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 to be 1.49 and the money multiplier to be 1.26. We construct deposit shocks by combining the within-bank geographic concentration of deposits – where at least 30% of deposits are concentrated in a single county – with local natural disasters. Natural disasters in deposit-concentrated areas negatively affect bank deposits and amplify through bank internal capital markets. These shocks can explain 5.80% 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; Diamond and Rajan, 2001; Kashyap, Rajan, and Stein, 2002). While a large empirical literature since the seminal work of Allen and Gale (2000) 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. This is because cross-sectional estimates do not capture general equilibrium effects on aggregate variables – such as prices, labor demand, etc. – that do not vary systematically with the identifying variation. As a result, these cross-sectional identification strategies may not account for broader economic responses, which can influence the aggregate elasticity between deposit shocks and economic growth. This shortcoming of cross-sectional approaches in identifying aggregate effects is commonly referred to in the literature as the *missing intercept* problem (Wolf, 2023). As a result, the debate on the macroeconomic effects of deposit shocks persists despite a large cross-sectional literature and the availability of aggregate data. 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 aggregate effect of deposit shocks. 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 (2024) by combining the within-bank geographic concentration of deposits with property damages caused by local natural disasters. 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

[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); Huber (2018); and Kundu and Vats (2021) 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 (2022) examine the effects of bank deposit volatility.

deposits – at least 30% of deposits for a given bank are concentrated in a single county. This result differs from Drechsler, Savov, and Schnabl (2017), which documents the within-county concentration of deposits. The geographic concentration of deposits is widespread across banks, including the Big 4 banks and the Top 20 banks. We show that our results are not driven by measurement error in the geography of deposits. Specifically, we do not find evidence that certain branches disproportionately report non-local deposits due to factors such as operational practices (e.g., recording deposits at headquarters or main branches), tax strategies, mergers and acquisitions, or the strategic co-location of deposits and lending activities to exploit synergies. This also applies to specific deposit types such as online, brokered, or uninsured time deposits. In counties with large deposit volumes, we observe that deposits are spread across multiple branches rather than concentrated in a single location, indicating that branch-specific reporting conventions are unlikely to drive our results. Finally, we validate the robustness of our findings by comparing the geographic distribution of deposits to that of branches, which is less vulnerable to location-based measurement error. Overall, our findings indicate that, within a bank, the source of deposits exhibits *granularity* in the sense of Gabaix (2011).

We find that natural disasters adversely impact local bank deposits. Specifically, a one standard deviation disaster shock, equivalent to a per-capita loss of $2,450, is associated with a 0.09 to 0.11 percentage points decline in deposit growth, placing the impact at the 25th percentile of deposit growth. Furthermore, the negative impact of these disaster shocks on deposit growth is permanent. We explore several mechanisms through which disasters affect deposits. First, analysis of local business activity, employment, and household income indicates that the negative income effect from disasters can reduce deposit growth in affected areas. Second, migration data indicates a modest increase in outflows from disaster-affected regions, suggesting that some deposits may be reallocated to branches near new residences. Finally, at the bank level, we observe a net decrease in aggregate deposits. These findings emphasize two critical points: (1) natural disasters reduce total deposits at the bank level when its large deposit markets are impacted; and (2) the economic consequences of negative income effects outweigh the effects of deposit reallocation due to migration.

We exploit these facts to construct idiosyncratic shocks to aggregate bank deposits, following the GIV methodology of Gabaix and Koijen (2024). 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 asset shares. Therefore, these shocks allow us to construct exogenous variation in aggregate deposit shocks that is likely to be 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 to be 1.49, i.e., a 10 basis point decrease in deposit growth is associated with a decline in economic growth by 14.89 basis points. This effect represents a 13.10% change relative to the mean and a 5.66% change relative to the standard deviation. In terms of relevance, we document that a granular deposit shock equivalent to the 90th (95th) percentile reduces economic growth by 0.01 to 0.03 pp (0.06 to 0.16 pp). Moreover, these shocks account for up to 5.80% of the variation in economic growth – comparable to, and in some cases, exceeding the explanatory power of common macroeconomic shocks such as uncertainty shocks, term spread, government expenditure shocks, and the granular residual from Gabaix (2011).

The identification of the aggregate effects of shocks to deposits on economic growth crucially hinges on a key identifying assumption that the interaction of deposit concentration with disasters does not serve as a proxy for other correlated interactions. We provide three pieces of evidence to support this identification strategy. First, we construct alternative granular shock variables at the county level to control for the geographic distribution of correlated economic factors, including employment, GDP, population, and the number of establishments. We find that the effects of deposit concentration are unlikely to be driven by the fat-tailed distribution of these local economic indicators, which could otherwise confound the relationship between disaster shocks and bank deposits. Second, we address the concern that bank deposit concentration may reflect the geographic concentration of other banking products, particularly credit. To test this, we create placebo granular lending shocks using the distribution of bank lending rather than deposits. Our findings indicate that it is the geographic distribution of deposits, rather than that of other banking products such as credit, that primarily drives our results. Third, we show that our results are unlikely to capture the direct effect of local natural disasters on the aggregate economy. Finally, we show that our findings are robust to potential measurement error in the geographic allocation of bank deposits, and they remain consistent when we extend the analysis back to 1981 using historical deposit data.

