	-44.80***	-13.02***
	(7.344)	(19.57)	(19.73)	(17.47)	(15.01)	(3.840)
Coefficient Sum	**28.25**	20.33	13.22	17.72	7.42	2.54
F(Sum of 12 Lags)	4.74	2.03	0.82	1.94	0.37	0.35
P-Value	0.0296	0.1546	0.364	0.1642	0.5429	0.5565
County by Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank by County FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of clusters (banks)	3,606	3,860	3,863	3,744	3,234	3,836
Observations	129,646	141,480	141,610	135,934	115,998	140,340
R-squared	0.583	0.560	0.569	0.574	0.581	0.718

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