The Geography of Bank Deposits and the Origins of Aggregate Fluctuations*

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Abstract

What are the aggregate effects of deposit shocks? Using the granular-instrumental-variable methodology, we identify the deposit elasticity of economic growth as 0.87 and the money multiplier as 1.18. We construct deposit shocks by combining a new fact regarding the within-bank geographic concentration of deposits – 30% of deposits are concentrated in a single county – with local natural disasters. Large natural disasters in deposit-concentrated areas negatively affect bank deposits and amplify through bank internal capital markets. These shocks can explain 3.30% of the variation in economic growth. Lender and borrower-side frictions are critical for the aggregation of local shocks.

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1 Introduction

Banks play a crucial role in providing liquidity in the economy by funding long-term, illiquid assets with liquid liabilities – primarily deposits (Diamond and Dybvig (1983), Allen, Gale et al. (2000)). While a large literature has focused on documenting the cross-sectional effects of shocks to bank deposits on credit allocation, identifying the aggregate impact of disruptions in bank deposits on economic growth remains a major challenge.[1] Although the cross-sectional identification approach is considered the gold standard, it cannot be used to provide aggregate estimates due to the missing intercept problem. This is because the general equilibrium effects are reflected in the *intercept* and not the *slope*. Specifically, other aggregate variables that do not exhibit cross-sectional variation can affect the aggregate elasticity between deposit shocks and aggregate outcomes (Nakamura and Steinsson (2018), Wolf (2021)). The alternative approach of using aggregate time-series data is limited by strong identification assumptions. As a result, the debate on the macroeconomic effects of deposit shocks persists despite a large cross-sectional literature and availability of aggregate data. Hence, this paper attempts to address this unanswered question in the macro-finance literature: what are the aggregate effects of deposit shocks?

This paper overcomes this major empirical challenge and attempts to identify the missing intercept. We achieve this objective through our four key findings. First, we introduce a new fact on the geographic concentration of bank deposits. Bank deposits are geographically concentrated within a bank, as at least 30% of deposits for a given bank are concentrated in a single county. Second, we construct novel bank deposit shocks using the granular instrumental variables (GIV) methodology of Gabaix and Koijen (2020) by combining the within-bank geographic concentration of deposits with local natural disaster-induced property damages. Third, we show that these deposit shocks can explain aggregate economic growth. Fourth, we demonstrate that financial frictions such as regulatory constraints, informational advantages, and borrower constraints are critical to the transmission mechanism.

We begin by documenting a new fact about the within-bank geographic concentration of deposits – at least 30% of deposits for a given bank are concentrated in a single county. Bank deposits are geographically concentrated within a bank, as at least 30% of deposits for a given bank are concentrated in a single county. This result differs from Drechsler, Savov and

[1] We direct readers to the seminal work of Khwaja and Mian (2008) that has used this approach to identify the effect of deposit shocks. Other works, for example, Peek and Rosengren (2000); Loutskina and Strahan (2009); Cetorelli and Goldberg (2012), Schnabl (2012), Chodorow-Reich (2014), and Huber (2018) also use a similar empirical approach to identify the relative effect of bank liquidity shocks on the allocation of credit. Most recently, Choudhary and Limodio (2021) examine the effects of bank deposit volatility.

Schnabl (2017) which documents the within-county concentration of deposits. The geographic concentration of deposits is widespread across banks, including the Big Four banks. Overall, this finding indicates that, within a bank, the source of deposits exhibits *granularity* in the sense of Gabaix (2011).

We exploit this fact to construct idiosyncratic shocks to aggregate bank deposits, following the GIV methodology. These shocks allow for credible identification for three reasons. First, we show that natural disasters result in a permanent decline in deposits. Second, banks have different exposures to natural disasters depending on the geographic distribution of their deposits. Third, banks have varying degrees of importance in the economy due to their relative shares in overall lending. Therefore, these shocks allow us to construct exogenous variation in aggregate deposit shocks that is orthogonal to other aggregate shocks.

We find that the deposit shocks have a significant effect on aggregate fluctuations. We estimate the deposit elasticity of economic growth as 0.87, i.e., a one percentage point decline in deposit growth is associated a 0.87 percentage points decline in economic growth. In terms of relevance, we document that a one standard deviation granular deposit shock reduces economic growth by 0.05 to 0.07 percentage points and these shocks can explain up to 3.30% of variation in economic growth – comparable and in some cases, higher than common macroeconomic shocks such as oil shocks, monetary policy surprises, uncertainty policy shocks, term spread, government expenditure shocks, and the granular residual from Gabaix (2011). Lastly, using a series of placebo tests we show that our key result crucially relies on three forces – the within-bank geographic concentration of deposits, the magnitude of disaster shocks, and the importance of the bank in the overall economy, measured by its share of lending activity.

The advantage of combining natural disaster-related losses with the GIV approach is that concerns of reverse causality are minute, as the decline in economic growth is unlikely to cause natural disasters. However, for disaster-related deposits shocks to be exogenous, disasters must primarily affect aggregate output through deposits. A potential concern with our analysis is that the disaster shock may directly affect aggregate output or correlate with shocks to bank capital or demand. We show that the concerns related to the direct aggregate effect and indirect effects through bank capital or demand have a limited role. Additionally, we show that the effects of deposit concentration are not mechanically driven by the fat-tailed distribution of county size. Thus, we argue that our identifying assumption that disasters primarily affect aggregate output through deposit is likely valid.

Next, we study the underlying mechanism through which deposit shocks can affect aggregate economic growth. We argue that the effect of deposit shocks on economic growth is mediated through lending. Specifically, we provide a estimate of the money multiplier – a $1 reduction in deposits is associated with a $1.18 reduction in lending. We add to the aggregate analysis by conducting a cross-sectional analysis, using micro-data on small business lending and mortgage lending. We document a negative relation between bank deposit shocks and lending activity – the key mechanism through which shocks to banks affect economic growth.

To lend support to the main hypothesis that the geography of bank deposits is a crucial dimension, we investigate whether disasters would generate a similar effect on bank lending if its deposits were uniformly distributed. In this counterfactual analysis, we find that banks would be better adept at smoothing out idiosyncratic shocks if its deposits were equally distributed across geography.

We document that financial frictions are crucial for aggregation as they impede banks' ability to replace deposits and borrowers' ability to substitute funding from alternative sources. First, we show that financial frictions such as banks' reliance on deposit funding, bank capital constraints, informational frictions, and contracting frictions are crucial for the transmission of deposit shocks. Second, by exploiting the inability of Fannie Mae and Freddie Mac to purchase jumbo mortgages, we demonstrate that the contraction in lending is more pronounced for loans that are more likely to be funded by deposits. Third, we show that the contraction in lending is concentrated among bank-dependent borrowers which percolates to the real economy. Overall, these tests provide empirical evidence in support of the theories that financial frictions are critical in explaining granular origins of aggregate fluctuations (Pasten, Schoenle and Weber (2017); Khorrami (2021)).

One may be concerned about mismeasurement in the geography of bank deposits. Deposits are typically assigned to the office in closest proximity to the account holder's address. However, in some instances, certain classes of deposits and customers may be assigned to a non-local branch, typically the headquarter branch. We attempt to address this concern by analyzing the concentration of deposits among banks after excluding the headquarter branch of each bank. Additionally, we also study the changes in the deposits at the headquarter branch for banks that relocated their headquarters to assess the extent of measurement error. We find that the geographic misattribution of bank deposits is unlikely to drive our results. Further, we note that while measurement-related concerns may pose a threat to the magnitude of deposit concentration, it does not challenge the validity of the paper's primary objective: to document the deposits channel of aggregate fluctuations, as such an error will cause us to associate local disaster shocks with non-local deposits, biasing our estimates downwards.

Our results have three main implications. First, the deposit elasticity of economic growth is large, indicating the importance of deposit shocks in driving economic growth. Second, the geographic concentration of bank deposits provides an explanation of how idiosyncratic shocks can aggregate to account for aggregate fluctuations. Third, this paper demonstrates how extreme disasters can propagate across the financial system through banking networks, especially when bank deposits are geographically concentrated.

Broadly, this paper presents a new source of financial fragility: the geography of deposits of multi-market banks. Banks provide liquidity to the economy by funding illiquid assets (loans) with liquid liabilities (deposits). Multi-market banks are an essential part of the modern economy, connecting geographically distant areas economically. Multi-market banks collect deposits from branches across geographies and allocate funds towards lending activity. As bank loans in one area may be financed by deposits from another, local shocks to bank deposits can transmit to distant areas. This problem is amplified when bank deposits are geographically concentrated. We show that the geography of banking assets and liabilities can make the economy, on aggregate, more susceptible to idiosyncratic shocks. Hence, we propose and test a new channel for the transmission of idiosyncratic shocks: the deposits channel.

1.1 Related Literature

The major contribution of this paper is overcoming the missing intercept problem that has eluded past cross-sectional studies. Past cross-sectional studies have causally identified a *relative* effect between deposit shocks and economic outcomes. However, the slope coefficients are not interpretable as macro counterfactuals. We estimate the *aggregate* effect between deposit shocks and economic growth, thereby identifying the missing intercept. Our novel empirical methodology allows us to estimate the deposit elasticity of economic growth and the money multiplier. Specifically, this paper estimates that a 1 percentage point decrease in deposit growth is associated with a 0.87 percentage point decrease in economic growth. Moreover, our estimate of money multiplier is 1.18, i.e., $1 decrease in deposits decreases lending by $1.18.

Our paper shows that there is a granular component of aggregate deposit fluctuations, relating to the literature examining the origins of aggregate fluctuations. Our work contributes to this literature by documenting that local deposit shocks can explain aggregate fluctuations when multi-market banks exhibit a fat-tailed geographic distribution of deposits. We combine the "granular" hypothesis of Gabaix (2011) and the network cascades hypothesis of Acemoglu et al. (2012) to show that (*i*) idiosyncratic shocks to regions that serve as large sources of bank deposits are transmitted through the network of multi-market banks, and (*ii*) can account for aggregate fluctuations if the banks are significant lenders in the economy. Thus, this paper provides a potential answer to Cochrane (1994) – "will we forever remain ignorant of the fundamental causes of economic fluctuations?"

Additionally, our methodology of constructing shocks provides an improvement over the baseline methodology of Gabaix (2011). The methodology for constructing shocks in Gabaix (2011) is susceptible to the "reflection" problem – large firms load more on common factors, i.e., larger firms exhibit greater procyclicality. Our reliance on natural disaster-induced property damages provides an exogenous source of variation, circumventing concerns of endogenous matching. The orthogonality of the granular residual and aggregate shocks allows us to cleanly identify the effect of a deposit shock on economic growth. We verify the orthogonality of our measure of the granular residual by testing it against weightings by other variables.

Moreover, our work builds on the recent theoretical advances that document the salience of financial frictions for explaining aggregate fluctuations. Khorrami (2021) presents a theoretical framework showing that aggregate fluctuations emerge from idiosyncratic shocks if and only if there are financial frictions. In an alternative framework, Pasten, Schoenle and Weber (2017) show that financial frictions, such as price rigidity, can strongly amplify the capacity of idiosyncratic shocks to drive aggregate fluctuations. We contribute to this literature by providing empirical evidence in support these claims. Specifically, we show that financial frictions such as banks' reliance on deposit funding, regulatory constraints, and informational advantages, as well as borrowers' constraints and inability to swiftly switch lenders, can amplify idiosyncratic shocks.

Our paper relates to the longstanding literature, examining the role of banks in transmitting shocks and increasing financial fragility.[2] We contribute to this literature by introducing a new fact regarding the geography of deposits – a new potential source of financial fragility. Additionally, we contribute by presenting novel bank-specific shocks, constructed using the GIV methodology of Gabaix and Koijen (2020), which can be employed in future research. This panel of shocks differs from single period systematic shocks, extensively used in the extant literature.

This paper is related to the burgeoning literature on "granular" effects in banking.

[2]Some works in this literature include Peek and Rosengren (2000); Khwaja and Mian (2008); Loutskina and Strahan (2009); Cetorelli and Goldberg (2012); Schnabl (2012); Chodorow-Reich (2014); and Huber (2018) among others. These papers constitute a small share of a very large literature, and is by no means, an exhaustive list. We also direct the readers to Berger, Molyneux and Wilson (2020) for a review of literature examining the effects of banking on the real economy.

The extant literature has mostly focused on the effects of idiosyncratic shocks of granular borrowers (Amiti and Weinstein (2018), Beaumont, Libert and Hurlin (2019), Galaasen et al. (2020)) and other granular agents in the economy (Kundu and Vats (2020)). Additionally, this paper is related to the emerging literature on the effects of bank industrial organization. Drechsler, Savov and Schnabl (2017), Drechsler, Savov and Schnabl (2018), and Drechsler, Savov and Schnabl (2022) document that bank market power, due to the within-county deposit concentration, can affect the transmission of monetary policy. We contribute to this literature by documenting that deposit concentration within a bank matters for explaining the origins of aggregate fluctuations.

This paper studies the aggregate consequences of deposit shocks, originating from natural disasters. There are key contributions in this domain. First, we examine the effect of natural disasters on bank funding, which affects bank lending through the credit supply channel. Moreover, we find persistence of bank funding shocks over multiple years. This channel is different from Cortés and Strahan (2017) which argues that the reallocation of bank lending to affected areas after natural disasters is driven by changes in local credit demand in the affected areas and that the effect of credit demand shocks dissipates within a year. Second, we focus on the importance of multi-market banks rather than local banks. Cortés (2014), Plosser (2012), Gilje, Loutskina and Strahan (2016), and Gilje (2019) document an increase in bank lending by local banks that have limited access to external debt and equity markets in counties affected by natural disasters and new energy developments. We add to this literature by showing that local disaster shocks are significant for multi-market banks because of the within-bank geographic concentration of deposits. Specifically, deposits are salient for large multi-market banks which are not able to fully substitute funds through capital markets in the short-run. Therefore, our results complement Doerr, Kabas and Ongena (2022) which documents that funding shocks due to population aging affect risk-taking by large banks. Third, our paper focuses on the transmission of negative liquidity shocks originating from disaster-induced property damages in counties that are salient sources of deposit funding for other counties, rather than positive shocks.

The rest of the paper proceeds as follows. Section 2 presents the data used in the analysis. Section 3 documents the new fact about the geographic concentration of deposits. Section 4 presents the methodology to construct deposit shocks and documents the aggregate effect of deposit shocks. Section 5 discusses the underlying channels through which deposit shocks can affect aggregate economic growth. Section 6 concludes the paper.

2 Data

We construct natural disaster shocks using the Spatial Hazard Events and Losses Database for the United States (SHELDUS). SHELDUS is a county-level hazard and loss dataset, providing detailed information on natural disaster dates, affected counties, and direct losses (e.g., property and crop losses, injuries, and fatalities). Coverage of natural disasters includes thunderstorms, hurricanes, floods, wildfires, and tornadoes. The data is sourced from the "Storm Data and Unusual Weather Phenomena" published by the National Climatic Data Center (NCDC). We report summary statistics on aggregate property damages in Table 1, property damages by hazard type in Table B.1, and present a heatmap of the property damage per capita in Figure B.1.

We obtain branch-level bank deposits data from the Federal Deposit Insurance Corporation (FDIC). The FDIC conducts an annual survey of branch office deposits, the Summary of Deposits (SOD), for all FDIC-insured institutions. The survey collects information on branch characteristics such as total deposits, information on parent banks, and detailed addresses as of June 30^{th} of each year. The data covers the universe of US bank branches and spans from 1994 until 2018. We restrict the sample to banks that have branches in more than a single county.[3]

To examine lending outcomes driven by the bank deposit shock, we leverage small business lending data collected under the Community Reinvestment Act (CRA), spanning from 1997 until 2018. The CRA defines small business loans as commercial and industrial loans of $1 million or less. All depository institutions above a certain asset threshold (e.g., $1.252 billion in 2018) must report the geographic distribution of their small business loans. The CRA data is the most comprehensive data on small business lending and covers approximately 86% of all loans under $1 million (Greenstone, Mas and Nguyen (2020)).

We supplement our analysis of bank lending with mortgage origination data collected under the Home Mortgage Disclosure Act (HMDA), spanning from 1995 to 2017. Notably, we categorize mortgage loans based on (1) loan type - mortgages for home purchases, refinancing and home-improvement, and (2) loan size - jumbo and non-jumbo. Jumbo loans are typically not sold to the Government Sponsored Enterprises (GSEs), Fannie Mae and Freddie Mac.

We extract balance sheet information of US non-financial and non-utilities firms from Compustat and merge this data with the information on firms' lead bank using Dealscan. The data on quarterly bank balance sheet and income statement comes from the call report data

[3]Our results are robust to changing this threshold.

and data on regulatory bank capital comes from SNL. These datasets span from 1994 until 2018.

We use several macroeconomic shocks in our analysis, measured at the quarterly frequency, spanning from 1994 until 2018. The data on common macroeconomic indicators such as yields, total government expenditure and gross domestic product (GDP) comes from FRED provided by the St. Louis Fed. The term spread is the government six-month yield minus the three-month yield. The government expenditure shock and economic growth are defined as the percentage change in the total government expenditure and GDP, respectively. The data on oil supply shocks and economic policy uncertainty index comes from Känzig (2021) and Baker, Bloom and Davis (2016), respectively. We construct data on monetary policy shocks as in Gorodnichenko and Weber (2016) and Vats (2020) and granular shocks to large firms as in Gabaix (2011).

3 Geographic Concentration of Bank Deposits

We present new findings on the geographic concentration of deposits. Deposits are concentrated within banks, and this has been the case since 1994. This concentration exists across all banks, regardless of size.

Banks Raise 30% of Deposits from a Single County: Figure 1 demonstrates that deposits are geographically concentrated within banks. Figure 1a presents the relationship between the share of deposits and the county number ordered by deposits. The county number refers to the rank of a county by the amount of deposits it raises, i.e., county #1 refers to the county that raised the greatest amount of deposits for a given bank. Hereafter, we describe county #1 as the *largest deposit county*. The share of deposits associated with each county number is measured using three methods: *Simple Avg*, *Weighted Avg*, and *Reg Margins*. The *Simple Avg* method takes the average share of deposits in each county number. The *Weighted Avg* method takes the average share of deposits in each county number, weighting by total assets of each bank. The *Reg Margins* method retrieves the estimates associated with the regression of share of deposits on the county number, after including bank × year fixed effects and county × year fixed effects. The three methodologies yield consistent results. Regardless of the methodology, we find that the largest deposit county accounts for almost 30% of bank deposits.

3.1 Is Geographic Concentration a New Phenomenon?

We complement this fact with a temporal analysis, investigating whether the geographic concentration of deposits within banks has varied over time. In Figure 1b, we conduct a temporal analysis to study how various measures of the share of deposits in the largest deposit county have varied from 1994-2018. We present the time series plots of the simple average, weighted average, first percentile, and tenth percentile of the share of deposits in the largest deposit county. We draw three noteworthy insights from this analysis. First, we find that geographic concentration of deposits within banks is apparent from 1994 – the first reported year in the Summary of Deposits data. Second, we find that there is considerable concentration even at the first and tenth percentile values of the share of deposits in the largest deposit county. Third, we find that the deposit concentration exhibits a marginally downward trend over time.

3.2 Does Geographic Concentration Vary with Bank Characteristics?

Next, we investigate the prevalence of the geographic concentration of bank deposits. To this end, Figure 2 examines the relationship between the geographic concentration of bank deposits and bank size.[4] Figure 2a reports the relationship between the percentile of bank assets and share of deposits in the largest deposit county. Figure 2a indicates that there are not any distinguishable differences in the share of deposits in the largest deposit county for banks which operate at lower percentiles of bank assets relative to banks which operate at the higher percentiles of bank assets. We investigate the issue further by documenting the geographic concentration of bank deposits among the Big Four banks in the US, as shown in Figure 2b. Figure 2b documents the relationship between the share of deposits and the county number for the Big Four banks in the US. The share of deposits in the largest deposit county is highest for Citibank (≈ 0.5), followed by JP Morgan (≈ 0.4), Wells Fargo (≈ 0.25), and Bank of America (≈ 0.1).[5] Overall, the results of this analysis indicate the prevalence of geographic concentration of bank deposits across the distribution of bank size.

[4] We replicate the analysis for other bank characteristics such as deposits, total liabilities, book value of equity, and total loans and find similar results, see Appendix Figure B.2.

[5] Appendix Figure B.3 shows the average share of deposits in the largest deposit county for the Big Four banks over our sample period.

3.3 Is Geographic Concentration Driven by Online Banking?

A potential concern of our analysis is that the deposit concentration may be spuriously attributed to online deposits being reported at the bank's headquarter branch. As a result, one would expect the geographic concentration to mechanically increase over time as banks raise a greater fraction of their deposits through their online branches. However, Figure 1b documents a downward temporal trend in deposit concentration, instead of an upward trend, hence, alleviating this concern. Further, Appendix Figure B.3 exhibits a decline in the average share of deposits in the largest deposit county for the Big Four banks over our sample period – the most active banks in online banking. Lastly, we restrict the sample to banks with branches in more than one county, hence, our analysis does not include pure single-branch online banks.

3.4 Does Geographic Mismeasurement of Deposits Drive Concentration?

An issue with the Summary of Deposits (SOD) data is that some branches, may have a disproportionately high number of non-local deposits. This may be particularly relevant for the headquarter branches of national banks.[6] Due to reporting stipulations, the total amount of non-local deposits measured in a bank's headquarter branch may significantly impact our measures of deposit concentration. While this is a limitation of the SOD dataset, we attempt to address this concern by examining the deposit concentration for banks that moved headquarters in our sample period. Specifically, we evaluate the change in total deposits in the headquarter county when banks changed their headquarter branch. We use this change to recalculate our measure of within-bank deposit concentration in three distinct ways. First, we remove the change in deposits at the headquarter county and distribute this change in deposits across all counties based on the previous year's county share of deposits. Second, we remove the change in deposits at the headquarter county and equally distribute this change across all counties. Third, we remove the change in deposits at the headquarter county and completely omit this change in calculating the deposit shares of all counties. Appendix Figure B.4 presents these results for the years in which the banks moved their headquarters. That is, our sample only consists of 160 banks that moved their headquarters during the year they changed headquarters. These results are similar to the results reported in Figure 1a, indicating

[6] According to the SOD reporting instructions, deposits should be assigned to the office in closest proximity to the account holder's address or where the account is most active, or where the account was opened. These guidelines imply that reported deposits in each branch reflect deposits raised by that branch in its county, and, as a general rule, is indeed so. However, the instructions also recognize that "certain classes of deposits and deposits of certain types of customers may be assigned to a single office for reasons of convenience or efficiency" (see, page 3 of the 2021 instruction manual). The implies that allocation of deposits such as brokered deposits, internet deposits, etc. may be assigned to any location that any single institution chooses, which is often the headquarter branch of the bank.

that the geographic misattribution of bank deposits due to SOD reporting guidelines are unlikely to drive our results.