Another key identifying assumption of our shocks is the importance of banks in the overall economy. We test this assumption using a placebo exercise in which we construct a series of placebo shocks by sequentially excluding the largest banks in each quarter. The intuition behind this test is that large banks affected by natural disasters can drive aggregate fluctuations, either directly, as in Gabaix (2011), or through their centrality in the network, as in (Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi, 2012; Corbae and D'Erasmo, 2021). To implement this test, we exclude banks with asset shares above the k^{th} percentile, where k ranges from the 95th to the 20th percentile in 5-point percentile steps. We find that both the effect size and the model's explanatory power for GDP growth decline steadily and converge toward zero as larger banks are removed from the shock construction. This finding indicates the importance of large banks in transmitting deposit shocks to aggregate economic growth.

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 an estimate of the money multiplier to be 1.26, i.e., a \$1 reduction in deposits is associated with a \$1.26 reduction in lending. We also present an estimate of the loan supply elasticity of economic growth. We document that a 10 basis point decline in the loan supply is associated with a 9.9 basis point decline in economic growth. This effect represents a 8.71% change relative to the mean and a 3.76% change relative to standard deviation. 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.

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 emphasize the critical role of financial frictions in explaining the granular origins of aggregate fluctuations (Pasten, Schoenle, and Weber, 2024; Khorrami, 2025).

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.

1.1 Related Literature

The major contribution of this paper is estimating the aggregate effect of deposit shocks on economic growth. Past cross-sectional studies have causally identified a *relative* effect between deposit shocks and economic outcomes. However, the cross-sectional estimates are not interpretable as macroeconomic counterfactuals. Our novel empirical methodology allows us to estimate the deposit elasticity of economic growth and the money multiplier, overcoming a major empirical challenge.

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, Carvalho, Ozdaglar, and Tahbaz-Salehi (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 and Koijen (2024). Their methodology for constructing shocks is susceptible to the "reflection" problem – large firms load more on common factors, i.e., larger firms exhibit greater procyclicality. Our use of natural disaster-induced property damages provides an exogenous source of variation, circumventing this concern as GDP growth and other common factors are unlikely to determine natural disasters.

Moreover, our work builds on the recent theoretical advances that document the salience of financial frictions for explaining aggregate fluctuations (Pasten, Schoenle, and Weber, 2024; Khorrami, 2025). We contribute to this literature by providing empirical evidence in support of these theories. 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 contributes to the longstanding literature on the role of banks in amplifying shocks and contributing to 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, 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. 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, Jamilov, Juelsrud, and Rey, 2023) and other granular agents in the economy (Kundu and Vats, 2021). 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, driven by 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 stemming from natural disasters. A closely related contribution is Cortés and Strahan (2017), who emphasize the demand side effects of such events. They document a short-term increase in credit demand in disaster-affected areas, primarily met by small banks, and argue that these effects dissipate within a year. In contrast, our paper focuses on the supply side by tracing the persistent impact of natural disasters on bank funding. We show that disasters can cause lasting economic harm – lower household income, reduced employment, and business closures – which in turn lead to sustained declines in local deposits. These funding shocks, when concentrated in key deposit regions, especially for large banks, can propagate to the aggregate level and suppress credit creation well beyond the immediate aftermath of a disaster.[3] The key distinction lies in both the mechanism and the agents driving these outcomes. Whereas Cortés and Strahan (2017) attribute lending responses to temporary demand shocks met by small, community-focused banks, our findings point to supply-side constraints driven by long-run reductions in

[2]Some works in this literature include Peek and Rosengren (2000); Khwaja and Mian (2008); Loutskina and Strahan (2009); Ivashina and Scharfstein (2010); Cetorelli and Goldberg (2012); Schnabl (2012); Chodorow-Reich (2014); Huber (2018); and Kundu and Vats (2021), 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 the literature examining the effects of banking on the real economy.

[3]Our focus on multi-market banks contrasts with prior work that emphasizes local banks' responses to localized shocks (e.g., Iyer, Kundu, and Paltalidis (2023)). For instance, Cortés (2014); Plosser (2014); Gilje, Loutskina, and Strahan (2016); Gilje (2019) document increased lending by local banks – often with limited access to capital markets — in counties affected by natural disasters or energy booms. We add to this literature by showing that local shocks matter even for large, multi-market banks, due to the geographic concentration of their deposit bases. Our findings also complement Doerr, Kabaş, and Ongena (2024), who show that funding shocks from population aging impact large-bank risk-taking.

depositor wealth, particularly affecting large banks. Importantly, these two sets of findings are not mutually exclusive. Natural disasters can generate short-run increases in borrowing needs while simultaneously impairing long-run wealth and savings. As a result, small banks may step in to meet immediate credit needs of their relationship borrowers, while large banks may contract lending over time as they are less inclined to lend under heightened informational frictions (Berger and Udell, 2002; Berger, Miller, Petersen, Rajan, and Stein, 2005; Berger, Bouwman, and Kim, 2017; DeYoung, Gron, Torna, and Winton, 2015).[4] Using detailed data, we further show that larger banks significantly reduce lending in counties affected by natural disasters. In contrast, the estimate associated with small banks is positive. Thus, the two sets of findings are not only compatible but also mutually reinforcing, once heterogeneity in bank characteristics and behavior is taken into account. We direct readers to Appendix B for a more detailed discussion.

The rest of the paper proceeds as follows. Section 2 describes the data used in the analysis. Section 3 presents new evidence on the geographic concentration of deposits. Section 4 outlines the methodology for constructing deposit shocks and discusses the channels through which local disaster shocks reduce local bank deposits. Section 5 documents the aggregate effects of deposit shocks. Section 6 discusses the underlying mechanisms. Finally, Section 7 concludes.

2 Data

We construct deposit shocks using three data sets: branch-level bank deposits from the Summary of Deposits (SOD), county-level disaster damages from the Spatial Hazard Events and Losses Database for the United States (SHELDUS), and bank financial information from Call Reports.

SHELDUS provides detailed, county-level information on natural disasters and their associated losses, including property and crop damages, injuries, and fatalities. It covers a wide range of natural disasters, such as thunderstorms, hurricanes, floods, wildfires, and tornadoes, based on the Storm Data and Unusual Weather Phenomena published by the National Climatic Data Center (NCDC). Table 1 reports summary statistics on aggregate property damages, Appendix Table C.1 breaks down damages by hazard type, and Figure C.1 presents a heatmap of property damages per capita.

[4]This distinction is supported by evidence that small banks specialize in distressed lending environments. Chavaz (2016) show that small banks originate a larger share of new mortgage and small business loans in disaster-affected areas. Similar patterns are found in Cortés (2014) for the U.S. and Koetter, Noth, and Rehbein (2020) for Germany. These studies underscore the role of small banks in stabilizing local economies following shocks, consistent with Cortés and Strahan (2017).

The SOD, compiled annually by the Federal Deposit Insurance Corporation (FDIC), reports branch-level deposits for all depository institutions operating in the U.S. as of June 30 of each year. The data includes detailed information on branch location at the ZIP code level, branch characteristics (e.g., total deposits), and parent bank identifiers. We use the data from 1994 to 2019 and restrict our sample to banks operating in at least two counties.

Finally, we obtain bank-level financial information from the Call Reports, which are quarterly regulatory filings submitted by all insured U.S. commercial banks to the Federal Financial Institutions Examination Council (FFIEC). The Call Reports provide detailed balance sheet data, including total assets, liabilities, loans, and deposits at the bank level. In particular, we use total assets to measure bank size, which serves as a weight when aggregating bank-level deposit shocks and reflects the granularity of the local banking industry. We use the standardized and cleaned version of the Call Report data compiled by Drechsler, Savov, and Schnabl (2017), which ensures consistency in variable definitions over time and facilitates long-term analysis. Appendix Table C.2 presents the summary statistics of supplementary bank-level and aggregate variables for our sample.

To examine the effects of deposit shocks, we use a range of outcome variables at both the aggregate and bank level. At the aggregate level, we use data on U.S. GDP growth, deposit growth, and commercial and industrial (C&I) lending growth from the Federal Reserve Economic Data (FRED). At the bank level, we focus on small business lending reported under the Community Reinvestment Act (CRA) from 1997 to 2019. The CRA data provide the most comprehensive coverage of small business lending in the U.S., capturing approximately 86% of all loans under $1 million (Greenstone, Mas, and Nguyen, 2020). These data are reported by all depository institutions above a certain asset threshold (e.g., $1.252 billion in 2018) and include the geographic distribution of small business loans, defined as commercial and industrial loans of $1 million or less. Small business loans are particularly suitable for our analysis because they are inherently risky and illiquid, making them difficult to securitize (Wilcox, 2011; Drechsler, Savov, and Schnabl, 2017). As a result, they are typically funded directly by bank deposits, providing a clean setting to examine how deposit shocks affect lending.

We also use mortgage origination data from the Home Mortgage Disclosure Act (HMDA) from 1994 to 2019. In particular, we distinguish between conforming loans and jumbo loans, as the latter exceed the GSE loan limits and are generally not securitized by Fannie Mae or Freddie Mac. This distinction allows us to test whether the effects of deposit shocks are stronger for mortgages that rely more heavily on deposit funding.