We complement this analysis by examining the effect of the within-bank deposit concentration, after removing the headquarter branch of the bank. Appendix Figure B.5 presents the results. We find that 20% to 25% of bank deposits come from a single county, even after removing the deposits at the headquarter branch to account for any geographic misattribution of deposits.[7] Nonetheless, we want to emphasize that while measurement-related concerns may pose a threat to the magnitude of deposit concentration, it does not challenge the validity of the paper's primary objective: to document the deposits channel of aggregate fluctuations. Specifically, mismeasurement of the geography of deposits will cause us to associate local disaster shocks with non-local deposits, biasing our estimates downward.

3.5 Geographic Distribution of Largest Deposit Counties

Lastly, we explore the geography of banks' largest deposit county in Figure 3. The heatmap illustrates two salient features associated with the largest deposit county: dispersion and granularity. The figure illustrates that the largest deposit county is geographically dispersed across the United States, as depicted in blue. The number of banks for whom a county is the largest deposit county is represented by the intensity of the shading; counties which serve as the largest deposit county for many (few) banks is shown in darker (lighter) blue. More than 50% of the largest deposit counties are the largest source of deposits for at least five banks. This indicates the presence of granularity, in the sense of Gabaix (2011), associated with the largest deposit county, i.e., certain counties are the largest deposit counties for several banks.

4 Aggregate Fluctuations

This section investigates the deposit channel of aggregate fluctuations by documenting the relationship between granular deposit shocks and aggregate economic growth. First, we document the short-run and the long-run affects of local disaster shocks on local bank deposits. Second, we develop a methodology to construct granular deposit shocks from local disaster shocks. Third, we present our key finding – granular deposit shocks can explain fluctuations in aggregate economic growth.

[7]Note that while we remove deposits at the headquarter branch from the total deposits raised in a county, they are still included in the measure of total bank deposits. This treatment induces a downward bias in our estimate of the share of deposits coming from the largest county.

4.1 Disasters and Deposit Growth

This section investigates the short-run and long-run responses of local disaster shocks on local deposit growth. Table 1 (panel B) presents the summary statistics of deposit growth and property damage following a disaster at the county-year level. The median deposit growth is 3.37%, while the standard deviation is 9.20%. The median total property damage per capita is $1.67 in 2018 dollars, while the median total property damage is $55,369 in 2018 dollars. The distribution of property damage is right skewed with significant damages in the tails of the distribution. We begin by studying the immediate response of deposit growth to disaster shocks. The empirical specification is the following,

$$\Delta ln(Deposits)_{c,t} = \beta \times \text{Disaster Shock}_{c,t-1} + \theta_c + \theta_{s(c\in s),t} + \varepsilon_{c,t} \tag{1}$$

where $\Delta ln(Deposits_{c,t})$ denotes year-over-year deposit growth at the county level, and Disaster Shock$_{c,t}$ is measured as the aggregate dollar amount of property damage per capita in county c in year t. θ_c and $\theta_{s(c\in s),t}$ indicate county and state $\times$ year fixed effects, respectively. The economic consequences of a disaster may depend on the degree of location-specific adaptation, and resilience (Guiteras, Jina and Mobarak (2015)), geography (Hsiang and Jina (2015)), and other location-specific factors such as vulnerability to natural disasters. County fixed effects help control for such location-specific factors, estimating β using only within county variation in disaster shocks, while controlling for state-level time-varying factors.

Table 2 presents the results from the estimation of equation 1. Columns 1-6 present the estimate of β for successive levels of year, county, and state $\times$ year fixed effects. Across all specifications, the point estimate is negative and statistically significant at the 1% level. The estimate of interest remains stable in magnitude despite the model R^2 increasing by 18 percentage points from column 1-6. Economically, a one standard deviation disaster shock, denoting a loss of $570 per capita, is associated with a 0.07-0.11 percentage points decline in deposit growth – comparable to the 25^{th} percentile of deposit growth.[8] These results are robust to the inclusion of lagged shocks, shown in Appendix Table B.2.[9]

Next, we conduct a Jordà projection to analyze the long-run response of deposit growth to disaster shocks. Figure 4 presents the results. The findings indicate that the effect of disaster

[8]The effect is computed by multiplying the point estimate with the standard deviation of deposit growth. Specifically, we multiply the estimate range $[-0.0080, -0.0121]$ with the standard deviation of deposit growth (9.2%) to get the effect range of $[-0.07, -0.11]$.

[9]We conduct a placebo test to validate the relationship between disaster shocks and deposit growth is not spurious. See Appendix Figure B.6 fr details.

shocks on deposit growth is permanent, exhibiting a strong negative effect of disaster shocks on deposit growth even ten years after the shock.

Overall, our findings indicate that local disaster shocks negatively affect local bank deposits, and this effect is permanent. The negative effect of natural disasters on local deposit growth is consistent with the extant literature which documents negative local short-run and long-run economic effects of natural disasters, particularly when the impact of disasters is measurable, using indicators such as physical losses (see meta-analysis presented in Lazzaroni and van Bergeijk (2014) and Klomp and Valckx (2014)). Using data from the Caribbean, Brei, Mohan and Strobl (2019) find that following a hurricane, banks face deposit withdrawals. Disasters can lead to a reduction in savings as households may need to consume their savings to cope with the destruction of capital. Furthermore, households may hold liquid deposits to protect themselves against future natural disasters. These factors may contribute to a permanent decline in savings.[10]

4.2 Effect of Deposits on Aggregate Fluctuations

This section presents – (1) the methodology to construct granular deposit shocks using local disaster shocks, and, (2) documents the effect of negative deposit shocks on aggregate economic growth using the GIV methodology developed in Gabaix and Koijen (2020).

4.2.1 Identifying Strategy

The primary objective of this paper is to study the relationship between deposit shocks and aggregate fluctuations in economic growth. The relationship of interest is the following,

$$\frac{\Delta GDP_t}{GDP_{t-1}} = \alpha + \beta \times \Delta ln(Deposits)_{t-1} + \epsilon_t \tag{2}$$

where $\frac{\Delta GDP_t}{GDP_{t-1}}$ is the US GDP growth at time t, and $\Delta ln(Deposits_t)$ is the total deposits growth in year t. The coefficient of interest is β, which estimates the deposit elasticity of economic growth. However, estimating the coefficient β directly as in equation 2 is likely to produce biased estimates due to a host of endogeneity issues. For example, the error term (ϵ_t) in equation 2 may capture unobserved latent factors correlated with demand and supply of deposits that can bias the estimate.

[10] Combining the household level savings data from Germany with the natural experiment of the European Flood of August 2002, Berlemann, Steinhardt and Tutt (2015) document that natural disasters depress savings. We direct the readers to the review of the literature presented in Botzen, Deschenes and Sanders (2019) for discussion and relevance of different direct and indirect channels through which natural disasters affect local long-run economic growth.

We address this issue by constructing granular deposit shocks using local disaster shocks à la Gabaix and Koijen (2020). Natural disasters are likely to be uncorrelated with the observed and unobserved latent factors, thereby circumventing concerns of endogeneity. We directly estimate the effect of the granular deposit shocks on aggregate fluctuations, under the identifying assumption that the granular deposit shocks, constructed using exogenous local disaster shocks, are uncorrelated to preexisting innovations in the GDP growth process. We discuss the construction and properties of these shocks next.

4.2.2 Bank Deposit Shocks: Construction & Properties

In this section, we describe the construction of bank deposit shocks.[11] Bank deposit shocks, $\Gamma_{b,t}$ for bank b at time t (quarter), are constructed by weighting county-level disaster shocks, $\epsilon_{c,t}$ – property damage per capita in county c at time t – by the bank-county deposit share, $D_{b,c,t-1}$. $D_{b,c,t-1}$ denotes deposits of bank b in county c. This is measured using the county-level deposits reported by banks in the SOD database on the 30^{th} of June of the previous year.

$$\Gamma_{b,t} = \sum_{c} \{ \frac{D_{b,c,t-1}}{\sum_c D_{b,c,t-1}} \times \varepsilon_{c,t} \} \tag{3}$$

Next, we investigate whether various bank characteristics can predict bank deposit shocks in Appendix Table B.3. The bank characteristics under study include size, loans, total equity, cash, demand deposits, net hedging, dividend on common stock, and operating income. Columns 1-8 present the estimates of a simple regression of the bank deposit shock, $\Gamma_{b,t}$, on each bank characteristic. Columns 9 and 10 present the estimates from regressing the bank deposit shocks on *all* bank characteristics. Column 10 includes bank and year fixed effects. Bank characteristics under consideration along with bank and year fixed effects can explain only 7% of total variation in bank deposit shocks. These findings demonstrate that bank characteristics cannot robustly predict bank deposit shocks in any statistical or quantitative sense.

We examine the cross-sectional and temporal dynamics of the bank deposit shocks in Figure 5. Figure 5a presents the kernel density of the coefficients of an AR(1) process for each bank's $\Gamma_{b,t}$ is plotted. A significant portion is concentrated around zero, with an average estimate of -0.03 (dashed red line), indicating low persistence among shocks. Figure 5b presents

[11] We direct readers to Appendix section C for discussion on the micro foundations and the underlying assumptions of our deposit shocks.

the kernel density of the bank-pairwise R^2. Similarly, the mass is concentrated around zero, with an average R^2 of 0.08 (dashed red line), indicating a low across-bank correlation.

Next, we provide supporting evidence that disaster-induced property damage to large deposit counties of a bank transmit to bank deposits and liquidity creation – the first stage of our analysis.[12] The results of the Jordà projections are presented in Figure 6 indicate that there is a negative effect of bank deposit shocks on deposit growth and growth in liquidity creation. Moreover, this effect is persistent and diminishes, starting five years after the initial shock.[13]

Overall, our results show that bank deposit shocks lack temporal dynamics, exhibit low correlation across banks, and can predict the aggregate bank-level decline in deposits and liquidity creation. Therefore, these shocks are unlikely to be correlated with latent factors and are a suitable candidate for bank-specific idiosyncratic shocks to deposits.

4.2.3 Aggregate and Granular Deposit Shocks

In this section, we describe the construction of aggregate and granular deposit shocks, using the bank deposit shocks described in section 4.2.2. Aggregate deposit shocks, Γ_t, are constructed by weighting the bank deposit shocks by each banks' lending share, $L_{b,t-1}$, in period $t-1$.

$$\Gamma_t = \sum_b \{ \frac{L_{b,t-1}}{\sum_b L_{b,t-1}} \times \Gamma_{b,t} \} \tag{4}$$

We present a time-series plot of the aggregate deposit shocks in Figure 7a. Based on a narrative analysis of the crests presented in Appendix Table B.4, we label each peak and assess the magnitude of the disaster(s). Major disasters include hurricanes, floods, wildfires, and earthquakes, which are geographically dispersed across the United States. The insurance payout was largest for Hurricane Katrina, at \$87.96 billion, and lowest for the Nisqually earthquake, at \$0.44 billion. Moreover, Figure 7b plots the relationship between insurance payouts and aggregate bank shocks, and illustrates the estimated regression equation. The figure demonstrates that there is a strong positive relation between insurance payouts and aggregate bank shocks.

Next, we compute granular deposit shocks from aggregate deposit shocks by subtracting equal-weighted natural disaster-induced property damages per capita from the aggregate

[12]We use "cat fat," the preferred liquidity creation measure of Berger and Bouwman (2009), as the measure of bank liquidity creation.

[13]A one standard deviation negative bank deposit shock results in an immediate decline of 0.98 percentage points in bank deposit growth. A one standard deviation negative bank deposit shock results in an immediate decline of 0.19 percentage points in growth in liquidity creation.

shocks,

$$\Gamma_t^* = \Gamma_t - \frac{1}{N_b}\{\sum_b\{\frac{1}{N_c} \times \sum_c \mathbb{1}_{b,c,t} \times \varepsilon_{c,t}\}\}, \tag{5}$$

where N_b is the number of banks and N_c is the number of counties. Gabaix and Koijen (2020) show that subtracting equal weighted shocks from the weighted shocks eliminates common observed and unobserved aggregate factors, assuming the loadings on these factors are approximately one. Hence, granular shocks provide for better identification as perfectly controlling for all aggregate factors may be impossible making them an optimal proxy for idiosyncratic shocks to deposit growth. Intuitively, granular deposit shocks captures the idiosyncratic deposit growth of large banks following natural disasters.

4.2.4 Case Study: Citibank and Hurricane Sandy

We use a case study to illustrate that idiosyncratic disaster shocks can result in bank-level aggregate deposit shocks by examining the effects of Hurricane Sandy on Citibank's deposits in October 2012. Hurricane Sandy caused severe damage to critical infrastructure in New York and New Jersey, resulting in power outages and an estimated $19 billion in damages and lost economic activity (Gov. (2023)).

We start by examining the effects of the hurricane on Citibank's deposits in its three largest deposit counties, which include New York County and nearby areas.[14] Appendix Figure B.7a shows a significant decline in deposit growth of almost 45% in these counties in 2012. Additionally, Appendix Figure B.7b presents the time-series plot of Citibank's deposit shock, constructed according to Equation 3. Taken together, Appendix Figures B.7a and B.7b clearly demonstrate that Hurricane Sandy had a significant negative effect on Citibank's aggregate deposits and this reduction in aggregate deposits was driven by decline in deposits in the largest deposit counties affected by Hurricane Sandy.

4.2.5 Granular Deposit Shocks and Aggregate Fluctuations

This section shows that granular deposit shocks can explain aggregate fluctuations. We begin by presenting a descriptive local linear polynomial plot of GDP growth and aggregate deposit

[14]To compare deposit growth, we divide the counties into two categories: Citibank's three largest deposit counties in each year, and all other counties. That is, a county is among the top three bin if it is one of Citibank's three largest deposit counties in any year. Specifically, there are a total of eight counties in the top three bin, with two from California, four from New York, and one each from Nevada and South Dakota. The top three counties are Los Angeles County, San Francisco, Clark County, Kings County, Nassau County, New York County, Queens County, and Minnehaha County. The counties among the top three in New York include Kings, Nassau, New York (Manhattan), and Queens.

shocks in Appendix Figure B.8. The figure indicates that large bank shocks are negatively related to GDP growth. We investigate this relationship formally in Table 3, in which we regress GDP growth on the granular deposit shock. Column 1 does not include any fixed effects. Columns 2 and 3 include quarter, and, quarter and year fixed effects, respectively. The results indicate that a one standard deviation granular deposit shock reduces economic growth by 0.05-0.07 percentage points, and granular shocks can explain 2.37% of variation in economic growth.[15]

Table 4 documents the amount of variation in economic growth that can be explained by granular deposit shocks. In columns 1-6, we regress GDP growth on lags of the granular deposit shock, sequentially. In column 7, we present the results of the regression of GDP growth on the granular deposit shock and five lags thereof. The R^2 associated with column 7 demonstrates that granular deposit shocks can explain 3.30% of variation in economic growth.

In order to assess the quantitative role of the geography of bank deposits – whether the 3.30% number is economically meaningful – consider a benchmark economy with one county per bank and i.i.d. county-level shocks, i.e., no granularity. Assume that the aggregate volatility in the benchmark economy is σ and the county-level growth volatility is σ_c. Piazzesi and Schneider (2016) documents that the city-level house price volatility is between 2.5-3X the size of aggregate house price volatility. For personal income, aggregate growth has a volatility of 0.027 while county-level growth has a size-weighted-average growth volatility of 0.04, a ratio of 1.5X. Let us aggressively calibrate our benchmark economy to have $\sigma_c = 3\sigma$ and $N \approx 3,000$. The aggregate variance coming purely from the finite sample is $\frac{3\sigma}{\sqrt{N}} = 0.055\sigma$. The standard iid calculation for this non-granular economy indicates that only 0.3% of total aggregate variance can be explained without any granularity. This is substantially smaller than our baseline finding – 3.30% of variation in economic growth is explained by granular deposit shocks. Hence, the geography of bank deposits considerably affects aggregate economic fluctuations.

To better understand the relevance of granular deposit shocks in explaining economic growth relative to other macroeconomic shocks, we conduct a horse race. We include oil shocks, monetary policy surprises, uncertainty policy shocks, term spread, government expenditure shocks, and the granular residual from Gabaix (2011). Table 5 presents these results. There are two takeaways from the horse-race. First, the effect of the granular deposit shocks on

[15] A concern with the findings reported in Table 3 is that the relationship may be driven by noise or sampling error given the small sample size. We address this concern by generating placebo shocks. We do so by fitting our aggregate shocks and common shocks to Pareto distributions. We generate placebo shocks by taking the difference of the random draws from the estimated aggregate and common shock distributions. We estimate our baseline regression and compute the model R^2 in 1,000 simulations of the placebo shocks. Appendix Figure B.9 reports the results from the simulations. Our placebo shocks can generate an R^2 that is greater than 2.37% – our baseline R^2 from Column 1 of Table 3 – in fewer than 10% of the cases. This indicates that sampling error alone does not explain variation in aggregate fluctuations.

GDP growth is robust to controlling for other macroeconomic shocks. Second, the explanatory power of granular deposit shocks is comparable, and in some cases, higher than other commonly used macroeconomic shocks such as oil shocks, monetary policy shocks, uncertainty shocks, term spread, and the granular residual from Gabaix (2011).

Next, we study the long-run responses of GDP growth to the granular deposit shocks. Figure 8a plots the long-run response of GDP growth to the granular deposit shocks using a Jordà projection. The figure indicates that the effect of granular deposit shocks on GDP growth is immediate, however, transitory; the effect wanes gradually over the course of several quarters. This result contrasts with the finding of Figure 4, in which we find that the effect of disaster shocks on deposit growth is permanent. This difference in the permanence of the response may be attributed to the salience of financing frictions. Granular deposit shocks affect GDP growth in the short-run when financial frictions are binding and acute. With time, firms and households may substitute to other sources of external financing, hence, the effect dissipates in the long-run.

A concern with the analysis, so far, is that our estimation strategy may be capturing the direct effect of disasters on economic growth rather than the effect of idiosyncratic shocks to deposit growth. We address this concern by examining the long-run response of GDP growth on the aggregate disaster shocks, measured using total property damage per capita, using a Jordà projection. Figure 8b reports these results. There is no statistically or economically relevant direct effect of disasters on economic growth, as the point estimate remains close to zero over time. This lends credence to our main finding that our results are driven by idiosyncratic shocks to deposit growth.

Another concern regarding the identification is that natural disasters in urban areas may have a more detrimental impact on GDP compared to natural disasters in rural areas, even if the total property damage is held constant. This would show up in the instrument because large banks are concentrated in large cities. We address this concern by directly controlling for such factors. We create alternative granular shock variables for each county. For example, the employment granular shock is calculated as the average of property damages per capita, weighted by the county's share of national employment. Similarly, we create GDP and population granular shocks which measure the average of property damage per capita, weighted by the county's share of national GDP and population, respectively. Table 6 presents the results of running a horse-race between our granular deposit shock and other county-level granular shocks. Across all columns, our estimate of interest associated with the granular deposit shocks is fairly stable in magnitude and sign, and remains statistically significant.

This indicates that the effects of deposit concentration are not mechanically driven by the fat-tailed distribution of county size.

Another potential concern with our analysis is that the disaster shock may be correlated with shocks to bank capital or demand. We address this concern by directly comparing the deposits channel with the bank capital and demand channels in Table 7. We run a horse-race between our granular deposit shock, granular bank capital shock and demand shock. First, the bank capital shock is constructed as the mortgage- and small business lending-weighted averages of the county-level disaster shocks. Then, using these shocks, we estimate aggregate bank capital shocks, as in equations 4 and 5. The granular bank capital shock used in Table 7 is the mean of the mortgage- and small business lending-weighted granular bank capital shocks. The results in columns 1-3 show that the bank capital channel is neither economically nor statistically significant in driving the aggregate response in GDP growth. The granular bank capital shock's point estimate is minute compared to the deposits channel, and the R^2 associated with the granular bank capital shock is insignificant (column 2). Therefore, the granular bank capital shock does not explain any variation in GDP growth.

Further, we supplement this test with demand shocks by directly controlling for home and business related disaster-losses reported in the SBA Disaster Loan Program dataset. These losses are proportional to the changes in demand caused by disasters. Columns 4-7 of Table 7 report the results using these controls. As before, our granular shock remains statistically and economically significant, even after accounting for these alternate channels.

4.2.6 Discussion on the Magnitude

For ease of interpretation, we convert our baseline estimate to units of deposit and lending growth. To this end, we estimate two-stage least square (2SLS) specifications that project the exogenous component of deposit and lending growth due to the granular shocks on economic growth. Potential threats to the identification include the direct effect of disasters on economic activity, correlation with granularity in the distribution of county employment, population, and GDP, and bank capital and demand channels. The evidence presented in section 4.2.5 indicates that the magnitude of these concerns is minute.

We regress deposit growth on the granular deposit shocks in the first stage, and use the predicted values of deposit growth from the first stage to identify the deposit elasticity of economic growth in the second stage. We similarly examine this relation with lending growth to identify the loan supply elasticity of economic growth. Further, we estimate the effect of deposit growth on loan supply growth. Table 8 reports these results. Columns 2 and 4 report the first stage for deposit growth and lending growth, respectively. Columns 1 and 3 report the deposit and loan supply elasticity of economic growth, respectively. Our loan supply elasticity of economic growth is 0.14. This indicates that a 1 percentage point decrease in the loan supply results in a decline of economic growth by 0.14 percentage points. While the f-statistic associated with this estimate is low, the magnitude is comparable to that documented in the literature so far. Kundu and Vats (2020) empirically estimate that a 1 percentage point increase in bank lending through the loan supply channel increases economic growth by 0.05-0.26 percentage points. Using a structural model, Herreño (2020) estimates that a 1 percent decline in aggregate bank lending supply reduces aggregate output by 0.2 percent. Our estimate for the deposit elasticity of economic growth is 0.87. The f-statistic associated with this estimate is 11.14. The results indicate that a 1 percentage point decrease in deposit growth results in a decline of economic growth by 0.87 percentage points. The deposit elasticity of economic growth is substantial, and corroborates that the deposits channel can significantly influence aggregate fluctuations. Hence, our empirical methodology allows us to estimate the aggregate elasticity of deposit shocks on economic growth, addressing the missing intercept problem.

Further, the deposit elasticity of economic growth is almost six times the lending supply elasticity of economic growth, and is consistent with the observation in column 5 that a 1 percentage point increase in deposit growth corresponds to a 6 percentage point increase in lending growth. This IV set-up provides a clean estimate of the money multiplier, indicating that a \$1 reduction in deposits is associated with a reduction of \$1.18 in C&I lending.

4.2.7 Salience of Deposit Concentration, Disaster Shocks and Lending Share

Our shocks constructed using the GIV methodology of Gabaix and Koijen (2020) relies on three forces to explain aggregate fluctuations – the within-bank geographic concentration of deposits, the magnitude of disaster shocks, and the importance of the bank in the overall economy, measured by its share of lending activity. This section highlights the salience of these three forces by examining the sensitivity of the estimate to placebo shocks that gradually dilute the importance of each force.

Our first exercise examines the importance of deposit concentration. We construct a series of placebo shocks by omitting the top K deposit counties for each bank, where K ranges from 1 to 15. For example, when $K = 6$, we omit each bank's six largest deposit counties in the construction of our granular shocks. The intuition of this test is that if the deposit concentration of banks does not matter for our shocks to explain aggregate fluctuations, we should observe similar results using the placebo shocks. Otherwise, if deposit concentration is an important ingredient, the ability of these placebo shocks to explain aggregate fluctuations should decline as K increases. Figure 9a reports the estimate from the baseline estimation for each placebo shock. $K = 0$ indicates the baseline coefficient associated with the regression of our baseline granular shocks on the GDP growth rate. Figure 9a shows that as K increases, the coefficient rapidly declines to zero. This test indicates the salience of the geographic concentration of bank deposits. Moreover, the test demonstrates that the disasters and the relative shares of bank lending are insufficient in and of themselves to generate aggregate fluctuations.

Our second placebo exercise examines the relevance of the importance of banks in the economy. We measure the relative importance of each bank in the economy using its share of total lending activity. Specifically, we construct a series of placebo shocks by excluding the most significant banks for each quarter. The intuition of this test is that if large disasters hit deposit counties of small banks, the aggregate effects are likely to be muted. However, if disasters hit the important deposit counties of large banks, the aggregate effect is expected to be larger à la Gabaix (2011). Moreover, large banks are vital nodes in the lending network structure, hence, more likely to transmit shocks across the country à la Acemoglu et al. (2012). This intuition is also consistent with Corbae and D'Erasmo (2021). We construct a series of shocks by varying the bank size. Specifically, we exclude banks with lending share above the Kth percentile, with K ranging from the 95th to the 40th percentile in 5 percentile increments. Figure 9b reports the estimate from the baseline estimation for each placebo shock. In the x-axis, *All* indicates the baseline coefficient associated with the regression of our baseline granular shocks on the GDP growth rate. The subsequent labels denote the percentile of the bank size distribution used to construct the shocks. The figure shows that as we construct our shocks by excluding systemically important banks, the effect gradually declines and converges to zero. This indicates the importance of shocks to large banks in explaining aggregate fluctuations.

Our third placebo exercise examines the relevance of the magnitude of disasters. We construct a series of placebo shocks by excluding the most significant disasters for each quarter. Specifically, we create a series of twelve shocks by excluding disasters with property damage per capita above the 95th and the 40th percentile in 5 percentile increments. Figure 9c reports the estimate from the baseline estimation for each placebo shock. In the x-axis, *All* indicates the baseline coefficient associated with the regression of our baseline granular shocks on the GDP growth rate. The subsequent labels denote the percentile of the disaster size distribution used to construct the shocks. The figure shows that as we construct shocks by omitting large disasters, the ability of the shocks to explain aggregate fluctuations gradually declines. The results indicate that small disasters are likely to have only a temperate effect even if they hit the top deposit counties of the largest banks.

5 Mechanism

Thus far, we have demonstrated that deposit shocks can affect aggregate economic growth. In this section, we explore the underlying channels through which this occurs. Using micro-data on small business and mortgage lending, we show that deposit shocks reduce lending. This effect is pronounced among large banks, which is necessary for idiosyncratic shocks to have an aggregate effect. We also show that financial frictions, such as banks' reliance on deposit funding, capital constraints, and informational advantages, play a crucial role in transmitting deposit shocks. Finally, our analysis demonstrates how borrower constraints transmit deposit shocks to the real economy.

5.1 Small Business Lending & Deposit Shocks

We begin by studying the relationship between small business lending growth and deposit shocks using specifciation 6. We focus on small business lending for two primary reasons. First, small businesses are the "lifeblood" of the US economy, accounting for 44% of economic activity and 48% of total employment (Kobe and Schwinn (2018)). Second, small business loans are risky and illiquid assets, and rarely securitized, hence, lending in this market is especially dependent on stable deposit funding from banks (Drechsler, Savov and Schnabl (2017)).

$$\Delta ln(Lending)_{b,c,t} = \beta \times \Gamma_{b,t-1} + \theta_{c,t} + \theta_{b,c} + \varepsilon_{b,c,t} \tag{6}$$

where $\Delta ln(Lending)_{b,c,t}$ denotes the growth in small business lending by bank b in county c and year t. $\Gamma_{b,t-1}$ denotes bank specific deposit shocks measured using banks' deposit weighted exposure to disasters in year $t-1$. $\theta_{c,t}$ and $\theta_{b,c}$ denote county × year and county × bank fixed effects, respectively. We interpret the estimate of β as a within-county estimator, identified using variation in deposit shocks across banks within a county-year observation. This estimator measures the effect of deposit shocks on bank lending under the identifying assumption that banks face identical investment opportunities within a county 'a la Drechsler, Savov and Schnabl (2017). County × year fixed effects also allow us to control for all direct economic effects of disasters. A threat to our identifying assumption is that banks may have comparative advantages in certain areas due to historical connections between the bank and the area. Therefore, we include county × bank fixed effects to control for the time-invariant importance of a bank in a county. A weaker version of our identifying assumption states that any friction that creates a wedge between available investment opportunities to different banks within a county, after controlling for county × bank fixed effects, is unrelated to the idiosyncratic disaster shocks elsewhere.

Table 9 reports the estimates from the estimation of equation 6. Column 1 presents results from a simple regression of lending growth of bank b in county c in year t on bank-specific deposit shock. Column 2-5 sequentially add several permutations of bank, year, and county fixed effects to finally estimate equation 6 in column 6 with county × year and county × bank fixed effects. Across all columns the point estimate of β is negative and statistically significant at the 1% level. Moreover, the magnitude of the estimate remains stable despite an increase of 20 percentage points in the model R^2. Economically, a one standard deviation deposit shock is associated with a decline of 1.09-1.87 percentage points in lending growth.[16] Additionally, Appendix Table B.5 replicates column 6 of Table 9 separately for counties unaffected and affected by disasters. Our findings indicate that the results are unlikely to be driven by counties which experience direct disaster shocks.

Moreover, we present the long-run response of small business lending growth on deposit shocks using a Jordà projection for two reasons. First, it allows us to quantify the long-run response of bank lending to bank deposit shocks. Second, examination of the long-run response allows us to distinguish our deposit-driven supply-side channel from the reallocation-driven demand-side channel of Cortés and Strahan (2017), which is a short-term effect that dissipates within one year following the disaster. Appendix Figure B.10 shows that the negative coefficients from the Jordà projection persist for several years after the disaster, resulting in a cumulative decline of 4.68 percentage points in lending growth five years after the shock. The results for affected and unaffected counties are similar (see Appendix Figure B.11). We extend the analysis to examine the effect of deposit shocks on mortgage lending and find similar results (see Appendix Figure B.12).

[16]Our results are robust to the exclusion of credit card banks from the sample. See Appendix Table B.6.

5.1.1 Does the Geography of Bank Deposits Matter?

Next, we investigate a counterfactual case, i.e., would disasters generate a similar effect on bank lending if its deposits were uniformly distributed? To this end, we construct an alternative measure of bank deposit shocks. The measure averages property damage per capita across the top K counties, assuming equal deposit distribution among them. Figure 10 reports the results. Small business lending is negatively related to property damage per capita when $K = 1$, but the effect declines as K increases and converges to zero after $K = 10$, indicating that idiosyncratic shocks to the largest deposit counties are crucial. This indicates that idiosyncratic shocks to the largest deposit counties are crucial. Disregarding the geography of bank deposits does not generate the effects presented earlier in the analysis. Importantly, this indicates that in the counterfactual case, where deposits are equally distributed across geography, banks would be better adept at smoothing out idiosyncratic shocks.

5.1.2 Large Banks Amplify Transmission

A necessary condition for idiosyncratic shocks to explain aggregate fluctuations is that the idiosyncratic shocks must affect the behaviour of the large players in the market. Theoretically, idiosyncratic bank-level shocks may explain aggregate fluctuations if the distribution of bank sizes is fat-tailed, as $\frac{1}{\sqrt{N}}$ diversification does not occur in an economy with a fat-tailed distribution (Gabaix (2011)). While Figure 2b demonstrates that the four largest banks in the US exhibit geographic concentration of their deposits, indicating the presence of fat tails, it does not necessarily imply that the large banks alter their lending behaviour following deposit shocks.

In this section, we empirically test whether larger banks contract lending activity in response to deposit shocks. Specifically, we examine the transmission of bank deposit shocks on lending growth for small, medium, and large banks. Small banks are banks with less than or equal to $2 billion in assets. Medium banks are banks with greater than $2 billion in assets and less than or equal to $35 billion in assets. Large banks are banks with greater than $35 billion in assets. Appendix Table B.7 reports the results for the estimation of equation 6 for small, medium, and large banks separately. The results indicate that large banks also reduce their lending growth by a substantial margin following a deposit shock.[17]

[17]Note that that while the economic magnitude of the effect varies across bank size, the estimates are statistically indistinguishable from each other.

5.2 Frictions and the Transmission of Idiosyncratic Shocks

This section shows how financial frictions are crucial for aggregation as they impede banks' ability to replace deposits and borrowers' ability to substitute funding from alternative sources.

5.2.1 Bank Frictions and the Transmission of Idiosyncratic Shocks

Table 10 presents the role of financial frictions in the transmission of idiosyncratic deposit shocks. Column 1 tests how banks' reliance on deposit funding affects the transmission of deposit shocks. As natural disasters lead to a decline in banks' core deposits, banks with greater reliance on such deposits as a primary source of deposit funding are more likely to cut lending following deposit shocks. We find that a one standard deviation deposit shock is associated with an additional decline in lending growth by 1.08-3.02 percentage points in for banks with high reliance on core deposits.[18]

Column 2 of Table 10 tests how banks' capital constraints affect the transmission of deposit shocks. As regulation imposes additional constraints and balance sheet costs, it can impair banks' resilience to unanticipated shocks by pushing banks closer to their constraints and result in lending contraction following a deposit shock. We find that a one standard deviation deposit shock is associated with an additional decline in lending growth by 21-25 percentage points for constrained banks relative to unconstrained banks. This result is consistent with Rehbein and Ongena (2021) which documents that firms connected to a strongly disaster-exposed bank with lowest-quartile capitalization significantly reduce their borrowings and tangible assets.[19]

Column 3 of Table 10 tests how informational (dis)advantages affect the transmission of deposit shocks across geographies. Specifically, we examine whether banks transmit shocks more to areas where they lack informational advantages, measured by the lack of a physical bank branch. We find that a one standard deviation deposit shock is associated with an additional decline in lending growth by 1.53-1.94 percentage points in counties where banks do not have a physical branch.[20]

Further, we examine the relevance of contracting frictions by estimating the effect of

[18]We present the step-wise estimation in Appendix Table B.8, by sequentially adding fixed effects and show that our estimate of interest is stable in magnitude.

[19]We present the step-wise estimation in Appendix Table B.9, by sequentially adding fixed effects and show that our estimate of interest is stable in magnitude.

[20]We present the step-wise estimation in Table B.10, by sequentially adding fixed effects and show that our estimate of interest is stable in magnitude. Further, Appendix Table B.11 reports the results using the second classification scheme in which core is defined by above-median share of lending in a county-year. The results indicate that a one standard deviation deposit shock is associated with an additional decline in lending growth by 1.52-2.17 percentage points in counties where banks have limited lending presence.

deposit shocks on mortgage lending growth in Table 11. We disaggregate mortgage lending by mortgage type. Column 1 reports the point estimate associated with mortgage lending for home purchases. Column 2 reports the point estimate associated with mortgage lending for refinancing. Column 3 reports the point estimate associated with mortgage lending for home improvement. The results indicate that a one standard deviation deposit shock is associated with declines in lending growth of 1.87 percentage points for home purchases, 1.20 percentage points for refinancing, and 0.82 percentage points for home improvements. The pecking order of effects on different mortgage types is consistent with the argument that contracting frictions are less pronounced for home refinancing and improvement relative to home purchases because borrowers have an established payment history for the former (Gilje, Loutskina and Strahan (2016)). This implies that lending contraction is dominant in loan types where banks face more contracting frictions.

We further examine the transmission of deposit shocks through the mortgage market by exploiting a unique feature of the market. Banks often securitize mortgages, replacing deposits with bonds as a source of finance. This securitization is due to the secondary market activities of the government-sponsored enterprises (GSEs, i.e., Fannie Mae and Freddie Mac). Loutskina and Strahan (2009) show that the supply of jumbo mortgages is driven by deposit funding and liquidity constraints, as GSEs do not securitize jumbo mortgages. We exploit the inability of Fannie Mae and Freddie Mac to purchase jumbo mortgages to identify loans that are likely to be funded by deposits. An additional advantage of this analysis is that we can include bank $\times$ county $\times$ year fixed effects in estimating the effect by comparing jumbo and non-jumbo mortgages for each county-bank-year observation. In addition, we include jumbo $\times$ bank $\times$ county fixed effects to control for the time-invariant importance of jumbo mortgages extended by a bank in a county. This innovation in fixed effects allows us to relax our weak identification assumption. Table 12 reports the results for estimating the difference in lending growth of jumbo and non-jumbo mortgages by affected banks. The results indicate that deposit shocks negatively affect the origination of jumbo mortgages more than non-jumbo mortgages. A one standard deviation deposit shock is associated with a 3.58 percentage points additional decline for jumbo mortgages relative to non-jumbo mortgages. Our findings are consistent with Bidder, Krainer and Shapiro (2021) which show that banks do not uniformly reduce credit supply after a damaging shock. The results indicate that the contraction in lending is pronounced for loans that are more likely to be funded by deposits.

5.2.2 Borrower Constraints and the Transmission of Idiosyncratic Shocks

This section examines the role of borrower constraints in the transmission of deposit shocks. Firms which are more dependent on banks as a source of external financing are hypothesized to drive the response in lending growth to deposit shocks. We use size as a proxy for external finance dependence, to identify firms which are most vulnerable to deposit shocks. A firm is small if its gross revenue is less than \$1 million, and large otherwise. Our empirical strategy estimates the effect of deposit shocks on lending growth to constrained borrowers by comparing small business loans to small firms and relatively large firms for each county-bank-year observation by including bank × county × year fixed effects. In addition, we include small × bank × county fixed effects to control for the time-invariant importance of small firms that obtain loans from a bank in a county. The inclusion of these fixed effects relaxes our weak identification assumption. Table 13 presents the estimates of the effect. The results indicate that deposit shocks transmit more to constrained borrowers relative to unconstrained borrowers. A one standard deviation deposit shock is associated with a 1.52-1.87 percentage points additional decline for small firms relative to large firms. Hence, the contraction in lending is pronounced for small firms.

5.3 Firm Response, Deposit Shocks & Financial Frictions

Lastly, we examine the effect of bank deposit shocks on real firm outcomes. For each firm, we identify the lead banks using Dealscan data. and aggregate the deposit shocks experienced by all lead banks of a firm. Further, we classify firms as being financially constrained based on the age of the firm, measured by the number of years since the initial public offering. Hadlock and Pierce (2010) document a linear relation between firm age and constraint indicating that young firms are more financially constrained. Moreover, young firms rely on lending relationships with banks to procure external financing (Petersen and Rajan (1994)). Hence, examining the heterogeneity in the cross-sectional response of young and old firms to deposit shocks experienced by their lead banks can shed light on the salience of bank-borrower lending relationships and financial constraints in transmitting bank deposit shocks to the real economy. This test highlights the role of frictions in the amplification of idiosyncratic shocks to aggregate fluctuations as discussed in Dinlersoz et al. (2018). We test this hypothesis, using the following specification:

$$ln(y_{f,t}) = \beta_1 \times Young_{f,t} \times \sum_b \Gamma_{b,t-1} + \beta_2 \times Young_{f,t} + \beta_3 \times \sum_b \Gamma_{b,t-1} + \theta_{i,t} + \theta_f + \varepsilon_{f,t} \quad (7)$$

where $ln(y_{f,t})$ denotes firm level outcome variables which include the natural logarithm of total debt, book value of assets, employment, and capital expenditure. $Young_{f,t}$ is an indicator variable that takes a value of one for firms with age lower than the median value of age for all firms in that year. $\sum_b \Gamma_{b,t-1}$ refers to the aggregate deposit shocks experienced by all banks associated with firm f. $\theta_{i,t}$ and θ_f denote industry $\times$ year and firm fixed effects, respectively. The estimate of β_1 is a within-firm estimator, while controlling for industry level business cycle.

Table 14 reports the results from the estimation of equation 7. Columns 1-4 use the natural logarithm of total debt, book value of assets, employment and capital expenditure as the key dependent variable, respectively. As expected, the estimates of both $Young_{f,t}$ and $\sum_b \Gamma_{b,t-1}$ are negative. The estimate of interest associated with the interaction term $Young_{f,t} \times \sum_b \Gamma_{b,t-1}$ is negative and statistically significant across all columns. This indicates that young firms are more responsive to deposit shocks experienced by their banks. Specifically, a one standard deviation deposit shock to the firms' lead banks is associated with a 16% decline in debt, 13% decline in the book value of assets, 9% decline in employment, and a 15% decline in capital expenditure. This result highlights the role of bank-borrower lending relationships and borrower financial constraints in transmitting deposit shocks to the real economy.

6 Conclusion

Liquidity transformation is a key function of banks. Banks provide liquidity in the economy by funding long-term, illiquid assets with liquid liabilities, primarily through demand deposits. While liquidity transformation is critical for financing long-term illiquid assets, it is also a source of vulnerability for banks and the economy. It is well-established that aggregate shocks to bank capital or deposits affect bank lending activity. This paper proposes a new source of financial fragility: the geography of bank deposits.

We introduce a new fact on the geographic concentration of bank deposits. On average, 30% of bank deposits are concentrated within a single county. The geographic concentration of bank deposits within-bank is widespread, across banks of all sizes, including the Big Four banks. We show that disaster shocks to counties which exhibit deposit concentration can negatively affect bank deposits. Multi-market banks transmit these deposit shocks to other counties through their internal capital markets. Moreover, the deposit shocks can explain aggregate fluctuations when large lenders in the economy are affected by the local disaster shocks. Hence, this paper overcomes a major empirical challenge of identifying the missing intercept between deposit shocks and economic growth and estimating the aggregate deposit elasticity of economic growth and money multiplier. Local disaster shocks result in aggregate fluctuations through their effect on deposits, which negatively affect bank lending. The negative effects on bank lending are large and persistent, and amplified in the presence of financial frictions including banks' reliance on deposit funding, regulatory constraints, informational advantages, and borrower constraints.

Our paper introduces a hitherto undocumented source of financial fragility that may inform academics and policymakers working on the design of optimal stabilization policies. Concretely, the US Department of Justice Antitrust Division and FTC's Bureau of Competition review banks mergers and acquisitions to enforce the nation's antitrust laws. In a similar spirit, our findings suggest that regulators ought to consider the deposit concentration of merged banks for its implications on financial stability.

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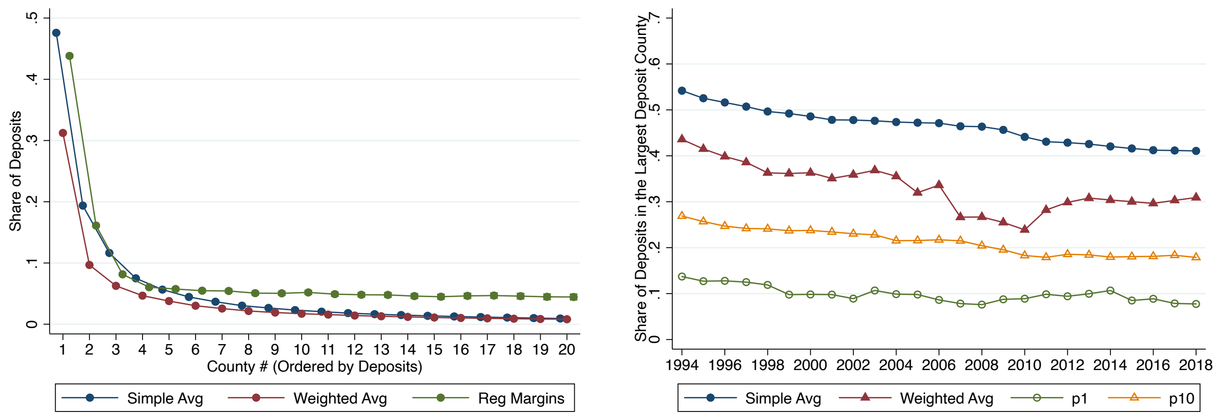
Figure 1: Geographic Concentration of Deposits

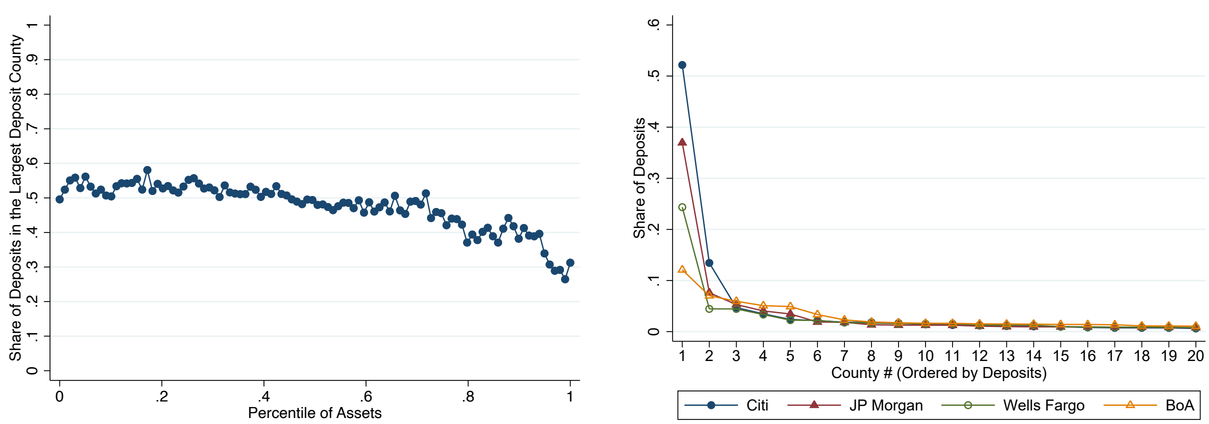


(a) Cross Section

(b) Time Series

This figure uses the summary of deposit (SOD) data from 1994 to 2018 and illustrates the geographic concentration of bank deposits. Figure 1a orders counties by their deposit shares for each bank (the county number refers to the rank of a county by the amount of deposits it raises, i.e., county #1 refers to the county that raised the greatest amount of deposits for a given bank.) and reports the average deposit share of the top 20 counties. The blue line shows the simple average of the deposit share, the red line shows the average deposit share weighted by bank total assets, and the green line shows the average deposit share controlling for bank-year and county-year fixed effects. Figure 1b reports the average deposit share of the counties with the largest deposit share (i.e., county # 1) by year from 1994 to 2018. The time series plots of the simple average, weighted average, first percentile, and tenth percentile of the share of deposits in the largest deposit county in blue, red, green, and yellow, respectively.