For robustness tests, we additionally use data on local economic conditions, firm characteristics, and other aggregate shocks. County-level information on establishments and employment comes from the County Business Patterns (CBP), migration data are obtained from the Internal Revenue Service (IRS), and firm-level financial information for U.S. non-financial and non-utilities firms is obtained from Compustat. We also use disaster-related losses to households and businesses, which we estimate using insurance payouts reported by the Small Business Administration (SBA). In addition, we control for a range of aggregate variables, including the term spread from FRED, oil supply shocks from Känzig (2021), the economic policy uncertainty index from Baker, Bloom, and Davis (2016), monetary policy shocks from Vats (2020), and granular shocks to large firms are constructed following Gabaix (2011).

Table 1 reports summary statistics for the key variables used in our analysis. Panel A presents county-year level variables, including deposit growth, natural disaster damages, and local economic conditions such as the number of establishments, employees, and migration flows. Panel B summarizes bank-year level variation in deposit shocks. Panel C presents national-level variables used in our main and robustness analyses, including GDP growth, C&I lending growth, monetary policy shocks, oil shocks, and government expenditure shocks. Notably, both deposit growth and disaster damages exhibit substantial variation across counties and over time.

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 raises 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 at least 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 1994-2019. 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 the geographic concentration of deposits within banks is evident starting from 1994 – the first reported year in the SOD 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 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.[5] Figure 2a reports the relationship between the percentile of bank assets and share of deposits in the largest deposit county. The findings indicate that while larger banks tend to exhibit lower deposit concentration compared to their smaller counterparts, their levels of concentration are still notably high. We investigate this issue further by documenting the geographic concentration of bank deposits among the Big 4 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 4 banks in the US. The share of deposits in the largest deposit county is highest for Citibank (≈ 0.59), followed by JP Morgan (≈ 0.49), Wells Fargo (≈ 0.17), and Bank of America (≈ 0.12).[6] Overall, the results of this analysis indicate the prevalence of geographic concentration of bank deposits across the distribution of bank size.

[5] 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 E.1.

[6] Appendix Figure E.2 shows the average share of deposits in the largest deposit county for the Big 4 banks over our sample period.

3.3 Does Geographic Mismeasurement of Deposits Drive Concentration?

Our analysis currently relies on the FDIC's Summary of Deposits (SOD) data, which presents certain challenges. Some branches may hold a disproportionately high share of non-local deposits, often due to practices such as recording deposits at a headquarters or main branch for operational convenience, tax considerations, or as a result of mergers and acquisitions that shift deposit records geographically. Other contributing factors include the treatment of specific deposit categories, such as online deposits, uninsured time deposits, brokered deposits, and the recording of deposits at major lending centers to leverage synergies between lending and deposits. We direct the reader to Appendix D, which presents a brief summary of the reporting process.

This section examines the role of these factors and argues that, despite these dynamics, our primary finding remains robust: bank deposits are geographically concentrated. We further support this conclusion with alternative concentration measures that are less affected by recording issues, reinforcing the robustness of our findings on deposit concentration.

3.3.1 Headquarter Location

The total amount of non-local deposits measured in a bank's headquarter branch may significantly impact our measure of deposit concentration, due to reporting stipulations.[7] We address this limitation in the SOD data by examining deposit concentration for banks that moved their headquarters during our sample period. Specifically, we evaluate the change in total deposits in the headquarters county when banks relocated their headquarters, using this shift to recalculate deposit concentration within banks in three distinct ways.

First, we remove the increase in headquarters county deposits and redistribute this amount across all counties based on each county's deposit share from the previous year. Second, we remove the headquarters increase and distribute it equally across all counties. Third, we remove the increase in headquarters deposits altogether in calculating deposit shares for all counties. Figure 3 presents these results for the years in which banks moved their headquarters; this sample consists of 50 banks that changed headquarters locations. The

[7] 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). This implies that the 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.

results align closely with those reported in Figure 1a, suggesting that geographic misallocation due to SOD reporting guidelines is unlikely to drive our findings.

Additionally, we complement this analysis by examining within-bank deposit concentration after excluding deposits from the headquarters branch. Appendix Figure E.3a shows that even with headquarters deposits removed, 20% to 30% of bank deposits still originate from a single county, reinforcing that geographic concentration of deposits persists despite potential misallocation. This pattern is apparent even for the largest banks, see Appendix Figure E.3b for the Big 4 banks and Appendix Figure E.3c for the top 20 banks.

3.3.2 Assessment of Measurement Error

We conduct a series of additional tests to assess the extent of measurement error in deposit concentration. This error could be due to various factors such as taxes, mergers and acquisitions, accounting practices related to uninsured time deposits or online deposits, and other reporting requirements. Additionally, operational efficiency issues may lead banks to report non-local deposits at their main office branches, operational branches in each state, and counties with the most lending opportunities. The baseline analysis reveals that the largest deposit county constitutes around 48% of all bank deposits, as shown in the first bar of Figure 4. We examine how this percentage changes as we adjust for potential factors influencing why banks may concentrate their deposits in particular regions. Figure 4 presents the results and Appendix Figure E.4 presents detailed data.