Figure 2: Bank Distribution of Deposit Concentration

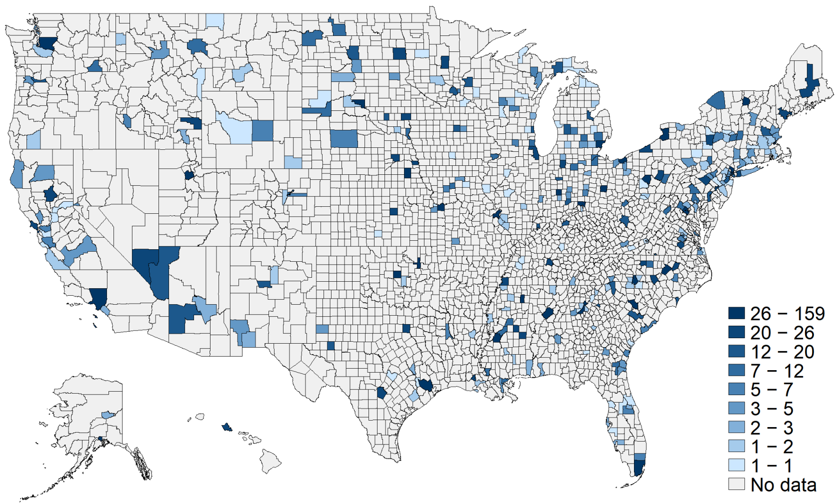


(a) Banks By Size

(b) Four Largest Banks

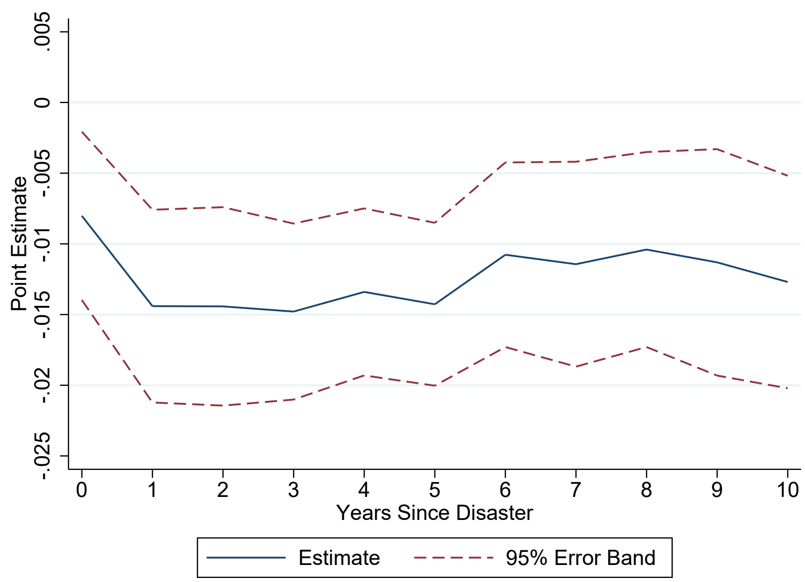
This figure uses the summary of deposit data (SOD) from 1994 to 2018 and illustrates the relation between the geographic concentration of bank deposits and bank size. Figure 2a sorts banks by their total assets and reports the average deposit share of counties with the largest deposit share against the percentile of the bank assets i.e., average value of deposit share in the largest deposit counties corresponding to the percentile of bank assets, over the sample period. Figure 2b reports the deposit shares in the top 20 counties for the four largest banks, averaged over the sample period: Citibank (blue line), JP Morgan (red line), Wells Fargo (green line), and Bank of America (yellow line). The county number refers to the rank of a county by the amount of deposits it raises, i.e., county #1 refers to the county that raised the largest amount of deposits for a given bank.

Figure 3: Geography of Largest Deposit County



This figure illustrates the geography of a county with the largest deposit share for a given bank, averaged over the period 1994 to 2018. The intensity of the blue shading represents the number of banks for whom a county has the largest deposit share.

Figure 4: Long-Run Response of Deposit to Disaster Shocks

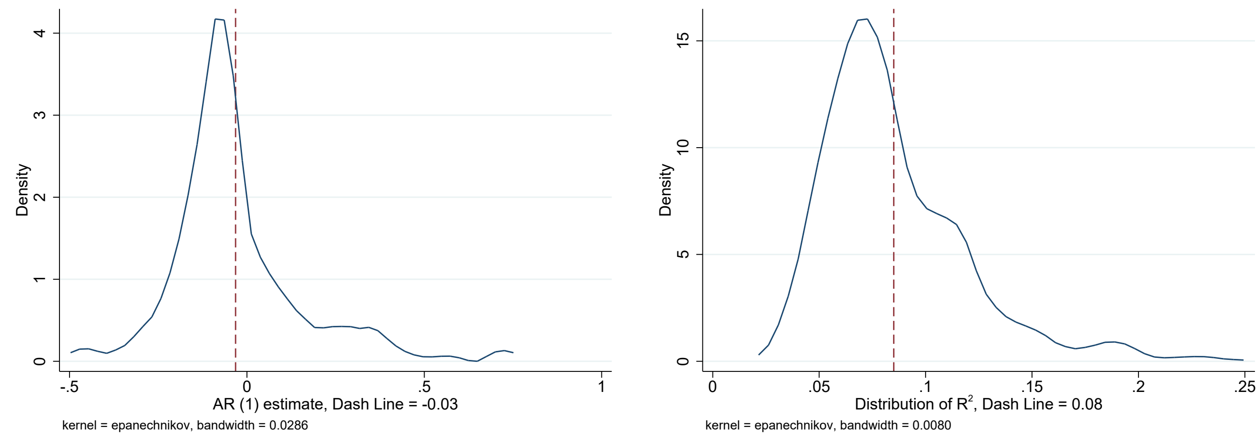


Note: This figure uses the Summary of Deposit (SOD) data matched with the Spatial Hazard Events and Losses Database for the United States (SHELDUS) and plots the estimated coefficient β_h's from the following specification:

$$ln(Deposit)_{c,t+h} - ln(Deposit)_{c,t-1} = \beta_h \times \text{Disaster Shock}_{c,t-1} + \theta_c + \theta_{s(c\in s),t} + \varepsilon_{c,t}.$$

The data spans from 1994 to 2018. The dependent variable is $ln(Deposit)_{c,t+h} - ln(Deposit)_{c,t-1}$ where $ln(Deposit)_{c,t}$ is the natural logarithm of the total deposit in county c and year t. The independent variable, Disaster Shock$_{c,t-1}$, is the standardized dollar amount of property damage per capita from natural disasters in county c and year $t-1$. θ_c and $\theta_{s(c\in s),t}$ represent county and state-year fixed effects, respectively. The solid blue line plots the point estimate β_h's with h from 0 to 10, and the dashed red line plots the 95% confidence interval for the point estimate β_h's. The confidence interval is computed from standard errors clustered at the county level.

Figure 5: Spatial and Temporal Properties of Bank Shocks

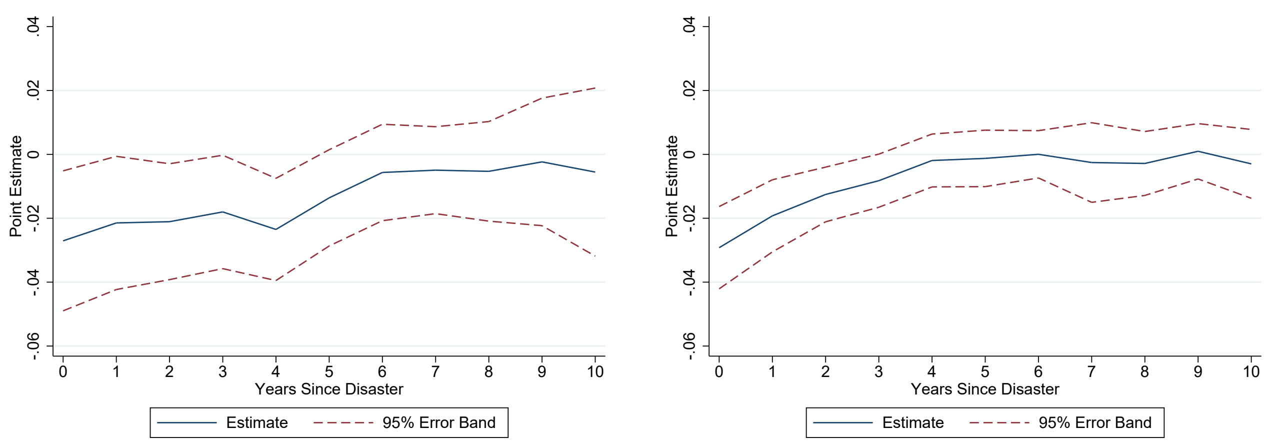


(a) AR(1) estimate for Bank Shocks

(b) Pairwise R^2 for Bank Shocks

This figure documents the properties of the bank-level disaster shocks, $\Gamma_{b,t}$. Figure 5a plots the kernel density of AR(1) coefficient for each bank's disaster shock. Figure 5b plots the kernel density of the R^2 from regressing the deposit shocks across bank pairs. The vertical dashed red lines indicate the means of estimated coefficients (Figure 5a) and R^2 (Figure 5b).

Figure 6: Long-Run Bank Response to Deposit Shocks



(a) Deposit

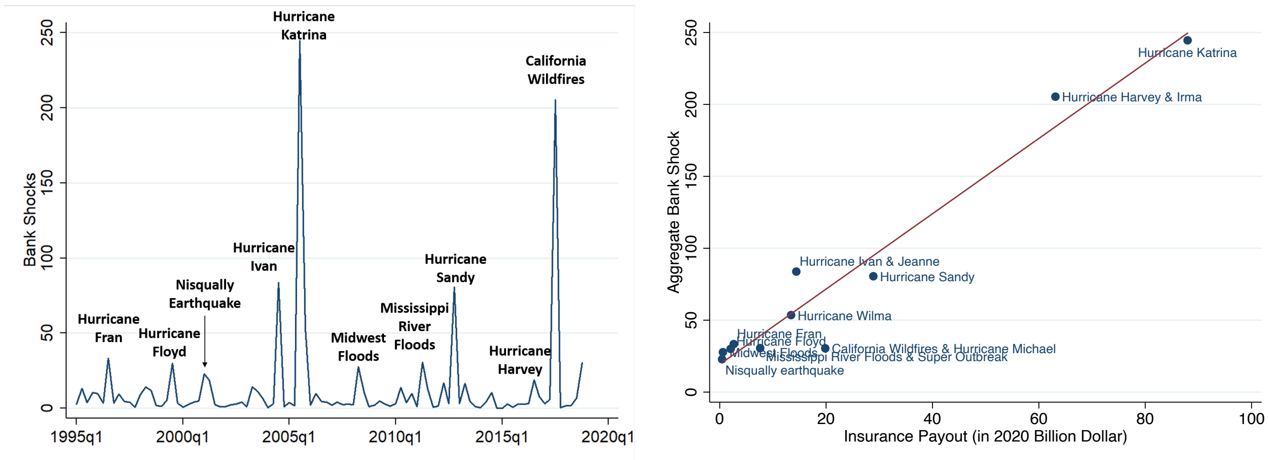
(b) Liquidity Creation

Note: This figure uses call reports and bank liquidity creation data matched with the Spatial Hazard Events and Losses Database for the United States (SHELDUS) and plots the estimated coefficient β_h's from the following specification:

$$y_{b,t+h} - y_{b,t-1} = \beta_h \times \text{Bank Deposit Shock}_{b,t-1} + \theta_b + \theta_t + \varepsilon_t.$$

The data used in Figure 6a spans from 1994 to 2018, and the data used in Figure 6b spans from 1995 to 2016. Figure 6a uses the natural logarithm of the aggregate deposits of bank b in year t as the dependent variable, $y_{b,t}$. Figure 6b uses the natural logarithm of the liquidity creation normalized by the gross total assets of bank b in year t as the dependent variable, $y_{b,t}$. The liquidity creation variable is constructed following Berger and Bouwman (2009). The independent variable, Bank Deposit Shock$_{b,t-1}$, is the standardized bank deposit shock for bank b and year $t-1$. θ_b and θ_t represent bank and year fixed effects, respectively. The solid blue line plots the point estimate β_h's with h from 0 to 10, and the dashed red line plots the 95% confidence interval for the point estimate β_h's. The confidence interval is computed from standard errors clustered at the bank level.

Figure 7: Aggregate Bank Deposit Shock

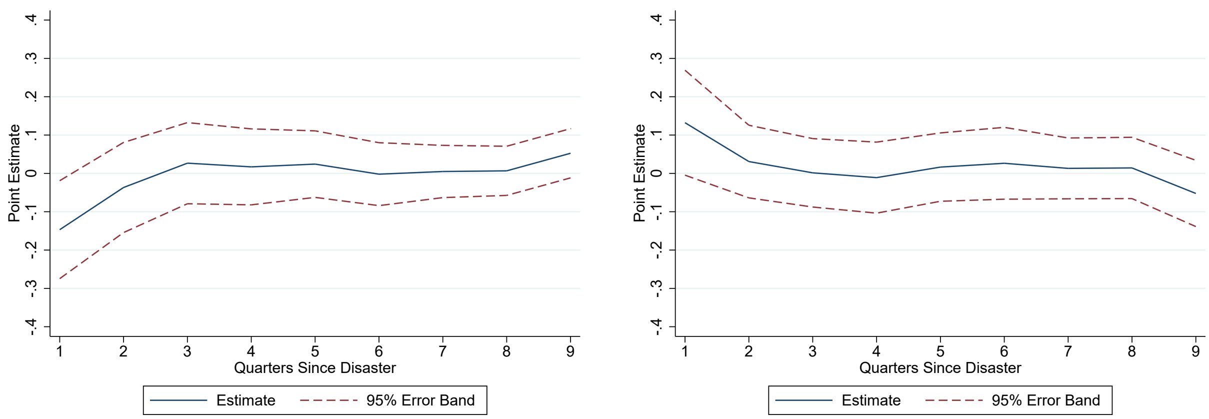


(a) Aggregate Shock over Time

(b) Aggregate Shock and Insurance Payout

Note: Figure 7a plots the aggregate bank deposit shock (Γ_t) from Q3-1994 until Q4-2018 and indicates major disasters at its notable peaks. Figure 7b plots the aggregate bank deposit shock against the insurance payout (blue dots) and illustrates the best-fit line (solid red line).

Figure 8: Long-Run Responses of Δ GDP to Granular and Aggregate Shocks



(a) Granular Shock

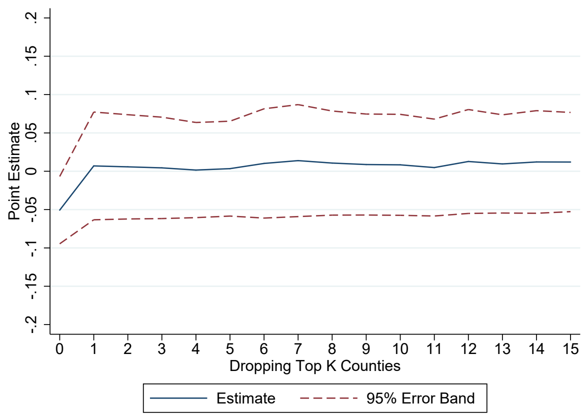
(b) Aggregate Disaster Shock

Note: This figure uses the quarterly series of GDP from 1994Q3 to 2018Q4 and plots the estimated coefficients, β_h, from the following specification:

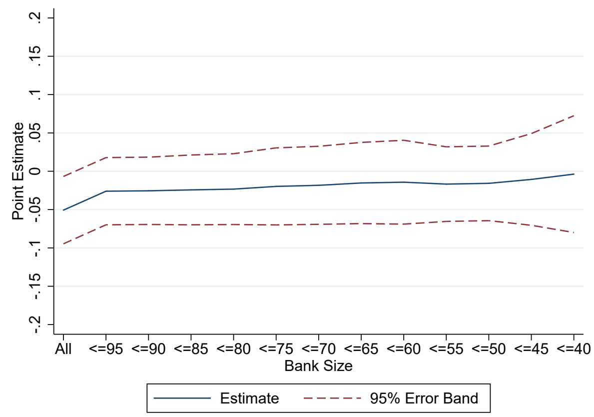
$$log(GDP)_{t+h} - log(GDP)_{t-1} = \alpha_h + \beta_h \times \text{Shock}_{t-1} + \varepsilon_t$$

, where t indicates quarter-year. Figure 8a uses the granular deposit shock Γ_t^* as the key independent variable. Figure 8b uses the aggregate disaster shock as the key independent variable, measured using total property damage per capita due to disasters in the preceding quarter. The solid blue line plots the point estimate β_h's with h from 1 to 9, and the dashed red line plots the 95% confidence interval for the point estimate β_h's. The confidence interval is computed from heteroskedasticity-robust standard errors.

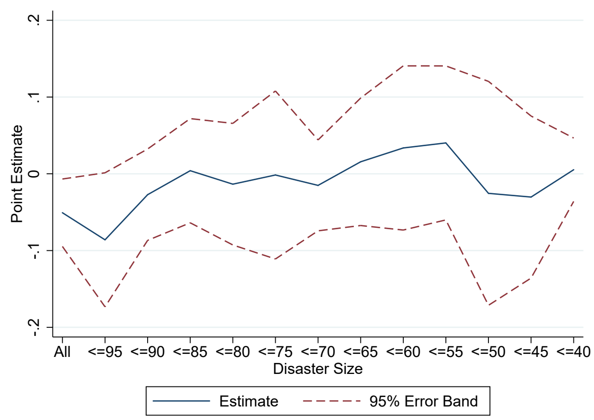
Figure 9: Placebo Test: Salience of deposit concentration, disaster shocks and lending share



(a) Dropping K Counties



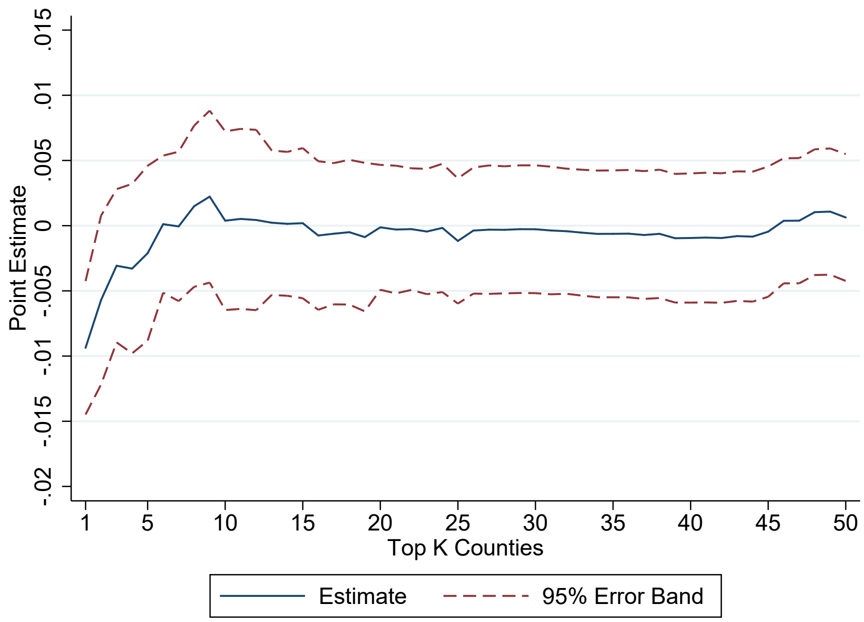
(b) Bank Size



(c) Disaster Size

Note: This figure examines the salience of deposit concentration, disaster shocks, and lending share. In Figure 9a, we construct a series of placebo shocks by omitting the top K deposit counties for each bank, where K ranges from 1 to 15. in Figure 9b, we construct a series of placebo shocks by excluding the most significant banks for each quarter. We construct a series of shocks by varying the bank size. Specifically, we exclude banks with lending share above the Kth percentile, with K ranging from the 95th to the 40th percentile in 5 percentile increments.In the x-axis, *All* indicates the baseline coefficient associated with the regression of our baseline granular shocks on the GDP growth rate. The subsequent labels denote the percentile of the bank size distribution used to construct the shocks. In Figure 9c, we construct a series of placebo shocks by excluding the most significant disasters for each quarter. Specifically, we create a series of twelve shocks by excluding disasters with property damage per capita above the 95th and the 40th percentile in 5 percentile increments. In the x-axis, *All* indicates the baseline coefficient associated with the regression of our baseline granular shocks on the GDP growth rate. The subsequent labels denote the percentile of the disaster size distribution used to construct the shocks.

Figure 10: Does the Geography of Bank Deposits Matter?



Note: This figure uses small business lending data collected under the Community Reinvestment Act (CRA) and plots the estimated coefficient β^k's in the following specification:

$$\Delta ln(Lending)_{b,c,t} = \beta^k \times \frac{1}{K} \cdot \sum_{j \in TopK} \text{Property Damage per capita}_{j,t-1} + \theta^h_{c,t} + \theta^h_{b,c} + \varepsilon_{b,c,t}$$

where b, c and t indicate bank, county, and year, respectively. j denotes the county where the bank b raises its deposits ordered by the share of deposits raised by the county for the bank. The data spans from 1997 to 2018. The dependent variable $\Delta ln(Lending)_{b,c,t}$ is the natural logarithm of small business loans originated by bank b in county c and year t. $\theta^h_{b,c}$ and $\theta^h_{c,t}$ are bank $\times$ county and county $\times$ year fixed effects, respectively. Property Damage per capita$_{j,t-1}$ refers to disaster-induced property damage per capita in county j where bank b raises deposits. All variables are standardized to a mean of zero and standard deviation of one and winsorized at the 1% level. The solid blue line plots the point estimate β_k's with k from 1 to 50, where K denotes the county ranked K by share of deposits for bank b. For example, $K = 1$ denotes the county that raised the highest share of deposits for bank b. The dashed red line plots the 95% confidence interval for the point estimate β_k's. $\frac{1}{K} \cdot \sum_{j \in TopK}$ Property Damage per capita$_{j,t-1}$ is computed using a simple average of property damage per capita across across top K counties. The confidence interval is computed from standard errors clustered by bank and county.