Tax Considerations: First, tax considerations may lead some depositors to report addresses in states without income taxes. We address this concern by excluding nine states without state income taxes: Alaska, Florida, Nevada, New Hampshire, South Dakota, Tennessee, Texas, Washington, and Wyoming. After adjusting for these tax incentives, the share of deposits from the largest deposit county remains largely unchanged, as shown in the second bar of Figure 4 (see Appendix Figure E.4a for details).

Mergers & Acquisitions: Second, mergers and acquisitions can shift the geographic allocation of deposit records. For example, when a bank acquires another, it may consolidate the acquired bank's deposits into its primary reporting locations rather than retaining them at the original branches. This consolidation often aims to streamline operations, align with the acquiring bank's organizational structure, or fulfill regulatory and tax requirements. Consequently, deposits previously recorded at the acquired bank's branches may now appear concentrated at the acquirer's headquarters or other main branches, potentially distorting the data's geographic distribution. We address this issue by excluding banks involved in mergers and acquisitions starting from the year of their first acquisition.[8] After excluding these banks, our measure of deposit concentration remains largely unchanged, as shown in the third bar of Figure 4 (see Appendix Figure E.4b for details).

Specific Non-Local Deposits: Third, we exclude non-local deposits from our analysis. Brokered deposits and uninsured time deposits may lack a clear geographic footprint, often leading them to be attributed to the main office. We identify each bank's main office using the main office indicator in the SOD data, where the indicator equals 1 for the main office and 0 for all other branches. Data on brokered and uninsured deposits are sourced from the Call Reports. We subtract the total amount of brokered and uninsured time deposits from the total deposits reported at the main office and find that, after adjusting for these non-local deposits, around 45% of all bank deposits are still attributed to the largest deposit county, as shown in the fourth bar of Figure 4 (see Appendix Figure E.4c for details).

Moreover, if online deposits were driving our results, we would expect geographic concentration to increase over time as banks raise a larger share of deposits through online channels. However, as shown in Figure 1b, deposit concentration exhibits a downward trend over time, rather than an upward trend, addressing this concern. Additionally, Appendix Figure E.2 reveals a decline in the average deposit share in the largest deposit county for the Big 4 banks – the most active in online banking—throughout our sample period. Finally, our analysis excludes pure single-branch online banks, further mitigating the concern that our concentration measure might be skewed by these banks.

Large Lending Centers: Fourth, banks may have greater incentives to record deposits at their largest lending hubs to leverage synergies between deposits and lending. As Thakor and Yu (2024) note, loans can create their own deposits. Therefore, the largest lending hubs may record disproportionately high amounts of deposits. We address this concern by removing the largest lending counties, addressing concerns about deposit concentration reflecting credit concentration. We find that the geographic concentration of deposits decreases to 42% after excluding the five largest lending counties for mortgage and small business lending for each

[8]The list of banks involved in M&A transactions is sourced from the Federal Financial Institutions Examination Council (FFIEC). Note that excluding banks involved in M&A leads to a sample consisting of smaller banks with a more limited geographic presence, which in turn increases the deposit share in the largest county.

bank, as shown in the fifth bar of Figure 4 (see Appendix Figure E.4d for details).

Main Office Branch: Fifth, we address the potential issue that main office branches may record disproportionately high non-local deposits, as these branches often serve as large operational centers and headquarters.

Our first test examines whether the observed deposit concentration is simply a result of deposits being disproportionately recorded at main office branches. This excess recording at main office branches may be due to operational efficiency purposes. To test this, we drop the main office branches and recompute the concentration of deposits in the largest deposit county. We find that the largest deposit county still accounts for around 41% of deposits, after dropping the main offices, as shown in the sixth bar of Figure 4 (see Appendix Figure E.4e for details). This suggests that our documented fact is unlikely to be driven by main office branches.

Our second test omits the largest deposit branch of each bank in each state, which may be associated with corporate offices and operational centers. After making this adjustment, the largest deposit county accounts for around 40% of deposits, as shown in the seventh bar of Figure 4 (see Appendix Figure E.4f for details).

All Adjustments Together: Lastly, we apply all of the above procedures to eliminate variation from potentially confounding variables in the deposit concentration measure. After accounting for these factors, the deposit concentration decreases to 37%, as shown in the eighth bar of Figure 4 (see Appendix Figure E.4g for details).

Overall, the findings from this section highlight that deposits remain geographically concentrated. Moreover, the geographic concentration is apparent even for the largest banks despite these corrections, see Appendix Figure E.5a (or Appendix Figure E.6) for the Big 4 banks and Appendix Figure E.5b (or Appendix Figure E.7) for top 20 banks.

3.3.3 Dispersion of Deposits within the Largest Deposit County

A potential concern with the observed deposit concentration is that the largest deposit county may be disproportionately influenced by a single "special" branch, which accounts for nearly all of the deposits in that county. This could result from accounting practices or reporting standards, particularly for deposits not directly linked to the nearest branch. However, if a county is truly an important source of bank deposits, we would expect deposits to be spread across multiple branches.

Figure 5 presents an analysis comparing the top deposit branch with all other branches in the three largest deposit counties. Specifically, it contrasts deposits from the "top branch" – the branch that raises the most deposits in a given county – from all other branches within that same county. For ease of comparison, we scale the total deposits at the top deposit branch in the largest deposit county to 100.

We observe that when a county is a significant source of deposits, these deposits are distributed across multiple branches within the county, not just concentrated in the top deposit branch. In fact, we observe that other branches within the top deposit county contribute at least as much, if not more, to the total deposits as the top branch itself. This holds not only for the full sample (Figure 5a) but also for the Big 4 banks (Figure 5b) and the Top 20 banks (Figure 5c).

This analysis suggests that the observed deposit concentration in the largest deposit counties is not solely due to a single branch but rather reflects deposits spread across multiple branches within the county, supporting the conclusion that the county itself is a significant source of bank deposits.

3.3.4 Alternative Measure: Geographic Concentration of Branches

In this section, we demonstrate the robustness of the geographic concentration of deposits by examining the geographic concentration of branches. This approach eliminates concerns related to potential mismeasurement in deposit reporting, such as the geographic misattribution of deposits due to factors like deposit recording practices, online banking, or treatment of specific deposit categories. By focusing solely on branch locations, we avoid these complexities, and provide a cleaner measure of geographic concentration. This method offers the advantage of directly capturing the physical presence and reach of banks, which are key indicators of local market penetration and service availability. As a result, this analysis offers a straightforward and reliable assessment of the geographic distribution of banking activity, without the confounding issues inherent in deposit data.

Figure 6 replicates our baseline Figure 1 using the number of branches, rather than deposits. Figure 6a demonstrates that branches are geographically concentrated within banks, with the largest branch county accounting for almost 30% of all bank branches. This result is consistent with the finding reported in Figure 1a using deposit share. Moreover, we document a significant correlation of 86% between the two measures of concentration – based on the number of branches and deposit amount (see Appendix Figure E.8).

As with the geographic concentration of deposits, the concentration of branches has been evident since 1994, as shown in Figure 6b. Even at the first and tenth percentile values of the share of branches in the largest deposit county, considerable concentration persists. While we observe a slight downward trend in branch concentration over time, the overall level remains high.

We find that larger banks have a slightly lower proportion of branches in their largest branch county, as shown in Figure 6c. Additionally, Appendix Figure E.9 documents a similar relationship between the share of branches and various bank characteristics, including deposits, liabilities, equity, and loans. Figure 6d provides additional details on the geographic concentration of branches among the Big 4 banks, which, while still present, is less pronounced compared to smaller banks. Despite the lower proportion of branches in their largest branch county and a less concentrated geographic footprint, larger banks still maintain a significant overall concentration of branches.

The overall persistence of branch concentration, even with this alternative measure, indicates that geographic clustering remains a significant feature of banking operations. This reinforces the robustness of our findings, indicating that geographic concentration is not driven solely by deposit reporting practices, but also reflects fundamental patterns in the physical distribution of bank branches.

3.4 Geographic Distribution of Largest Deposit Counties

Lastly, we explore the geography of banks' largest deposit county in Figure 7. 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 which 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 Bank Deposit Shocks

We begin by describing the construction of bank deposit shocks which exploits the geographic concentration of bank deposits documented earlier.[9] Later, we use these shocks to analyze their effects on lending and economic outcomes, both at the individual bank level and the aggregate level.

Specifically, 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 at time $t-1$. This is measured using the county-level deposits reported by banks in the SOD database on the 30th of June of the previous year.

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

In this section, we establish that bank deposit shocks lack temporal dynamics, exhibit low correlation across banks, and most importantly, can predict the aggregate bank-level decline in deposits and liquidity creation. Therefore, these shocks appear to be a suitable candidate for bank-specific idiosyncratic shocks to deposits.

4.1 Natural Disasters & Local Deposits

A crucial assumption underlying the construction of these shocks is that natural disasters affect bank deposits. We validate this assumption by studying the immediate response of deposit growth to disaster shocks using the following specification,

$$\Delta ln(Deposits)_{c,t} = \beta \times \text{Disaster Shock}_{c,t-1} + \theta_c + \theta_{s(c \in s),t} + \varepsilon_{c,t} \tag{2}$$

where $\Delta ln(Deposits)_{c,t}$ denotes year-over-year deposit growth at the county level, and Disaster $\text{Shock}_{c,t}$ 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. County fixed effects account for the possibility that the economic consequences of a disaster may vary depending on location-specific factors such as adaptation, resilience, and other geographic