Table 1: Summary Statistics

	# Obs	Mean	SD	P25	P50	P75
***Panel A:** Bank-County-Year Level Data*						
Small Business Lending Growth (%)	553,345	4.85	117.15	-43.63	0.00	49.72
Mortgage Origination Growth: All (%)	1,136,531	1.83	255.73	-50.72	0.00	57.72
Mortgage Origination Growth: Jumbo (%)	1,136,531	3.84	221.23	0.00	0.00	0.00
Mortgage Origination Growth: Non-Jumbo (%)	1,136,531	1.41	254.15	-49.43	0.00	55.34
***Panel B:** County-Year Level Data*						
Deposit Growth (%)	76,755	4.48	9.20	0.17	3.37	7.12
Total Property Damage (2018 USD)	79,575	3,107,809	30,200,000	933	55,369	446,661
Total Property Damage per capita (2018 USD)	79,575	75.25	569.31	0.02	1.67	14.23
***Panel C:** Bank-Year Data*						
Bank-Level Disaster Shock (Γ_{bt})	9,892	93.71	993.34	1.00	5.09	21.76
Ln(Assets)	9,892	14.00	1.74	12.72	13.64	15.00
Loan/Assets	9,892	0.63	0.13	0.56	0.65	0.73
Equity/Assets	9,892	0.10	0.03	0.08	0.09	0.11
Cash/Assets	9,892	0.05	0.04	0.03	0.04	0.06
Deposits/Assets	9,892	0.10	0.07	0.05	0.09	0.13
Hedge/Assets	9,892	-0.05	0.42	0.00	0.00	0.00
Dividend/Assets	9,892	0.00	0.00	0.00	0.00	0.00
Operating Income/Assets	9,892	0.02	0.01	0.01	0.02	0.02
***Panel D:** Aggregate Data*						
GDP Growth	98	1.09	0.65	0.81	1.16	1.44
Γ_t	97	13.12	33.98	2.02	3.67	10.56
Oil Shock	97	0.00	1.01	-0.55	-0.03	0.72
Monetary Shock	97	-0.03	0.10	-0.03	-0.00	0.00
Political Uncertainty Shock	97	0.02	0.16	-0.10	0.02	0.12
Term Spread	97	1.10	0.74	0.60	1.08	1.55
Government Expenditure Shock	97	4.40	2.51	2.97	4.34	6.17
Γ_t^{Gabaix}	29	-0.00	0.01	-0.01	0.00	0.00
Deposit Growth	98	1.6402	0.5515	1.2337	1.6924	1.9896
C&I Lending Growth	98	1.3873	5.6219	-1.1126	3.0400	4.9582

Note: This table reports summary statistics of key variables explored in this paper. The observations in Panel A are at the bank-county-year level. The small business lending data spans from 1997 to 2018. The mortgage data spans from 1995 to 2017. The observations in Panel B are at the county-year level and span from 1994 to 2018. The observations in Panel C are at the annual level and span from 1994 to 2018. The observations in Panel D are at the quarterly level and span from 1994 to 2018, except Γ_t^{Gabaix} which are measured at the annual level and span from 1994 to 2018.

Table 2: Disaster Shock and Deposit Growth

Dep Var: $\Delta ln(Deposits)_{c,t}$	(1)	(2)	(3)	(4)	(5)	(6)
Disaster Shock$_{c,t-1}$	-0.0091***	-0.0121***	-0.0080***	-0.0111***	-0.0097***	-0.0080***
	(0.0028)	(0.0027)	(0.0030)	(0.0028)	(0.0028)	(0.0030)
Year FE		✓		✓		
County FE			✓	✓		✓
State × Year FE					✓	✓
# Obs	76,336	76,336	76,336	76,336	76,336	76,336
R^2	0.0001	0.0469	0.0523	0.0993	0.1348	0.1813

Note: This table uses the Summary of Deposit (SOD) data matched with the Spatial Hazard Events and Losses Database for the United States (SHELDUS) and reports the estimated coefficient β in the following specification:

$$\Delta ln(Deposit)_{c,t} = \beta \times \text{Disaster Shock}_{c,t-1} + \theta_c + \theta_{s(c \in s),t} + \varepsilon_{c,t}$$

where c and t indicate county and year, respectively. The data spans from 1994 to 2018. The dependent variable $\Delta ln(Deposit)_{c,t}$ is the first difference of natural logarithm of total deposit of all banks in county c and year t. The independent variable, Disaster Shock$_{c,t-1}$, is the dollar amount of property damage per capita from natural disasters in county c and year $t-1$. θ_c and $\theta_{s(c \in s),t}$ represent county and state × year fixed effects, respectively. All variables are standardized to a mean of zero and standard deviation of one, and winsorized at the 1% level. Standard errors clustered at the county level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 3: Granular Shock and Aggregate Fluctuations

Dep Var: GDP Growth$_t$	(1)	(2)	(3)
Γ^*_{t-1}	-0.0631***	-0.0679***	-0.0491***
	(0.0177)	(0.0162)	(0.0125)
Constant	1.0836***		
	(0.0768)		
Quarter FE		✓	✓
Year FE			✓
# Obs	97	97	96
R^2	0.0237	0.0259	0.5178

Note: This table uses quarterly GDP series from 1994Q3 to 2018Q4 and reports the estimated coefficient β in the following specification:

$$\%\Delta GDP_t = \alpha + \beta \times \Gamma^*_{t-1} + \varepsilon_t$$

where t indicates quarter-year. $\%\Delta GDP_t$ is a percentage change in the seasonally adjusted quarterly GDP, and Γ^*_t is the granular deposit shock. The granular shock is standardized to a mean of zero and standard deviation of one, and winsorized at the 1% level. Newey-West heteroskedasticity and auto-correlation robust standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 4: Lagged Granular Shock and Aggregate Fluctuation

Dep Var: GDP Growth$_t$	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Γ^*_t	-0.0068						-0.0109
	(0.0111)						(0.0133)
Γ^*_{t-1}		-0.0631***					-0.0622***
		(0.0177)					(0.0190)
Γ^*_{t-2}			0.0091				0.0065
			(0.0141)				(0.0139)
Γ^*_{t-3}				0.0374***			0.0347**
				(0.0139)			(0.0136)
Γ^*_{t-4}					0.0077		0.0093
					(0.0133)		(0.0142)
Γ^*_{t-5}						-0.0102	-0.0112
						(0.0158)	(0.0163)
Constant	1.0874***	1.0836***	1.0837***	1.0866***	1.0849***	1.0844***	1.0844***
	(0.0768)	(0.0768)	(0.0768)	(0.0779)	(0.0787)	(0.0813)	(0.0795)
# Obs	98	97	96	95	94	93	93
R^2	0.0003	0.0237	0.0005	0.0084	0.0004	0.0006	0.0330

Note: This table uses quarterly GDP series from 1994Q3 to 2018Q4 and reports the estimated coefficient β_h in the following specification:

$$\%\Delta GDP_t = \alpha + \beta_h \times \Gamma^*_{t-h} + \varepsilon_t$$

where t indicates quarter-year and h indicates the number of lags. $\%\Delta GDP_t$ is a percentage change in the seasonally adjusted quarterly GDP, and Γ^*_{t-h} denotes the granular deposit shock and its lags. The granular shock is standardized to a mean of zero and standard deviation of one, and winsorized at the 1% level. Newey-West heteroskedasticity and auto-correlation robust standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 5: Horse Race: Granular Shock & Other Macroeconomic Shocks

Dep Var: GDP Growth$_t$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Γ^*_{t-1}	-0.0631***	-0.0717***	-0.0612***	-0.0621***	-0.0627***	-0.0753***	-0.0647***	-0.0806***
	(0.0177)	(0.0131)	(0.0186)	(0.0186)	(0.0197)	(0.0118)	(0.0179)	(0.0121)
Oil Shock$_{t-1}$		-0.0531						-0.0560*
		(0.0383)						(0.0333)
Monetary Shock$_{t-1}$			0.0763**					0.0532**
			(0.0334)					(0.0220)
Uncertainty Shock$_{t-1}$				-0.0573				-0.0425
				(0.0365)				(0.0350)
Term Spread$_{t-1}$					-0.0141			-0.0113
					(0.0492)			(0.0527)
Gvt Exp Shock$_{t-1}$						-0.1027		-0.0828
						(0.0918)		(0.0832)
Γ^{Gabaix}_{t-1}							0.0261	0.0150
							(0.0186)	(0.0177)
Constant	1.0836***	1.0845***	1.0841***	1.0828***	1.0837***	1.0832***	1.0836***	1.0841***
	(0.0768)	(0.0749)	(0.0771)	(0.0751)	(0.0771)	(0.0826)	(0.0749)	(0.0783)
# Obs	97	97	97	97	97	97	97	97
R^2	0.0237	0.0394	0.0581	0.0428	0.0248	0.0854	0.0277	0.1315

Note: This table uses quarterly GDP series from 1994Q3 to 2018Q4 matched with other macroeconomic variables and reports the estimated coefficients β_1 and the vector β_2 in the following specification:

$$\%\Delta GDP_t = \alpha + \beta_1 \times \Gamma^*_{t-1} + \beta_2 \times \text{Macro-Shock}_{t-1} + \varepsilon_t$$

where t indicates quarter-year. $\%\Delta GDP_t$ is a percentage change in the seasonally adjusted quarterly GDP, Γ^*_t denotes the granular deposits shock, and Macro-Shock$_t$ denotes the vector of macroeconomic shocks. Column (2) through (7) use oil supply surprises defined as the first principal component of the one-day OPEC announcement return on WTI futures contracts with maturities ranging from one month to one year (Column (2)), monetary policy shock defined as the change in fed funds futures rate within 30 minutes window around press releases of the Federal Open Market Committee (Column (3)), economic policy uncertainty shock defined as the percentage change in the economic policy uncertainty index constructed by Baker, Bloom and Davis (2016) (Column (4)), the term spread defined as the difference between the three- and six-month treasury constant maturity rate (Column (5)), the government expenditure shock defined as the percentage change in the total government expenditure (Column (6)), and the granular residual of Gabaix (2011) defined as the sum of the top 100 firms' idiosyncratic productivity shocks, weighted by the share of firms sales in GDP (Column (7)), respectively. The idiosyncratic productivity shock is computed by taking the log difference of sales per employee and controlling for industry-level mean productivity growth. The granular shock and macroeconomic shocks are standardized to a mean of zero and standard deviation of one, and winsorized at the 1% level. Newey-West heteroskedasticity and auto-correlation robust standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 6: Granularity or Banking Transmission?

Dep Var: GDP Growth$_t$	(1)	(2)	(3)	(4)	(5)
Γ^*_{t-1}	-0.0631***	-0.0610***	-0.0617***	-0.0593***	-0.0735**
	(0.0177)	(0.0174)	(0.0171)	(0.0182)	(0.0288)
Γ^{Emp}_{t-1}		0.0002			-0.0559***
		(0.0005)			(0.0186)
Γ^{GDP}_{t-1}			0.0002		-0.0091
			(0.0003)		(0.0056)
Γ^{Pop}_{t-1}				0.0004	0.0558***
				(0.0004)	(0.0197)
Constant	1.0836***	1.0795***	1.0144***	1.0766***	1.0723***
	(0.0416)	(0.0419)	(0.0530)	(0.0427)	(0.0588)
# Obs	97	97	97	97	97
R^2	0.0237	0.0241	0.0241	0.0254	0.1507

Note: Note: This table uses quarterly GDP series from 1994Q3 to 2018Q4 and reports the estimated coefficient, βs, in the following specification:

$$\%\Delta GDP_t = \alpha + \beta \times \Gamma^*_{t-1} + \beta_1 \times \Gamma^{Emp}_{t-1} + \beta_2 \times \Gamma^{GDP}_{t-1} + \beta_3 \times \Gamma^{Pop}_{t-1} + \varepsilon_t$$

where t indicates quarter-year. $\%\Delta GDP_t$ is a percentage change in the seasonally adjusted quarterly GDP, and Γ^*_t is the granular deposit shock. Γ^{Emp}_{t-1} refers to the employment granular shock constructed as the average of county-level property damages per capita weighted by the county's share of US employment. Similarly, we construct Γ^{GDP}_{t-1} and Γ^{Pop}_{t-1} as the average of county-level property damages per capita weighted by the county's share of US GDP and population respectively. All granular shocks are standardized to a mean of zero and standard deviation of one, and winsorized at the 1% level. Newey-West heteroskedasticity and auto-correlation robust standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 7: Granular Bank Capital Shock and Aggregate Fluctuation

Dep Var: GDP Growth$_t$	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Γ^*_{t-1}	-0.0645***		-0.0770***			-0.0655***	-0.0800***
	(0.0167)		(0.0159)			(0.0209)	(0.0125)
Γ^C_{t-1}		-0.0003	0.0336				0.0375
		(0.0421)	(0.0421)				(0.0418)
ln(Total Home Loss)				0.0817**		0.2118	0.2159
				(0.0378)		(0.1924)	(0.1700)
ln(Total Business Loss)					0.0725*	-0.1465	-0.1543
					(0.0376)	(0.1992)	(0.1805)
Constant	1.0588***	1.0596***	1.0587***	1.0219***	1.0225***	1.0170***	1.0154***
	(0.0470)	(0.0477)	(0.0472)	(0.0509)	(0.0512)	(0.0512)	(0.0513)
N	83	83	83	70	70	70	70
R^2	0.0262	0.0000	0.0313	0.0336	0.0250	0.0699	0.0771

Note: This table uses quarterly GDP series from 1994Q3 to 2018Q4 and reports the estimated coefficient β in the following specification:

$$\%\Delta GDP_t = \alpha + \beta_1 \times \Gamma^*_{t-1} + \beta_2 \times \Gamma^C_{t-1} + \varepsilon_t$$

where t indicates quarter-year. $\%\Delta GDP_t$ is a percentage change in the seasonally adjusted quarterly GDP, Γ^*_t is the granular deposit shock, and Γ^C_t is the granular bank capital shock. The bank capital shock is computed by weighting the county-level disaster shocks by the amount of small business lending and mortgage lending conducted by each bank in each county, respectively. We use these bank-level shocks to produce aggregate bank capital shocks, as indicated in equations 4 and 5. The granular bank capital shock used in the table is the mean of the granular bank capital shock based on mortgage lending and the granular bank capital shock based on small business lending. ln(Total Home Loss) and ln(Total Business Loss) are the natural-logarithm transformed total dollar amount of home and business losses verified by the Small Business Administration, respectively. These variables are identified in the US Small Business Administration (SBA) Disaster Loan Program. The granular shocks are standardized to a mean of zero and standard deviation of one, and winsorized at the 1% level. Newey-West heteroskedasticity and auto-correlation robust standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 8: Instrumental Variables Regression

	(1)	(2)	(3)	(4)	(5)	(6)
	2nd Stage	1st Stage	2nd Stage	1st Stage	2nd Stage	1st Stage
	Δ GDP	Δ Deposits	Δ GDP	Δ Loans	Δ Loans	Δ Deposits
Deposits Growth	0.8755**				6.0853**	
	(0.3155)				(2.7757)	
C&I Lending Growth			0.1438*			
			(0.0837)			
Γ^*_{t-1}		-0.0016***		-0.0099**		-0.0016***
		(0.0004)		(0.0043)		(0.0004)
# Obs	97	97	97	97	97	97
R^2	0.0256	0.0187	0.0256	0.0066	0.0066	0.0187
KP LM Statistic		1.182		0.942		1.182
KP Wald F Statistic		11.137		5.511		11.137

Note: This table presents the estimates of our IV strategy. Columns (1) and (3) report the second stage regression of GDP growth on aggregate deposit growth and aggregate lending growth, using the instrumented measures from the first stage, respectively. The first stage regression reported in column (2) establishes a causal relation between aggregate deposit growth and aggregate deposit shocks. The first stage regression reported in column (4) establish a causal relation between aggregate commercial and industrial lending growth and aggregate deposit shocks. Column (6) reports the first stage regression of deposit growth on aggregate deposits shocks, and column (5) reports the second stage estimate of the regression of lending growth on deposit growth. Newey-West heteroskedasticity and auto-correlation robust standard errors are reported in parentheses.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Small Business Lending and Deposit Shocks

Dep Var: $\Delta ln(Lending)_{b,c,t}$	(1)	(2)	(3)	(4)	(5)	(6)
$\Gamma_{b,t-1}$	-0.0111***	-0.0131***	-0.0112***	-0.0160***	-0.0093***	-0.0148***
	(0.0022)	(0.0023)	(0.0023)	(0.0027)	(0.0023)	(0.0028)
County FE		✓	✓			
Year FE		✓	✓			
County × Year FE				✓		✓
Bank × County FE					✓	✓
Bank FE			✓			
# Obs	553,345	553,345	553,345	553,345	553,345	553,345
R^2	0.0001	0.0104	0.0163	0.1245	0.0747	0.1985

Note: This table uses small business lending data collected under the Community Reinvestment Act (CRA) and reports the estimated coefficient β in the following specification:

$$\Delta ln(Lending)_{b,c,t} = \beta \times \Gamma_{b,t-1} + \theta_{b,c} + \theta_{c,t} + \varepsilon_{b,c,t}$$

where b, c and t indicate bank, county, and year, respectively. The data spans from 1997 to 2018. The dependent variable $\Delta ln(Lending)_{b,c,t}$ is the natural logarithm of small business loans originated from bank b in county c and year t. $\theta_{b,c}$ and $\theta_{c,t}$ are bank-county and county-year fixed effects, respectively. $\Gamma_{b,t-1}$ refers to bank specific deposit shocks, measured using the previous year's deposit weighted average of disaster damage per capita. All variables used in this table are standardized to mean zero and standard deviation of one and winsorized at the 1% level. Standard errors clustered at the bank and county level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 10: Small Business Lending and Deposit Shocks by Bank Characteristics

Dep Var: $\Delta ln(Lending)_{b,c,t}$	(1)	(2)	(3)
High Sh. $CD_{b,t-1} \times \Gamma_{b,t-1}$	-0.0280***		
	(0.0054)		
High Sh. $CD_{b,t-1}$	0.0183***		
	(0.0044)		
Low Tier 1 $Ratio_{b,t-1} \times \Gamma_{b,t-1}$		-0.2196***	
		(0.0137)	
Low Tier 1 $Ratio_{b,t-1}$		-0.0277***	
		(0.0044)	
$NC_{b,c,t-1} \times \Gamma_{b,t-1}$			-0.0147***
			(0.0045)
$NC_{b,c,t-1}$			0.3570***
			(0.0080)
$\Gamma_{b,t-1}$	-0.0070**	-0.0067**	-0.0036
	(0.0035)	(0.0027)	(0.0031)
County × Year FE	✓	✓	✓
County × Bank FE	✓	✓	✓
# Obs	549,136	547,031	553,345
R^2	0.1991	0.2002	0.2017

Note: This table uses small business lending data collected under the Community Reinvestment Act (CRA) matched with the SNL bank regulatory data and reports the estimated coefficient β's in the following specification:

$$\Delta ln(Lending)_{b,c,t} = \beta_1 \times \lambda_{b,t-1} \times \Gamma_{b,t-1} + \beta_2 \times \lambda_{b,t-1} + \beta_3 \times \Gamma_{b,t-1} + \theta_{c,t} + \theta_{b,c} + \varepsilon_{b,c,t}$$

where b, c and t indicate bank, county, and year, respectively. The data spans from 1997 to 2018. The dependent variable $\Delta ln(Lending)_{b,c,t}$ is the natural logarithm of small business loans originated from bank b in county c and year t. $\theta_{b,c}$ and $\theta_{c,t}$ are bank-county and county-year fixed effects, respectively. $\Gamma_{b,t-1}$ refers to bank specific deposit shocks, measured using the previous year's deposit weighted average of disaster damage per capita. High Sh. $CD_{b,t-1}$ or High Core Deposit Share is an indicator variable that takes a value of one if a bank's ratio of demand deposits and time deposits to total bank deposits is above the median value in year $t-1$. Low Tier 1 Ratio is an indicator variable that takes a value of one for banks whose tier 1 capital ratio is lower than its median value in year $t-1$. $NC_{b,c,t-1}$ is an indicator variable that takes a value of one for counties in which bank b has a branch in year $t-1$. All variables used in this table are standardized to mean zero and standard deviation of one and winsorized at the 1% level. Standard errors clustered at the bank and county level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 11: Mortgage Lending and Deposit Shocks

Dep Var: $\Delta ln(Lending)_{b,c,t}$	(1) Purchase	(2) Refinancing	(3) Improvement
$\Gamma_{b,t-1}$	-0.0073***	-0.0047***	-0.0032*
	(0.0020)	(0.0017)	(0.0018)
County × Year FE	✓	✓	✓
County × Bank FE	✓	✓	✓
# Obs	1,136,531	1,136,531	1,136,531
R^2	0.1302	0.1821	0.1166

Note: This table uses Home Mortgage Disclosure Act (HMDA) data and reports the estimated coefficient β in the following specification: $\Delta ln(Lending)_{b,c,t} = \beta \times \Gamma_{b,t-1} + \theta_{c,t} + \theta_{b,c} + \varepsilon_{b,c,t}$ where b, c and t indicate bank, county, and year, respectively. The data spans from 1995 to 2017. The dependent variable $\Delta ln(Lending)_{b,c,t}$ is the first difference of the natural logarithm of mortgage lending towards home purchases (Column (1)), first difference of the natural logarithm of mortgage lending towards refinancing (Column (2)), and first difference of the natural logarithm of mortgage lending towards home improvement (Column (3)) originated from bank b in county c and year t. $\theta_{b,c}$ and $\theta_{c,t}$ are bank-county and county-year fixed effects, respectively. $\Gamma_{b,t-1}$ refers to bank specific deposit shocks, measured using the previous year's deposit weighted average of disaster damage per capita. All variables used in this table are standardized to mean zero and standard deviation of one and winsorized at the 1% level. Standard errors clustered at the bank and county level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 12: Jumbo vs Non-Jumbo Mortgage Loans and Deposit Shocks

Dep Var: $\Delta ln(Lending)_{b,c,t,j}$	(1)	(2)	(3)	(4)
$\text{Jumbo}_j \times \Gamma_{b,t-1}$	-0.0125***	-0.0125***	-0.0125***	-0.0140***
	(0.0022)	(0.0022)	(0.0022)	(0.0024)
Jumbo_j	0.0099***	0.0099***	0.0099***	
	(0.0006)	(0.0006)	(0.0006)	
$\Gamma_{b,t-1}$	0.0091***	0.0006		
	(0.0016)	(0.0018)		
County × Year FE		✓		
County × Bank FE		✓		
County × Bank × Year FE			✓	✓
County × Bank × Jumbo FE				✓
# Obs	2,276,662	2,276,662	2,276,662	2,276,662
R^2	0.0000	0.0626	0.5322	0.5513

Note: This table uses Home Mortgage Disclosure Act (HMDA) data and reports the estimated coefficient β in the following specification: $\Delta ln(Lending)_{b,c,t,j} = \beta_1 \times Jumbo_j \times \Gamma_{b,t-1} + \beta_2 \times Jumbo_j + \theta_{b,c,t} + \theta_{b,c,j} + \varepsilon_{b,c,t,j}$ where b, c, t and j indicate bank, county, year, and loan type (jumbo or non-jumbo), respectively. The data spans from 1995 to 2017. The dependent variable $\Delta ln(Lending)_{b,c,t,j}$ is the change in the natural logarithm of total mortgage lending of type j (jumbo or non-jumbo) originated from bank b in county c and year t. $\Gamma_{b,t-1}$ refers to bank specific deposit shocks, measured using the previous year's deposit weighted average of disaster damage per capita. $Jumbo_j$ is an indicator variable that takes a value of one for jumbo mortgages and zero for non-jumbo mortgages. $\theta_{b,c,t}$ indicates bank-county-year fixed effects. $\theta_{b,c,j}$ indicates jumbo-bank-county fixed effects. All variables are standardized to mean zero and standard deviation of one and winsorized at the 1% level. Standard errors clustered at the bank and county level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 13: Small vs Large Recipients of Small Business Loans and Deposit Shocks