[9] We direct readers to Appendix section A.1 for discussion on the micro foundations and the underlying assumptions of our deposit shocks.

characteristics. Therefore, we estimate β using variation in disaster shocks within counties, while also controlling for time-varying factors at the state level

Table 2 presents the results from the estimation of equation 2. 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 20 percentage points from column 1-6. Economically, a one standard deviation disaster shock, denoting a loss of $2,450 per capita, is associated with a 0.09-0.11 percentage points decline in deposit growth – comparable to the 25$^{\text{th}}$ percentile of deposit growth.[10] These results are robust to the inclusion of lagged shocks, as shown in Appendix Table F.1.[11]

Next, we conduct a Jordà projection to analyze the long-run response of deposit growth to disaster shocks. Figure 8 presents the results. The findings indicate that the effect of disaster 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 Brei, Mohan, and Strobl (2019), who document that banks experience deposit withdrawals following a hurricane in the Caribbean.

4.2 How do Natural Disasters Affect Deposits?

This section presents a discussion of channels through which natural disasters can affect bank deposits. Specifically, we discuss the role of the income effect and the migration channel in explaining the decline in bank deposits, followed by a brief discussion of other channels.

4.2.1 Income Effect

The income effect posits that natural disasters can have a long-run negative effect on local economic activity, resulting in a decline in bank deposits in the area. This section examines the impact of natural disasters on local economic activity. Specifically, we document that natural disasters negatively impact local economic activity, which in turn may reduce deposit growth in the affected areas.

[10] The effect is computed by multiplying the point estimate with the standard deviation of deposit growth. Specifically, we multiply the estimate range $[-0.0144, -0.0179]$ with the standard deviation of deposit growth (6.32%) to get the effect range of $[-0.09, -0.11]$.

[11] We also conduct a placebo test to validate that the relationship between disaster shocks and deposit growth is not spurious. See Appendix Figure F.3 for details.

We begin by analyzing the impact of natural disasters on local business activity using data from the County Business Patterns (CBP) series, spanning from 1994 to 2019. Panel A of Table 3 shows the relationship between the natural logarithm of the number of establishments and per capita property damages caused by natural disasters. We find a strong negative correlation between per capita property damages from natural disasters and the number of local establishments. Specifically, a one standard deviation increase in property damages is associated with a 0.06% decrease in the total number of establishments. This result aligns with Basker and Miranda (2018), who document similar negative effects of Hurricane Katrina on business closures. Moreover, the results align with the numbers reported by FEMA on their website – almost half of the small businesses affected by a disaster never reopen after the disaster, and an additional 29% go out of business within 2 years of the disaster (FEMA, 2024).

The closure of establishments can have a significant negative impact on local bank deposits. As shown in Panel B of Table 3, there is a positive correlation between the number of establishments and local bank deposits. This relationship operates through two main channels. First, businesses hold accounts with local banks to manage their operations, contributing directly to deposits. Second, these businesses create jobs, and the wages paid to local employees flow into local bank branches, further boosting deposits. Thus, when establishments close, local bank deposits can suffer both directly, through the loss of business accounts, and indirectly, through the reduction of employment and, subsequently, household deposits. While it is challenging to fully separate these two effects, we present evidence suggesting that the employment channel may play a role in addition to the direct impact.

We analyze the relationship between employment and per capita property damages from natural disasters, using employment data from the County Business Patterns (CBP) series covering 1994 to 2019. Panel C of Table 3 illustrates the association between the natural logarithm of employment and disaster-related property damages per capita. Our results show a negative correlation between county-level employment and property damages from the prior year. Specifically, a one standard deviation increase in per capita damages is associated with a 0.14% decline in employment.

To further assess the relationship between natural disasters and employment, we analyze household income data from the Community Population Survey (CPS) for the period 1994 to 2019. Appendix Table F.2 reports a negative association between disaster-related property damages and household income. Taken together, the results from Table 3 and Appendix Table F.2, suggest that natural disasters are negatively associated with both local employment and household income. These results are consistent with the extant literature which documents similar economic effects of different types of natural disasters (for a survey, see Lazzaroni and van Bergeijk (2014) and Klomp and Valckx (2014)).

4.2.2 Role of Migration

Next, we examine the effects of natural disasters on migration patterns. The motivation behind this analysis stems from the hypothesis that our findings regarding the county-level effects of natural disasters on bank deposits may be driven by migration patterns. Specifically, some households may relocate following natural disasters, resulting in a change of address with their financial institutions. As a result, their deposits are attributed to a different branch corresponding to their new address. Consequently, our findings may simply reflect a geographical reallocation of deposits, which alone may not lead to significant impacts on the overall economy.