Dep Var: $\Delta ln(Lending)_{b,c,t,s}$	(1)	(2)	(3)	(4)
$\text{Small}_s \times \Gamma_{b,t-1}$	-0.0160***	-0.0160***	-0.0160***	-0.0130***
	(0.0042)	(0.0044)	(0.0042)	(0.0047)
Small_s	-0.0133***	-0.0133***	-0.0133***	
	(0.0014)	(0.0014)	(0.0014)	
$\Gamma_{b,t-1}$	0.0070**	0.0057		
	(0.0034)	(0.0036)		
County × Year FE		✓		
County × Bank FE		✓		
County × Bank × Year FE			✓	✓
Small × County × Bank FE				✓
# Obs	552,344	552,344	552,344	552,344
R^2	0.0001	0.1710	0.5345	0.5684

Note: This table uses small business lending data collected under the Community Reinvestment Act (CRA) and reports the estimated coefficient β in the specification:

$$\Delta ln(Lending)_{b,c,t,s} = \beta_1 \times Small_s \times \Gamma_{b,t-1} + \beta_2 \times Small_s + \theta_{b,c,t} + \theta_{b,c,s} + \varepsilon_{b,c,t,s}$$

where b, c, t and s indicate bank, county, year, and firm size (small or large), respectively. The data spans from 1995 to 2017. The dependent variable $\Delta ln(Lending)_{b,c,t,s}$ is the change in the natural logarithm of total small business lending to firm type s (small or large) originated from bank b in county c and year t. $\Gamma_{b,t-1}$ refers to bank specific deposit shocks, measured using the previous year's deposit weighted average of disaster damage per capita. $Small_j$ is an indicator variable that takes a value of one for loans given to firms with gross revenue less than $1 million and 0, otherwise. $\theta_{b,c,t}$ indicates bank-county-year fixed effects. $\theta_{b,c,s}$ indicates bank-county-small fixed effects. All variables are standardized to mean zero and standard deviation of one and winsorized at the 1% level. Standard errors clustered at the bank and county level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 14: Bank-Borrower Lending Relationship and Real Effects

	(1) Debt	(2) Size	(3) Employment	(4) CapEx
$\text{Young}_f \times \sum_b \Gamma_{b,t-1}$	-0.1305**	-0.0928**	-0.0951**	-0.1379**
	(0.0654)	(0.0436)	(0.0446)	(0.0632)
$\sum_b \Gamma_{b,t-1}$	-0.0124**	-0.0053	-0.0023	-0.0017
	(0.0060)	(0.0037)	(0.0028)	(0.0045)
Firm FE	✓	✓	✓	✓
Industry × Young × Year FE	✓	✓	✓	✓
# Obs	11,388	11,996	11,383	10,648
R^2	0.9289	0.9723	0.9712	0.9516

Note: This table uses Dealscan data matched with Compustat data and reports β's in the following specification:

$$y_{f,t} = \beta_1 \times Young_f \times \sum_b \Gamma_{b,t-1} + \beta_2 \times Young_f + \beta_3 \times \sum_b \Gamma_{b,t-1} + \theta_{i,g,t} + \theta_f + \varepsilon_{f,t}$$

where f, and t indicates borrowing firm, and year, respectively. The dependent variable $y_{f,t}$ is the natural logarithm of total debt (Column (1)), natural logarithm of the book value of assets (Column (2)), natural logarithm of employment (Column (3)), and natural logarithm of capital expenditure (Column (4)). Firm age is defined as the years passed since IPO, and the variable $Young_f$ is an indicator variable that takes one for the firms with age less than the median firm age. $\Gamma_{b,t-1}$ refers to bank specific deposit shocks, measured using the previous year's deposit weighted average of disaster damage per capita. $\sum_b \Gamma_{b,t-1}$ refers to the sum of bvank deposit shocks for lead banks of firm f identified using the Dealscan database. $\theta_{i,g,t}$ and θ_f are industry-young-year and firm fixed effects, respectively. Industries refer to the 38 Fama-French industries. All variables used in this table are standardized to mean zero and standard deviation of one and winsorized at the 1% level. Standard errors clustered at the firm level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Online Appendix for:

The Geography of Bank Deposits and the Origins of Aggregate Fluctuation

Appendix A Framework

In this section, we present a simple model of optimal bank allocation of funds for a multi-market bank. This model is similar in spirit to the model of multinational firms discussed in Giroud and Mueller (2019). This model illustrates how banks allocate internal funds upon experiencing a local shock through their internal capital markets and the role of financial frictions in the transmission of the shock.

Consider a multi-market bank operating in n regions with one branch in each region denoted by i with $i \in \{1, ..., n\}$. Each bank branch receives deposits d_i from households and disburses loans l_i at the start of the period. Each branch produces a revenue of $\alpha_i \times f(l_i)$ at the end of the period, where $f(l_i)$ satisfies the neoclassical conditions $f^{'}(l_i) > 0$, $f^{''}(l_i) < 0$, $f(0) = 0$, $\lim_{x\to 0} f^{'}(l_i) = \infty$, and $\lim_{x\to\infty} f^{'}(l_i) = 0$. Branches differ in their productivity, as indicated by the term α_i. α_i captures the advantage that a bank may have in certain regions. For example, branches may vary in their ability to produce valuable information about hard-to-evaluate credits in certain regions. A branch may differ in its ability to procure valuable information as a result of historical presence of the branch, presence of a physical infrastructure, or extensive activity in that region (see Petersen and Rajan (2002), Berger et al. (2005), Hauswald and Marquez (2006), Agarwal and Hauswald (2010), Huber (2018), and Granja, Leuz and Rajan (2021) among others). Better than average access to local information can allow branches to earn rents, captured by α_i. α_i increases as the information advantage of a branch increases. Each branch must return an amount of $(1 + r_i) \times d_i$ to its depositors at the end of the period. Bank lending decisions are funded out of deposit inflows. Banks have internal capital markets that allow them to move deposits across branches to make lending decisions to maximize overall bank value (Stein (1997)). Thus, the relevant budget constraint is at the overall bank level, i.e., $\sum_i d_i \geq \sum_i l_i$. The firm solves the following problem (equation A.1) where λ denotes the Lagrange multiplier associated with the budget constraint.

$$\max_{\{l_i,\lambda\}_{i=1}^{i=n}} [\sum_i \alpha_i \times f(l_i) - \sum_i (1 + r_i) \times d_i] + \lambda[\sum_i (d_i - l_i)] \tag{A.1}$$

The first order conditions are:

$$[l_i]: \qquad \alpha_i f'(l_i) - \lambda = 0 \qquad \forall i \tag{A.2}$$

$$[\lambda]: \qquad \lambda[\sum_i d_i - \sum_i l_i] = 0 \qquad \lambda \geq 0 \tag{A.3}$$

We draw two insights from the first order conditions. First, if the budget constraint is slack or $\lambda = 0$, bank allocation of funds is first-best. The bank will allocate funds to each region i until the marginal revenue product generated by l_i is equal to zero. If the budget constraint is tight, i.e., the bank is constrained, the marginal revenue product generated by ł$_i$ is then equal to λ, which is greater than zero. This suggests that when the bank is constrained, the amount of funds allocated to each region i is strictly less than the amount of funds allocated to each region i when the bank is unconstrained. Hence, when the bank is unconstrained, the allocation of funds is first-best.

Next, we consider how a deposit shock in region j ($j \neq i$) affects lending in region i. To study this, we differentiate the first-order conditions presented in equation A and A.3 with respect to d_j. This yields the following equations.

$$\frac{\partial l_i}{\partial d_j} = \frac{1}{\alpha_i \cdot f''(l_i)} \times \frac{\partial \lambda}{\partial d_j} > 0 \tag{A.4}$$

$$\frac{\partial \lambda}{\partial d_j} = [\sum_i \frac{1}{\alpha_i f''(l_i)}]^{-1} < 0 \tag{A.5}$$

Hence, a robust prediction of this framework is that negative shocks to deposits in one region lead to a contraction in lending in all regions, including regions which are not directly affected by the shock. Intuitively, a negative deposit shock in region j raises the shadow value of a marginal dollar of funds, λ. As a result, banks adjust their lending activity in each region to ensure that the optimality condition is satisfied. This is driven by the decreasing returns to scale of loans, i.e., $f''(l_i) < 0$. Simply put, multi-market banks smooth out negative deposit shocks in one region by decreasing lending in all regions.

Additionally, we derive two other testable implications from this framework. First, the decline in lending is larger for banks facing tighter financial constraints. This is represented by the change in the shadow value of the marginal dollar of funds, following a deposit shock $\frac{\partial \lambda}{\partial d_j}$. Intuitively, it implies that negative deposit shocks push banks closer to their constraints resulting in a reduction in lending. Second, the decline in lending is lower in regions where banks earn rents due to their superior ability in accessing information, as represented by α_i. The decline in lending, following a negative deposit shock, is lower in regions where banks possess greater informational advantages. Intuitively, banks cut lending more in regions where returns to lending are lower.

Appendix B Figures and Tables

Table B.1: Property Damage from Natural Disasters

Hazard Type	Number of Affected Counties	Total Damage (in 2018 Billion $)	Property Damage Distribution (in 2018 Million $)				
			P25	P50	P75	P95	P99
Hurricane	3,044	240.13	0.04	0.55	4.71	223.46	1,379.27
Flooding	23,397	181.29	0.01	0.07	0.51	8.19	58.64
Tornado	11,691	39.66	0.02	0.09	0.42	5.76	53.90
Earthquake	30	38.16	0.66	18.19	22.32	945.26	33,887.58
Wildfire	1,652	33.73	0.00	0.06	0.81	11.16	151.38
Hail	11,538	33.20	0.00	0.02	0.08	1.81	33.92
Wind	49,493	19.00	0.01	0.02	0.07	0.55	3.53
Severe Storm	42,793	13.90	0.00	0.02	0.05	0.32	1.93
Winter Weather	16,327	12.88	0.00	0.03	0.19	2.51	13.96
Landslide	687	5.67	0.00	0.01	0.24	14.63	82.02
Drought	752	3.12	-	-	-	3.91	17.26
Coastal	309	1.85	-	-	0.00	1.68	72.97
Lightning	8,216	1.25	0.00	0.02	0.08	0.50	1.69
Tsunami/Seiche	47	0.11	0.02	0.03	0.10	15.85	42.36
Heat	691	0.05	-	-	-	0.08	0.17
Fog	345	0.05	0.00	0.03	0.09	0.43	1.48
Volcano	3	0.02	-	0.00	0.05	15.38	15.38
Avalanche	207	0.01	-	-	0.00	0.02	0.59
All Hazard Types	171,222	624.08	0.00	0.02	0.11	1.90	21.16

Note: This table reports property damages from natural disasters in the Spatial hazard Events and Losses Database for the Unites States (SHELDUS). The data are at the county and year level. The sample includes all natural disasters reported in SHELDUS that occurred in the US between 1994 and 2018.

Table B.2: Disaster Shock and Deposit Growth with Control of Lagged Shocks

$\Delta ln(Deposits)_{c,t}$	(1)	(2)	(3)
Disaster Shock$_{c,t-1}$	-0.0080***	-0.0086***	-0.0089***
	(0.0030)	(0.0031)	(0.0032)
Disaster Shock$_{c,t-2}$		-0.0140***	-0.0143***
		(0.0028)	(0.0029)
Disaster Shock$_{c,t-3}$			-0.0070**
			(0.0032)
County FE	✓	✓	✓
State-Year FE	✓	✓	✓
# Obs	76,336	76,336	76,336
R^2	0.1813	0.1815	0.1815

Note: This table uses the Summary of Deposit (SOD) data matched with the Spatial Hazard Events and Losses Database for the United States (SHELDUS) and reports the estimated coefficient β_k's in the following specification:

$$\Delta ln(Deposit)_{c,t} = \sum_{k=1}^{k=3} \beta_k \times \text{Disaster Shock}_{c,t-k} + \theta_c + \theta_{s(c\in s),t} + \varepsilon_{c,t}$$

where c and t indicate county and year, respectively. The data spans from 1994 to 2018. The dependent variable $\Delta ln(Deposit)_{c,t}$ is the first difference of natural logarithm of total deposit of all banks in county c and year t. The independent variable Disaster Shock$_{c,t-1}$ is the dollar amount of property damage per capita from natural disasters in county c and year $t-1$. θ_c and $\theta_{s(c\in s),t}$ represent county and state-year fixed effects, respectively. All variables used in this table are standardized to a mean of zero and standard deviation of one, and winsorized at the 1% level. Standard errors clustered at the county level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table B.3: Orthogonality of Bank Characteristics to Bank-Level Disaster Shock

Dep Var: $\Gamma_{b,t}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\ln(\text{Assets})_{b,t-1}$	-0.0199**								-0.0149	-0.0681
	(0.0087)								(0.0093)	(0.0538)
$\text{Loan/Assets}_{b,t-1}$		-0.0137							-0.0154	0.0249
		(0.0092)							(0.0108)	(0.0164)
$\text{Equity/Assets}_{b,t-1}$			0.0051						0.0060	-0.0109
			(0.0090)						(0.0090)	(0.0155)
$\text{Cash/Assets}_{b,t-1}$				-0.0080					-0.0213***	-0.0075
				(0.0050)					(0.0066)	(0.0109)
$\text{Deposits/Assets}_{b,t-1}$					0.0283**				0.0302**	0.0205
					(0.0123)				(0.0140)	(0.0210)
$\text{Hedge/Assets}_{b,t-1}$						0.0063***			0.0013	-0.0029
						(0.0017)			(0.0032)	(0.0028)
$\text{Div/Assets}_{b,t-1}$							-0.0074		-0.0092	-0.0171*
							(0.0054)		(0.0059)	(0.0092)
$\text{Income/Assets}_{b,t-1}$								-0.0042	-0.0050	0.0135
								(0.0059)	(0.0060)	(0.0117)
Bank FE										✓
Year FE										✓
# Obs	9,892	9,892	9,892	9,892	9,892	9,892	9,892	9,892	9,892	9,892
R^2	0.0004	0.0002	0.0000	0.0001	0.0008	0.0000	0.0001	0.0000	0.0017	0.0737

Note: This figure uses the Spatial Hazard Events and Losses Database for the United States (SHELDUS) and bank call report data to report the estimated coefficient β in the following specification:

$$\Gamma_{b,t} = \beta \times \text{Bank-Characteristics}_{b,t} + \theta_b + \theta_t + \varepsilon_{b,t}$$

where b and t indicate bank and quarter, respectively. The data spans from 1995 to 2018. The dependent variable is the bank-level disaster shock $\Gamma_{b,t}$. The independent variables $Bank-Characteristics_{b,t}$ is the natural logarithm of total bank assets (Column (1)), the average loan balance divided by total assets (Column (2)), the total equity divided by total assets (Column (3)), the total cash holdings divided by total bank assets (Column (4)), the total deposits divided by total assets (Column (5)), the net derivatives contract held for hedging divided by total assets (Column (6)), the total dividend on common stocks divided by total assets (Column (7)), and the operating income divided by total assets (Column (8)). Column (9) and (10) use all the bank characteristics mentioned above. All variables are standardized to a mean of zero and standard deviation of one, and winsorized at the 1% level. Standard errors clustered at the bank level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table B.4: Aggregate Shock and Major Disasters

Quarter	Aggregate Bank Shock	Major Disaster #1	Affected States	Major Disaster #2	Affected States	Insurance Payout (in 2020 billion $)
1996q3	33.3705	Hurricane Fran	NC			2.63
1999q3	30.0705	Hurricane Floyd	NC			2.05
2001q1	22.8630	Nisqually earthquake	WA			0.44
2004q3	83.7900	Hurricane Ivan	FL, AL	Hurricane Jeanne	FL	14.40
2005q3	244.5543	Hurricane Katrina	LA, MS			87.96
2005q4	53.5566	Hurricane Wilma	FL			13.42
2008q2	27.7731	June 2008 Midwest floods	IN, IA, WI			0.60
2011q2	30.5780	Mississippi River floods	MS, MO	Super Outbreak (Tornado)	AL, MS, TN	7.60
2012q4	80.5528	Hurricane Sandy	NJ			28.88
2017q3	205.3722	Hurricane Harvey	TX	Hurricane Irma	FL	63.11
2018q4	30.4282	California wildfires	CA	Hurricane Michael	FL	19.84

Note: This table provides a narrative analysis of major disasters at the notable peaks of the aggregate bank deposit shock Γ_t shown in Figure 7a. The table reports the natural disasters, states affected by the disasters and the insurance payout associated with these disasters.

Table B.5: Small Business Lending and Deposit Shocks: Robustness Test

Dep Var: $\Delta ln(Lending)_{b,c,t}$	(1) Unaffected	(2) Affected
$\Gamma_{b,t-1}$	-0.0382***	-0.0134***
	(0.0131)	(0.0030)
County × Year FE	✓	✓
Bank × County FE	✓	✓
# Obs	96,259	436,349
R^2	0.3222	0.2089

Note: This table uses small business lending data collected under the Community Reinvestment Act (CRA) and reports the estimated coefficient β in the following specification:

$$\Delta ln(Lending)_{b,c,t} = \beta \times \Gamma_{b,t-1} + \theta_{b,c} + \theta_{c,t} + \varepsilon_{b,c,t}$$

where b, c and t indicate bank, county, and year, respectively. The data spans from 1997 to 2018. The dependent variable $\Delta ln(Lending)_{b,c,t}$ is the natural logarithm of small business loans originated from bank b in county c and year t. $\theta_{b,c}$ and $\theta_{c,t}$ are bank-county and county-year fixed effects, respectively. $\Gamma_{b,t-1}$ refers to bank specific deposit shocks, measured using the previous year's deposit weighted average of disaster damage per capita. Column (1) restricts sample to the counties that were not affected by any disaster in year $t-1$, and column (2) restricts sample to counties that were affected by a disaster in year $t-1$. All variables used in this table are standardized to mean zero and standard deviation of one and winsorized at the 1% level. Standard errors clustered at the bank and county level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Robust to Exclusion of Credit Card Banks

Further, another concern in our analysis is the inclusion of small business credit card banks in the sample. This is problematic for two reasons. First, credit card loans may be unrepresentative compared to traditional small business loans. Second, the geography of bank deposits for credit card banks may be misrepresented due to its funding structure. For example, Chase USA's banking office is not open to the public, and the majority of their deposits come from JP Morgan Chase Bank as well as other affiliates (Schaffer and Segev (2021)). Appendix Table B.6 shows that our results are not sensitive to the inclusion of credit card banks. We identify loans from credit card bank, using two alternate definitions. In column 1, we drop banks that have at least $1 billion in loans under $100K and these loans constitute at least 75% of these loans, following Adams, Brevoort and Driscoll (2020). In column 2, we drop banks that have at least 99% of loans under $100K, and where the average loan amount is less than $15K, following Board of Governors of the Federal Reserve System (2010). Our results indicate that a one standard deviation deposit shock is associated with a decline of 1.29-1.48 percentage points in lending growth. This estimate is statistically significant at the 1% level, and is within range of the estimates produced in our baseline table. Hence, we rule out concerns that our effects are driven by credit card banks.

Table B.6: Small Business Lending and Deposit Shocks: Exclusion of Credit Card Banks

Dep Var: $\Delta ln(Lending)_{b,c,t}$	(1)	(2)
$\Gamma_{b,t-1}$	-0.0129***	-0.0148***
	(0.0030)	(0.0028)
County × Year FE	✓	✓
Bank × County FE	✓	✓
# Obs	474,887	553,227
R^2	0.2139	0.1985

Note: This table uses small business lending data collected under the Community Reinvestment Act (CRA) and reports the estimated coefficient β in the following specification:

$$\Delta ln(Lending)_{b,c,t} = \beta \times \Gamma_{b,t-1} + \theta_{b,c} + \theta_{c,t} + \varepsilon_{b,c,t}$$

where b, c and t indicate bank, county, and year, respectively. The data spans from 1997 to 2018. The dependent variable $\Delta ln(Lending)_{b,c,t}$ is the natural logarithm of small business loans originated from bank b in county c and year t. $\theta_{b,c}$ and $\theta_{c,t}$ are bank-county and county-year fixed effects, respectively. $\Gamma_{b,t-1}$ refers to bank specific deposit shocks, measured using the previous year's deposit weighted average of disaster damage per capita. We drop credit card banks from the sample. Column (1) drops banks that have at least $1 billion in loans under $100K and these loans constitute at least 75% of these loans, following Adams, Brevoort and Driscoll (2020). Column (2) drops banks that have at least 99% of loans under $100K, and where the average loan amount is less than $15K, following Board of Governors of the Federal Reserve System (2010). All variables used in this table are standardized to mean zero and standard deviation of one and winsorized at the 1% level. Standard errors clustered at the bank and county level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table B.7: Small Business Lending and Deposit Shocks by Bank Size

Dep Var: $\Delta ln(Lending)_{b,c,t}$	(1) Small Banks	(2) Medium Banks	(3) Large Banks	(4) Top 20 Banks
$\Gamma_{b,t-1}$	-0.0061	-0.0128***	-0.0357***	-0.0251**
	(0.0308)	(0.0037)	(0.0087)	(0.0098)
County × Year FE	✓	✓	✓	✓
County × Bank FE	✓	✓	✓	✓
# Obs	35,632	165,547	298,355	235,454
R^2	0.4609	0.3254	0.2722	0.3133

Note: This table uses small business lending data collected under the Community Reinvestment Act (CRA) matched with bank call report data and reports the estimated coefficient β in the following specification:

$$\Delta ln(Lending)_{b,c,t} = \beta \times \Gamma_{b,t-1} + \theta_{c,t} + \theta_{b,c} + \varepsilon_{b,c,t}$$

where b, c and t indicate bank, county, and year, respectively. The data spans from 1997 to 2018. The dependent variable $\Delta ln(Lending)_{b,c,t}$ is the natural logarithm of small business loans originated from bank b in county c and year t. $\theta_{b,c}$ and $\theta_{c,t}$ are bank-county and county-year fixed effects, respectively. $\Gamma_{b,t-1}$ refers to bank specific deposit shocks, measured using the previous year's deposit weighted average of disaster damage per capita. Sample banks are banks with total assets less than or equal to $2 billion (Column (1)), banks with total assets greater than $2 billion but less than or equal to $35 billion (Column (2)), banks with total assets greater than $35 billion (Column (3)), and 20 largest banks by assets (Column (4)). All variables used in this table are standardized to mean zero and standard deviation of one and winsorized at the 1% level. Standard errors clustered at the bank and county level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table B.8: Small Business Lending and Deposit Shocks by Reliance on Deposit Funding

Dep Var: $\Delta ln(Lending)_{b,c,t}$	(1)	(2)	(3)	(4)	(5)	(6)
High Sh. $CD_{b,t-1} \times \Gamma_{b,t-1}$	-0.0163***	-0.0223***	-0.0178***	-0.0302***	-0.0108**	-0.0280***
	(0.0047)	(0.0048)	(0.0049)	(0.0051)	(0.0050)	(0.0054)
High Sh. $CD_{b,t-1}$	-0.0073***	-0.0042*	0.0182***	-0.0020	0.0164***	0.0183***
	(0.0023)	(0.0024)	(0.0039)	(0.0024)	(0.0042)	(0.0044)
$\Gamma_{b,t-1}$	-0.0057*	-0.0060**	-0.0059*	-0.0076**	-0.0061*	-0.0070**
	(0.0030)	(0.0030)	(0.0031)	(0.0033)	(0.0032)	(0.0035)
County FE		✓	✓			
Year FE		✓	✓			
County × Year FE				✓		✓
County × Bank FE					✓	✓
Bank FE			✓			
# Obs	549,136	549,136	549,136	549,136	549,136	549,136
R^2	0.0001	0.0105	0.0164	0.1254	0.0744	0.1991

Note: This table uses small business lending data collected under the Community Reinvestment Act (CRA) matched with the SNL bank regulatory data and reports the estimated coefficient β's in the following specification:

$$\Delta ln(Lending)_{b,c,t} = \beta_1 \times \text{Sh. CD}_{b,t-1} \times \Gamma_{b,t-1} + \beta_2 \times \text{Sh. CD}_{b,t-1} + \beta_3 \times \Gamma_{b,t-1} + \theta_{c,t} + \theta_{b,c} + \varepsilon_{b,c,t}$$

where b, c and t indicate bank, county, and year, respectively. The data spans from 1997 to 2018. The dependent variable $\Delta ln(Lending)_{b,c,t}$ is the natural logarithm of small business loans originated from bank b in county c and year t. $\theta_{b,c}$ and $\theta_{c,t}$ are bank-county and county-year fixed effects, respectively. $\Gamma_{b,t-1}$ refers to bank specific deposit shocks, measured using the previous year's deposit weighted average of disaster damage per capita. High Sh. $CD_{b,t-1}$ or High Core Deposit Share is an indicator variable that takes a value of one if a bank's ratio of demand deposits and time deposits to total bank deposits is above the median value in year $t-1$. All variables used in this table are standardized to mean zero and standard deviation of one and winsorized at the 1% level. Standard errors clustered at the bank and county level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table B.9: Small Business Lending and Deposit Shocks by Bank Constraint

Dep Var: $\Delta ln(Lending)_{b,c,t}$	(1)	(2)	(3)	(4)	(5)	(6)
Low Tier 1 Ratio$_{b,t-1} \times \Gamma_{b,t-1}$	-0.1784***	-0.2045***	-0.1978***	-0.2161***	-0.1815***	-0.2196***
	(0.0113)	(0.0118)	(0.0125)	(0.0124)	(0.0124)	(0.0137)
Low Tier 1 Ratio$_{b,t-1}$	-0.0056***	-0.0031	-0.0281***	-0.0033	-0.0305***	-0.0277***
	(0.0021)	(0.0021)	(0.0038)	(0.0022)	(0.0042)	(0.0044)
$\Gamma_{b,t-1}$	-0.0036*	-0.0053**	-0.0046**	-0.0076***	-0.0023	-0.0067**
	(0.0022)	(0.0022)	(0.0023)	(0.0026)	(0.0023)	(0.0027)
County FE		✓	✓			
Year FE		✓	✓			
County × Year FE				✓		✓
County × Bank FE					✓	✓
Bank FE			✓			
# Obs	547,031	547,031	547,031	547,031	547,031	547,031
R^2	0.0006	0.0113	0.0172	0.1267	0.0746	0.2002

Note: This table uses small business lending data collected under the Community Reinvestment Act (CRA) matched with the SNL bank regulatory data and reports the estimated coefficient β's in the following specification:

$$\Delta ln(Lending)_{b,c,t} = \beta_1 \times \lambda_{b,t-1} \times \Gamma_{b,t-1} + \beta_2 \times \lambda_{b,t-1} + \beta_3 \times \Gamma_{b,t-1} + \theta_{c,t} + \theta_{b,c} + \varepsilon_{b,c,t}$$

where b, c and t indicate bank, county, and year, respectively. The data spans from 1997 to 2018. The dependent variable $\Delta ln(Lending)_{b,c,t}$ is the natural logarithm of small business loans originated from bank b in county c and year t. $\theta_{b,c}$ and $\theta_{c,t}$ are bank-county and county-year fixed effects, respectively. $\Gamma_{b,t-1}$ refers to bank specific deposit shocks, measured using the previous year's deposit weighted average of disaster damage per capita. $\lambda_{b,t-1}$ is an indicator variable that takes a value of one if a bank's tier 1 capital ratio is lower than its median value in year $t-1$. All variables used in this table are standardized to mean zero and standard deviation of one and winsorized at the 1% level. Standard errors clustered at the bank and county level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table B.10: Core vs Non-Core Markets by the Presence of Branch

Dep Var: $\Delta ln(Lending)_{b,c,t}$	(1)	(2)	(3)	(4)	(5)	(6)
$\text{NC}_{b,c,t-1} \times \Gamma_{b,t-1}$	-0.0145***	-0.0155***	-0.0166***	-0.0151***	-0.0131***	-0.0147***
	(0.0037)	(0.0037)	(0.0037)	(0.0044)	(0.0039)	(0.0045)
$\text{NC}_{b,c,t-1}$	0.0823***	0.0902***	0.0965***	0.0873***	0.3792***	0.3570***
	(0.0016)	(0.0018)	(0.0020)	(0.0019)	(0.0074)	(0.0080)
$\Gamma_{b,t-1}$	-0.0004	-0.0014	0.0009	-0.0044	0.0002	-0.0036
	(0.0022)	(0.0022)	(0.0022)	(0.0032)	(0.0022)	(0.0031)
County FE		✓	✓			
Year FE		✓	✓			
Bank FE			✓			
County × Year FE				✓		✓
County × Bank FE					✓	✓
# Obs	553,345	553,345	553,345	553,345	553,345	553,345
R^2	0.0015	0.0119	0.0178	0.1259	0.0792	0.2017

Note: This table uses small business lending data collected under the Community Reinvestment Act (CRA) and reports the estimated coefficient β's in the following specification:

$$\Delta ln(Lending)_{b,c,t} = \beta_1 \times NC_{b,c,t-1} \times \Gamma_{b,t-1} + \beta_2 \times NC_{b,c,t-1} + \beta_3 \times \Gamma_{b,t-1} + \theta_{c,t} + \theta_{b,c} + \varepsilon_{b,c,t}$$

where b, c and t indicate bank, county, and year, respectively. The data spans from 1997 to 2018. The dependent variable $\Delta ln(Lending)_{b,c,t}$ is the natural logarithm of small business loans originated from bank b in county c and year t. $\theta_{b,c}$ and $\theta_{c,t}$ are bank-county and county-year fixed effects, respectively. $\Gamma_{b,t-1}$ refers to bank specific deposit shocks, measured using the previous year's deposit weighted average of disaster damage per capita. $NC_{b,c,t-1}$ is an indicator variable that takes a value of one for counties in which bank b does not have a branch in year $t-1$. All variables used in this table are standardized to mean zero and standard deviation of one and winsorized at the 1% level. Standard errors clustered at the bank and county level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table B.11: Core vs Non-Core Markets by the Share of Lending

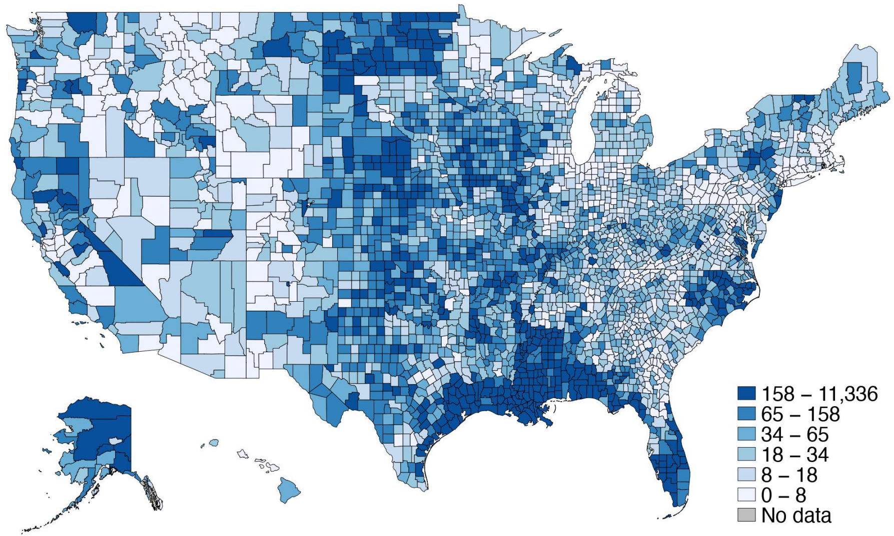
Dep Var: $\Delta ln(Lending)_{b,c,t}$	(1)	(2)	(3)	(4)	(5)	(6)
$NC_{b,c,t-1} \times \Gamma_{b,t-1}$	-0.0130***	-0.0160***	-0.0185***	-0.0148***	-0.0132**	-0.0165***
	(0.0048)	(0.0050)	(0.0049)	(0.0053)	(0.0051)	(0.0055)
$NC_{b,c,t-1}$	0.4846***	0.4873***	0.5563***	0.4861***	1.0018***	1.0610***
	(0.0029)	(0.0029)	(0.0033)	(0.0029)	(0.0051)	(0.0050)
$\Gamma_{b,t-1}$	-0.0035	-0.0050**	-0.0022	-0.0076***	-0.0040*	-0.0058**
	(0.0022)	(0.0023)	(0.0023)	(0.0028)	(0.0023)	(0.0028)
County FE		✓	✓			
Year FE		✓	✓			
Bank FE			✓			
County × Year FE				✓		✓
County × Bank FE					✓	✓
# Obs	553,345	553,345	553,345	553,345	553,345	553,345
R^2	0.0554	0.0660	0.0793	0.1777	0.1814	0.3045

Note: This table uses small business lending data collected under the Community Reinvestment Act (CRA) and reports the estimated coefficient β's in the following specification:

$$\Delta ln(Lending)_{b,c,t} = \beta_1 \times NC_{b,c,t-1} \times \Gamma_{b,t-1} + \beta_2 \times NC_{b,c,t-1} + \beta_3 \times \Gamma_{b,t-1} + \theta_{c,t} + \theta_{b,c} + \varepsilon_{b,c,t}$$

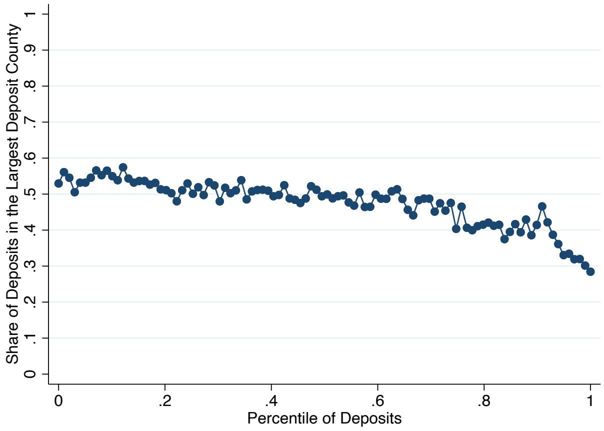
where b, c and t indicate bank, county, and year, respectively. The data spans from 1997 to 2018. The dependent variable $\Delta ln(Lending)_{b,c,t}$ is the natural logarithm of small business loans originated from bank b in county c and year t. $\theta_{b,c}$ and $\theta_{c,t}$ are bank-county and county-year fixed effects, respectively. $\Gamma_{b,t-1}$ refers to bank specific deposit shocks, measured using the previous year's deposit weighted average of disaster damage per capita. $NC_{b,c,t-1}$ is an indicator variable that takes a value of one for county c in which bank b has small business lending market share below the median market share in $t-1$. All variables used in this table are standardized to mean zero and standard deviation of one and winsorized at the 1% level. Standard errors clustered at the bank and county level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Figure B.1: Property Damage Per Capita across Counties from 1994 to 2018

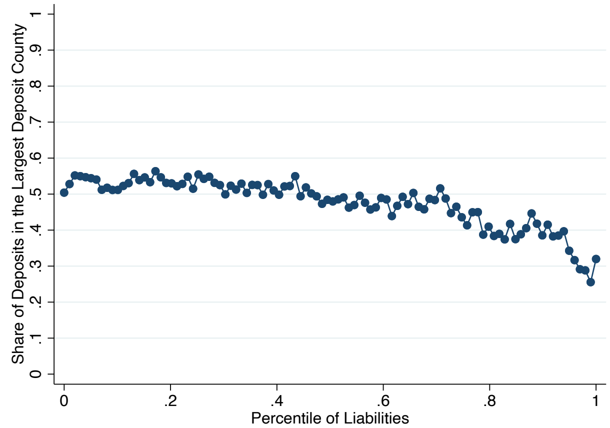


Notes: This figure illustrates the average natural disaster-induced property damage per capita across counties from 1994 to 2018. The intensity of the blue shading represents the dollar amount of property damage from natural disasters.

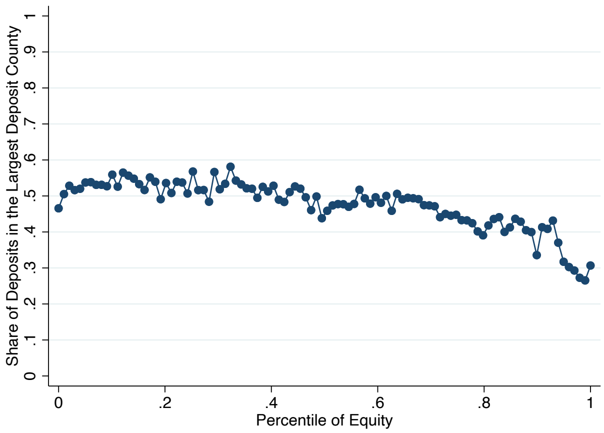
Figure B.2: Geographic Concentration Across Bank Characteristics



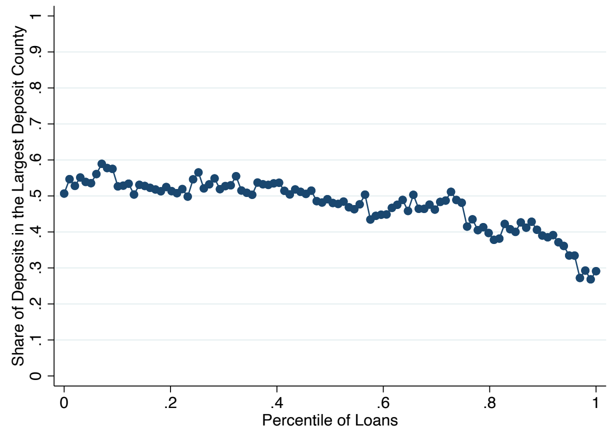
(a) Deposits



(b) Liabilities



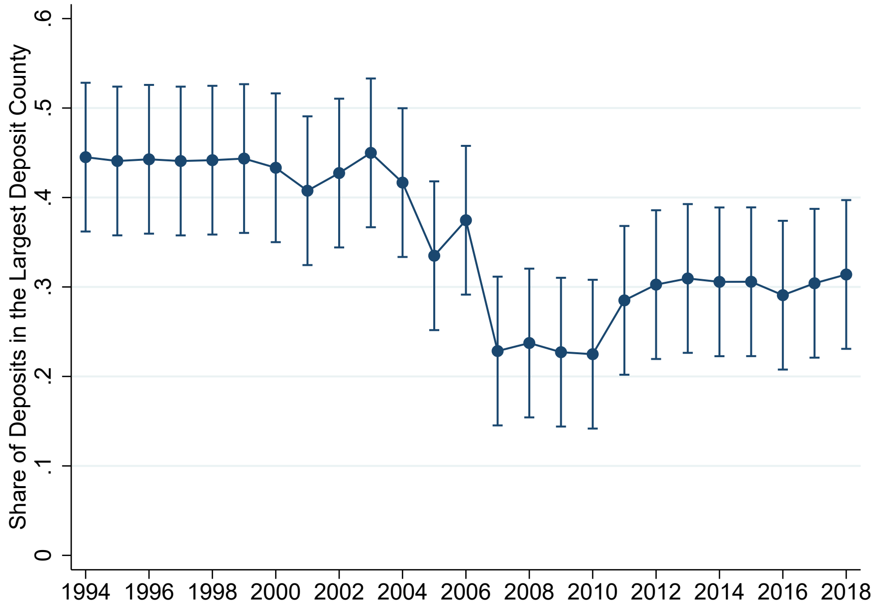
(c) Equity



(d) Loans

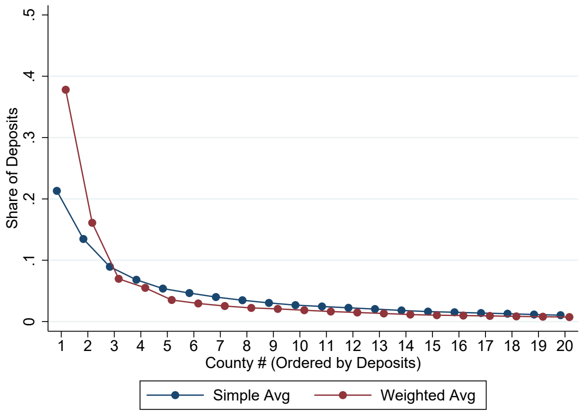
Note: This figure uses the summary of deposit data (SOD) from 1994 to 2018 and illustrates the relation between the geographic concentration of deposits (Figure B.2a), liabilities (Figure B.2b), equity (Figure B.2c), and loans (Figure B.2d). Each figure sorts banks by their deposits, total liabilities, book value of equity, and loans in figures B.2a, B.2b, B.2c, and B.2d, and reports the average deposit share of counties with the largest deposit share against the percentile of the bank deposits, total liabilities, book value of equity, and loans, respectively, i.e., average value of deposit share in the largest deposit counties corresponding to the percentile of bank deposits, total liabilities, book value of equity, and loans, respectively.

Figure B.3: Time Series of Deposit Concentration for Big Four Banks

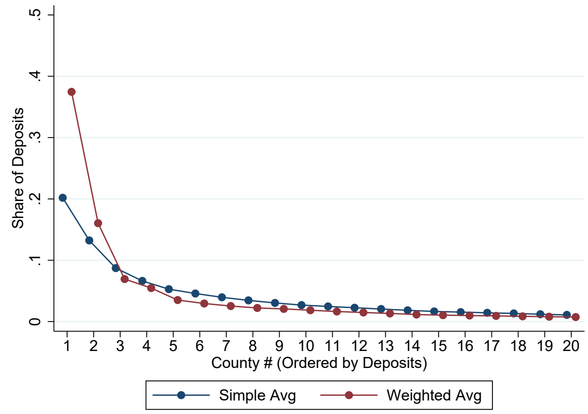


This figure uses the summary of deposit data (SOD) from 1994 to 2018 and illustrates the geographic concentration of bank deposits over time. The figure reports the share of deposits in the largest deposit county for the Big Four banks over time. The Big Four banks are Citibank, JP Morgan, Wells Fargo, and Bank of America.

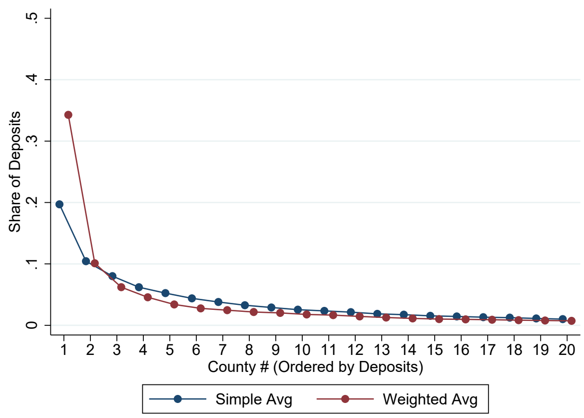
Figure B.4: Deposit Concentration of Banks that Changed Headquarters



(a) Deposit-Weighted Distribution



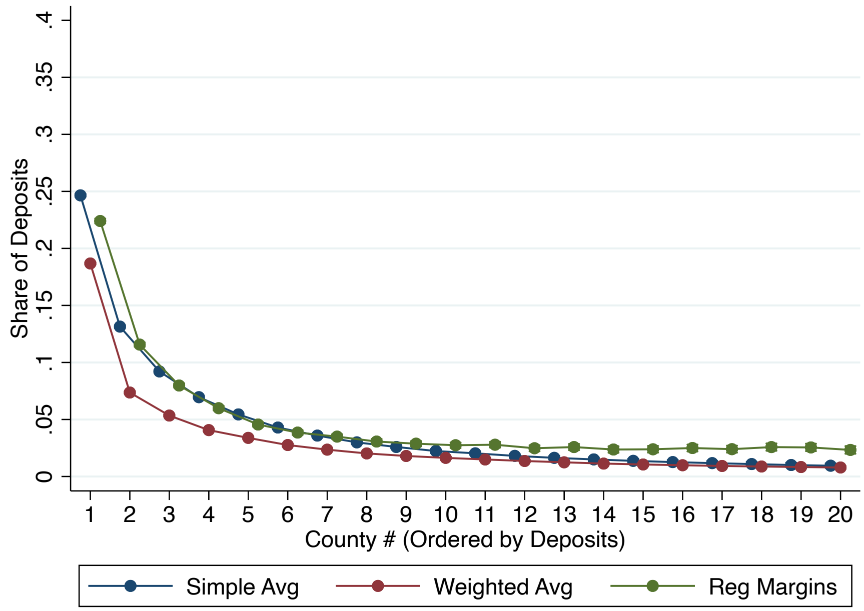
(b) Equal Distribution



(c) Omission

Note: This figure uses the summary of deposit (SOD) data and illustrates the geographic concentration of bank deposits for banks that changed headquarters in our sample period. The figure is plotted for the years in which the bank changed its headquarter (not all years). The y-axis represents the share of deposits and the x-axis represents counties by the order of their deposit shares for each bank (the county number refers to the rank of a county by the amount of deposits it raises, i.e., county #1 refers to the county that raised the greatest amount of deposits for a given bank.). The figure reports the average deposit share for each of the top 20 counties. The blue line shows the simple average of the deposit share across all banks, and the red line shows the average deposit share weighted by total bank assets. Figure B.4a plots the deposit concentration after removing the change in deposits at the headquarter county and distributing this change in deposits across all counties based on the previous year's county share of deposits. Figure B.4b plots the deposit concentration after removing the change in deposits at the headquarter county and equally distributing this change across all counties. Figure B.4b plots the deposit concentration after removing the change in deposits at the headquarter county and completely omitting this change in calculating the deposit shares.

Figure B.5: Geographic Concentration of Deposits after Excluding the HQ Branch

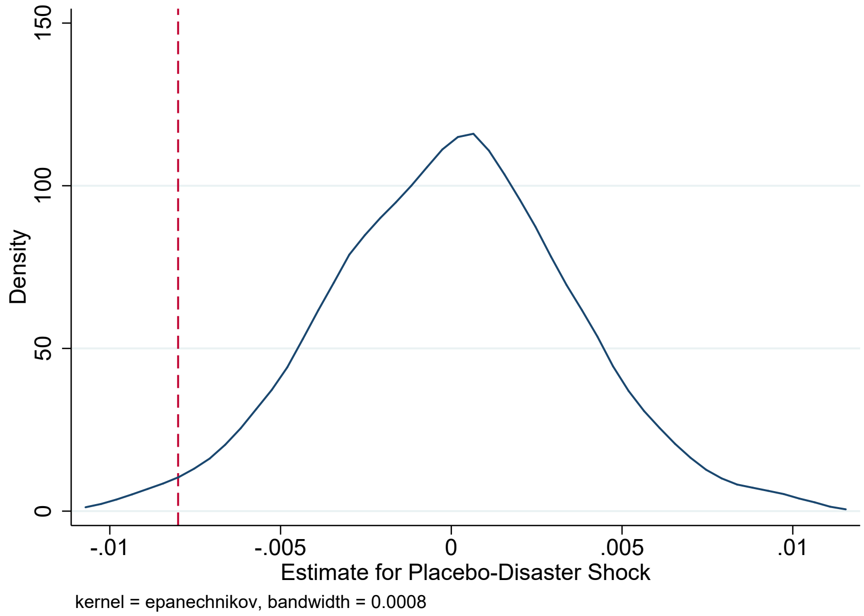


This figure uses the summary of deposit (SOD) data from 1994 to 2018 and illustrates the geographic concentration of bank deposits after excluding the HQ branch. The figure orders counties by their deposit shares for each bank (the county number refers to the rank of a county by the amount of deposits it raises, i.e., county #1 refers to the county that raised the greatest amount of deposits for a given bank.) and reports the average deposit share of the top 20 counties. When computing the deposit share at the HQ county, the figure excludes the deposit at the HQ branch. The blue line shows the simple average of the deposit share, the red line shows the average deposit share weighted by bank total assets, and the green line shows the average deposit share controlling for bank-year and county-year fixed effects. .

Placebo Test: Disaster Shocks and Deposit Growth

We conduct a placebo test to validate the relationship between disaster shocks and deposit growth is not spurious. We estimate equation 1, using the random assignment of disaster shocks. We refer to this as *Placebo Disaster Shock*. Placebo Disaster Shock is generated for each county-year from a standard normal distribution. We estimate the coefficient associated with Placebo Disaster Shock variable from 1,000 simulations. To negate the validity of the baseline results, the null hypothesis that the point estimate associated with Placebo Disaster Shock is zero, must be rejected. Appendix Figure B.6 presents the kernel density of β, coefficient associated with Placebo Disaster Shock from 1,000 simulations. The distribution of β is centered around 0, varying from -0.0099 to 0.0107 with a standard deviation of 0.0035. The dashed red line denotes the location of the coefficient of the interaction term from column 6 of Appendix Table 2. 1.6% of estimates, among the 1,000 simulated placebo β, lie to the left of the dashed red line. Hence, we fail to reject the null hypothesis. The average point estimate from the placebo analysis is statistically indistinguishable from zero. The results of the placebo test corroborate that the baseline results are not spurious.

Figure B.6: Disaster Shock and Deposit Growth: Placebo Test



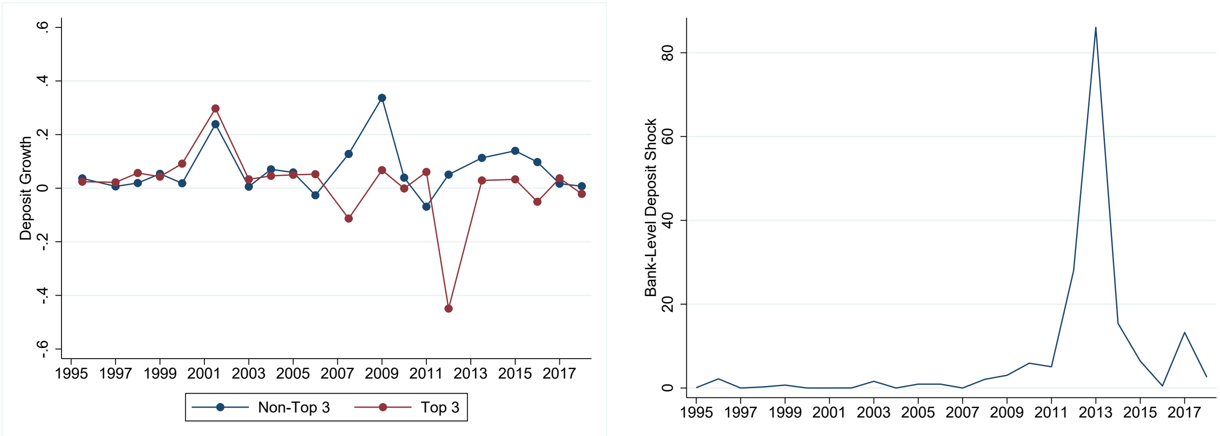
Min	p1	p5	p25	p50	p75	p95	p99	Max	Mean	St Dev
-0.0099	-0.0083	-0.0058	-0.0024	0.0001	0.0024	0.0059	0.0091	0.0107	0.0000	0.0036

Notes: This figure uses the Summary of Deposit (SOD) data matched with the Spatial Hazard Events and Losses Database for the United States (SHELDUS) and plots the kernel density of the estimated coefficient β's obtained from 1,000 simulations of disaster shock in the following specification:

$$\Delta ln(Deposit)_{c,t} = \beta \times \text{Placebo Disaster Shock}_{c,t-1} + \theta_c + \theta_{s(c \in s),t} + \varepsilon_{c,t}$$

where c and t indicate county and year, respectively. The table below the figure reports the summary statistics for the distribution of β. The data used in this figure and table spans from 1994 to 2018. The dependent variable $\Delta ln(Deposit)_{c,t}$ is the first difference of the natural logarithm of total deposit by all banks in county c and year t (i.e., $ln(Deposit)_{c,t} - ln(Deposit)_{c,t-1}$)). The independent variable Placebo Disaster Shock$_{c,t-1}$ measures the dollar amount of property damage per capita from natural disasters in county c and year $t-1$ and is generated randomly from a standard normal distribution. θ_c and $\theta_{s(c \in s),t}$ represent county and state-year fixed effects, respectively. The dashed red line indicates the point estimate β from a baseline regression in Column 6 of Appendix Table 2. Among the 1,000 βs obtained from simulated placebo disaster shock, 1.6% of them lie to the left of the dashed red line.

Figure B.7: Case Study: Impact of Hurricane Sandy on Citibank

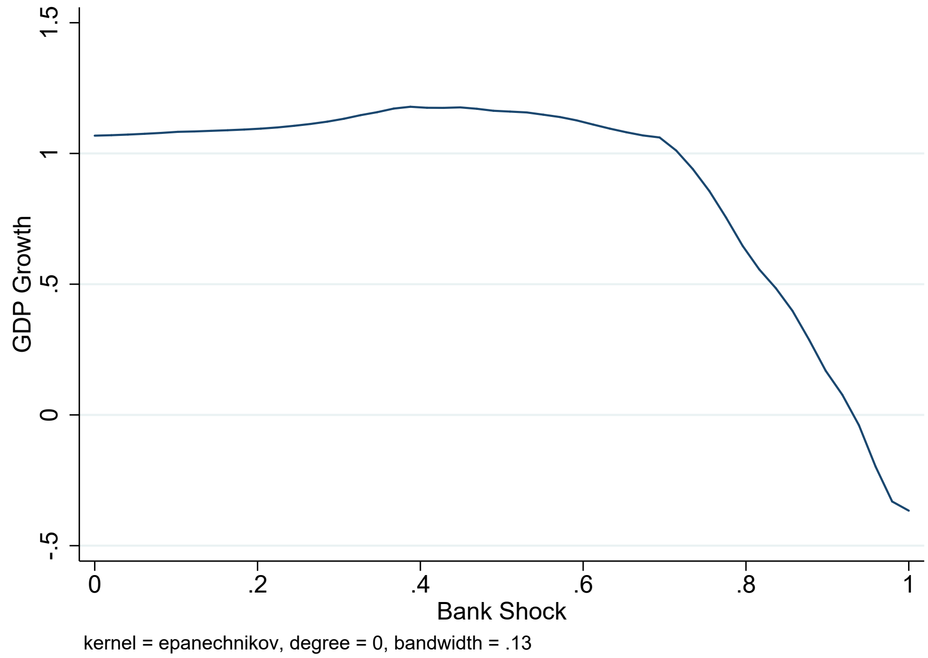


(a) Deposit Growth

(b) Bank-level Shock

Note: This figure presents the effect of Hurricane Sandy on Citibank. Figure B.7a presents the deposit growth for top-3 and non-top 3 counties for Citibank. To compare deposit growth, we divide the counties into two categories: Citibank's three largest deposit counties in each year, and all other counties. Specifically, a county is among the top three bin if it is one of Citibank's three largest deposit counties in any year. The top three counties are Los Angeles County, San Francisco, Clark County, Kings County, Nassau County, New York County, Queens County, and Minnehaha County. The counties among the top three in New York include Kings, Nassau, New York (Manhattan), and Queens. Figure B.7b presents the aggregate bank-level deposit shock for Citibank computed according to Equation 3.

Figure B.8: Aggregate Deposit Shock and GDP Growth



Note: This figure presents the relation between GDP growth and aggregate deposit shocks. Aggregate deposit shocks, Γ_t, are constructed by weighting the bank deposit shocks by each banks' lending share, $L_{b,t-1}$, in period $t-1$ as in equation 4.

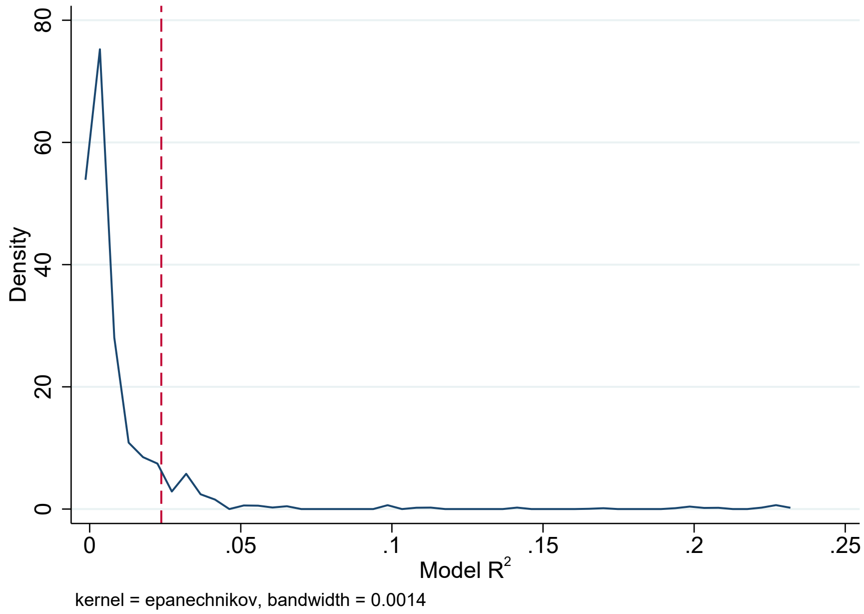
$$\Gamma_t = \sum_b \{ \frac{L_{b,t-1}}{\sum_b L_{b,t-1}} \times \Gamma_{b,t} \}$$

where, $\Gamma_{b,t}$ denotes bank-level deposit shock for bank b at time t (quarter). Bank deposit shocks are constructed by weighting county-level disaster shocks, $\epsilon_{c,t}$ – property damage per capita in county c at time t – by the bank-county deposit share, $D_{b,c,t-1}$. $D_{b,c,t-1}$ denotes deposits of bank b in county c.

$$\Gamma_{b,t} = \sum_c \{ \frac{D_{b,c,t-1}}{\sum_c D_{b,c,t-1}} \times \varepsilon_{c,t} \}$$

The aggregate deposit shocks are scaled to lie between 0 and 1 in this figure.

Figure B.9: R^2 of Placebo Granular Shocks

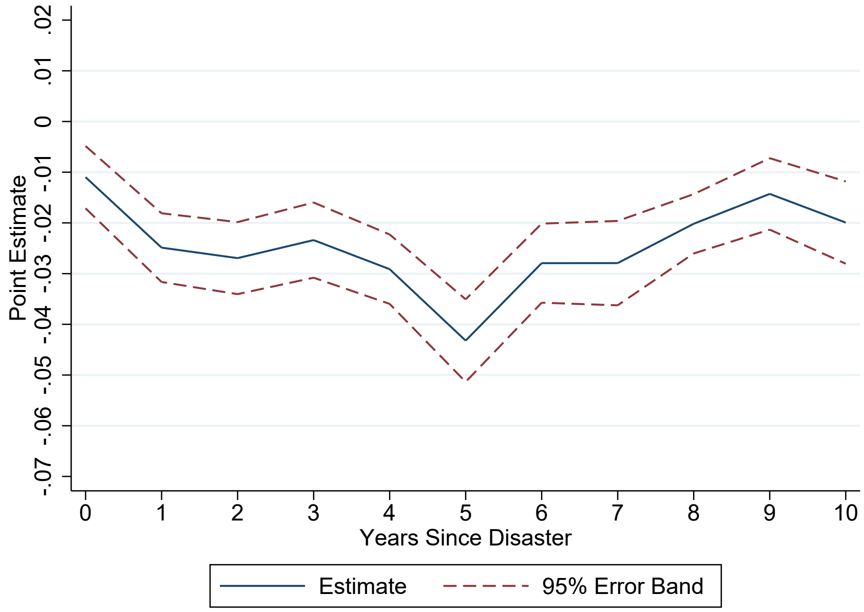


Notes: This figure presents the kernel density of the R^2 from regressing aggregate GDP growth on placebo granular shocks. Pareto distributions are fitted to our bank level shocks and common shocks. Placebo granular shocks are generated from subtracting the random draws from the fitted pareto distribution for bank level shocks from the random draws from the fitted pareto distribution for common shocks. The figure plots the kernel density of the estimated model R^2 obtained from 1,000 simulations of placebo granular shock from the following specification:

$$\%\Delta GDP_t = \alpha + \beta \times \Gamma^*_{placebo,t-1} + \varepsilon_t$$

The dashed red line indicates the R^2 from a baseline regression in Column 1 of Table 3. Among the 1,000 R^2s obtained from the regressions of economic growth on placebo shocks, 90.90% of them lie to the left of the dashed red line.

Figure B.10: Long-Run Response of Small Business Lending to Disaster Shocks

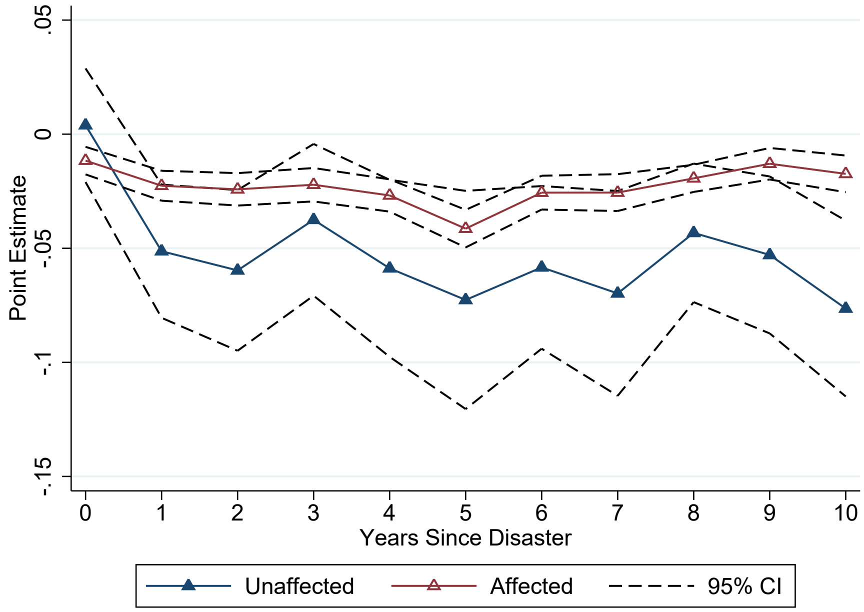


Note: This figure uses small business lending data collected under the Community Reinvestment Act (CRA) and plots the estimated coefficient β^h's in the following specification:

$$ln(Lending)_{b,c,t+h} - ln(Lending)_{b,c,t-1} = \beta^h \times \Gamma_{b,t-1} + \theta^h_{c,t} + \theta^h_{b,c} + \varepsilon_{b,c,t}$$

where b, c and t indicate bank, county, and year, respectively. The data spans from 1997 to 2018. The dependent variable $\Delta ln(Lending)_{b,c,t}$ is the natural logarithm of small business loans originated by bank b in county c and year t. $\theta^h_{b,c}$ and $\theta^h_{c,t}$ are bank $\times$ county and county $\times$ year fixed effects, respectively. $\Gamma_{b,t-1}$ refers to bank specific deposit shocks, measured using the previous year's deposit weighted average of disaster damage per capita. All variables are standardized to a mean of zero and standard deviation of one and winsorized at the 1% level. The solid blue line plots the point estimate β_h's with h from 0 to 10, and the dashed red line plots the 95% confidence interval for the point estimate β_h's. The confidence interval is computed from standard errors clustered by bank and county.

Figure B.11: Disaster Affected and Unaffected Counties

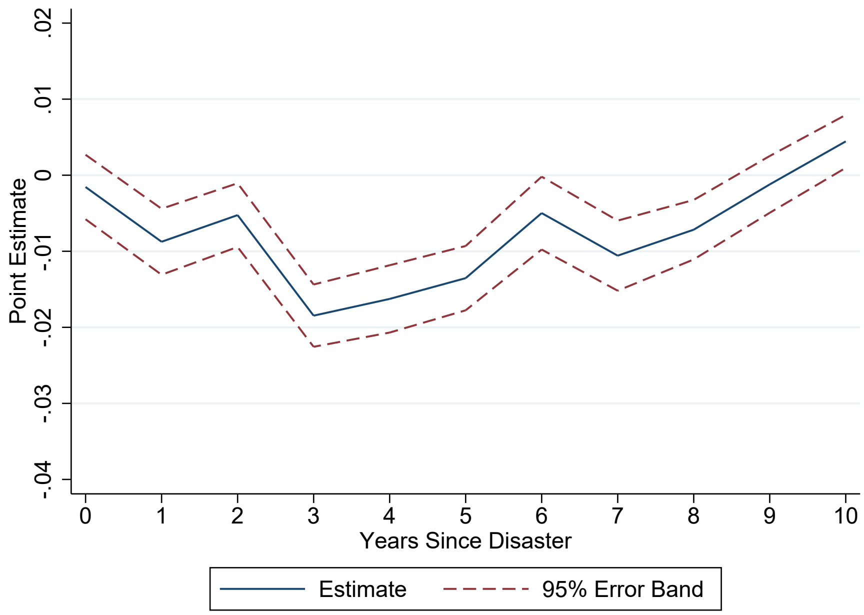


Note: This figure uses small business lending data collected under the Community Reinvestment Act (CRA) and plots the estimated coefficient β^h's in the following specification for disaster affected and unaffected counties:

$$ln(Lending)_{b,c,t+h} - ln(Lending)_{b,c,t-1} = \beta^h \times \Gamma_{b,t-1} + \theta^h_{c,t} + \theta^h_{b,c} + \varepsilon_{b,c,t}$$

where b, c and t indicate bank, county, and year, respectively. The data spans from 1997 to 2018. The dependent variable $\Delta ln(Lending)_{b,c,t}$ is the natural logarithm of small business loans originated from bank b in county c and year t. $\Gamma_{b,t-1}$ refers to bank specific deposit shocks, measured using the previous year's deposit weighted average of disaster damage per capita. $\theta^h_{b,c}$ and $\theta^h_{c,t}$ are bank × county and county × year fixed effects, respectively. All variables are standardized to mean zero and standard deviation of one and winsorized at the 1% level. The solid blue line plots the point estimate β_h's with h from 0 to 10, and the dashed red line plots the 95% confidence interval for the point estimate β_h's. The confidence interval is computed from standard errors clustered by bank and county.

Figure B.12: Long-Run Response of Mortgage Lending to Deposit Shocks



Note: This figure uses data collected under the Home Mortgage Disclosure Act (HMDA) and plots the estimated coefficient β^h's in the following specification:

$$ln(Lending)_{b,c,t+h} - ln(Lending)_{b,c,t-1} = \beta^h \times \Gamma_{b,t-1} + \theta^h_{c,t} + \theta^h_{b,c} + \varepsilon_{b,c,t}$$

where b, c and t indicate bank, county, and year, respectively. The data spans from 1995 to 2017. $\Delta ln(Lending)_{b,c,t}$ refers to the natural logarithm of mortgage amount originated of bank b in county c and year t. $\theta^h_{b,c}$ and $\theta^h_{c,t}$ are bank-county and county-year fixed effects, respectively. $\Gamma_{b,t-1}$ refers to bank specific deposit shocks, measured using the previous year's deposit weighted average of disaster damage per capita. All variables are standardized to a mean of zero and standard deviation of one and winsorized at the 1% level. The dashed red line plots the 95% confidence interval for the point estimate β_h's. The confidence interval is computed from standard errors clustered at the bank and county level.

Appendix C Microfoundation of Deposit Shock

We begin by assuming that withdrawals occur uniformly across banks, i.e., the expected deposit growth at bank b in county c is proportional to $(D_{b,c,t-1}/\sum_b D_{b,c,t-1})$. Then, for bank b, we have:

$$\mathbb{E}_t\left(\frac{\Delta D_{b,c,t}}{\sum_b D_{b,c,t-1}}\right) = \frac{D_{b,c,t-1}}{\sum_b D_{b,c,t-1}} \times \epsilon_{c,t} \tag{C.1}$$

$$\Rightarrow \mathbb{E}_t(\Delta D_{b,c,t}) = D_{b,c,t-1} \times \epsilon_{c,t} \tag{C.2}$$

Dividing both sides of equation C.2 by $\sum_c D_{b,c,t-1}$ yields the aggregate growth in deposits for bank b due to a disaster shock in county c.

$$\mathbb{E}_t\left(\frac{\Delta D_{b,c,t}}{\sum_c D_{b,c,t-1}}\right) = \frac{D_{b,c,t-1}}{\sum_c D_{b,c,t-1}} \times \epsilon_{c,t} \tag{C.3}$$

Aggregating equation C.3 across all counties for a bank b gives us the relationship between shocks to bank deposit growth and disaster shocks as follows:

$$\sum_c \frac{\mathbb{E}_t(\Delta D_{b,c,t})}{\sum_c D_{b,c,t-1}} = \sum_c \frac{D_{b,c,t-1}}{\sum_c D_{b,c,t-1}} \times \epsilon_{c,t} \tag{C.4}$$

Equation C.4 allows us to define bank shocks as follows:

$$\Gamma_{b,t} := \sum_c \left\{\frac{D_{b,c,t-1}}{\sum_c D_{b,c,t-1}} \times \varepsilon_{c,t}\right\} \tag{C.5}$$

Aggregating bank-specific shocks across all banks allows us to define aggregate shocks as follows:

$$\Gamma_t := \sum_b \Gamma_{b,t} = \sum_b \left(\sum_c \left\{\frac{D_{b,c,t-1}}{\sum_c D_{b,c,t-1}} \times \varepsilon_{c,t}\right\}\right) \tag{C.6}$$