To this end, we utilize IRS data on population inflows and outflows from 1994 to 2018. Table 4 presents the results. Our analysis indicates an increase in the outflow of residents from counties that experience natural disasters. Specifically, we find that a one standard deviation increase in per capita property damages is associated with a 0.06 percentage point rise in population outflow, measured as the ratio of the emigrating population in a given year to the total population in the previous year. This increase corresponds to a 0.9% uptick relative to the average outflow per capita. Additionally, we observe a 0.02 percentage point decrease in population inflow to counties affected by natural disasters, which corresponds to a 0.2% decline in average per capita inflow. In summary, the net population outflow following a disaster increases by 0.08 percentage points for each standard deviation increase in per capita property damages.

Our results of a decline in net outflow following disasters are consistent with Strobl (2011). Using a dataset of U.S. coastal counties from 1970-2005, Strobl (2011) documents an increase in net outflows from counties struck by hurricanes. Fussell, Curran, Dunbar, Babb, Thompson, and Meijer-Irons (2017) and Boustan, Kahn, Rhode, and Yanguas (2020) document similar results, using a longer time series, on the increase in out-migration following different types of natural disasters in the US.

4.2.3 Other Channels

Apart from income and migration, other channels that may affect bank deposits include liquidity demand, precautionary savings motives, and health. The liquidity demand channel negatively affects deposits, as individuals and businesses may need to draw on their savings to cover expenses following a disaster. This increased spending could arise from capital losses that are not covered by insurance (Cookson, Gallagher, and Mulder, 2024) or the rising costs of essential goods (Newman, 2013). Under precautionary motive, households may opt to withdraw their deposits to boost their cash reserves in anticipation of future natural disasters or mitigate the challenges posed by infrastructure destruction, which can make digital transactions difficult in the aftermath of such events (FDIC, 2024). Furthermore, natural disasters can disrupt economic activity by increasing mortality (Frankenberg, Sumantri, and Thomas, 2020) and negatively affecting overall well-being (Hudson, Botzen, Poussin, and Aerts, 2019). All these factors can contribute to a decline in bank deposits. A comprehensive examination of all these channels is beyond the scope of this paper, which we leave for future work.[12]

4.2.4 Case study: Hurricane Katrina & Persistence of Local Economic Impact

This section presents two case studies from New Orleans that illustrate the long-term negative effects of Hurricane Katrina on local economic activity. The first case focuses on Six Flags New Orleans, which was severely damaged by the hurricane in August 2005, resulting in its permanent closure. The area where the park was located remains economically dormant, even twenty years later. For visual references, see Appendix Figure F.1. As a major employer in the region, the closure negatively affected the local community, impacting not only the workforce but also related businesses such as food trucks, convenience stores, motels and bed-and-breakfast establishments. Once a vibrant entertainment destination, its shutdown serves as a lasting symbol of the hurricane's long-term economic devastation.

The second case focuses on the Lower Ninth Ward, one of the hardest-hit areas during Hurricane Katrina. This neighborhood experienced catastrophic flooding, with water levels reaching up to 20 feet in some areas due to breached levees. The destruction resulted in significant loss of homes and widespread displacement of residents. Appendix Figure F.2 presents before and after aerial images of the area, illustrating the lack of recovery even ten years after the hurricane. The Lower Ninth Ward stands as a symbol of the challenges faced in rebuilding after the disaster, highlighting long-term economic consequences of natural disasters on local communities.

[12]For example, Cramer, Ghosh, Kulkarni, and Vats (2024) presents a review of these channels in the context of emerging economies.

4.3 Effect on Bank Deposits

This section establishes that bank-level disaster shocks negatively affect aggregate bank deposits, highlighting two key points. First, it demonstrates that natural disasters lead to a decline in bank-level deposits. Second, it shows that the economic losses from business closures and lost employment following disasters outweigh the effects of deposit reallocation due to migratory patterns.

We document the net impact of disasters on total bank deposits, by examining the link between bank-level deposit shocks (as constructed in Equation 1) and bank-level deposits. Table 5 presents the correlation between these shocks and deposits. We examine various deposit account types, including all deposit accounts in column 1, transaction deposits in column 2, non-transaction savings deposits in column 3, and time deposits in column 4. Our results indicate that banks with greater exposure to disaster shocks experience a significant decline in their deposits, primarily driven by savings and time deposits, which account for over 80% of total deposits.

There are two key takeaways from this analysis. First, banks more exposed to natural disasters experience a greater outflow of deposits. This result is consistent with Berlemann, Steinhardt, and Tutt (2015), who combines the household level savings data from Germany with the natural experiment of the European Flood of August 2002 to document that natural disasters can depress savings. Second, this result suggests that the deposit reallocation across geography due to emigration does not explain our results. The inability of the migration channel to completely account for the effect on deposits suggests that the effect of natural disasters on local economic activity dominates.

4.3.1 Case Study: Capital One (erstwhile Hibernia) & Hurricane Katrina

This section presents a case study demonstrating how shocks to individual counties can lead to negative deposit shocks. Between 2005 and 2019, Capital One experienced remarkable growth, rising from the 48th largest bank in the US to the eighth largest by total deposits. In 2005, Capital One entered the retail banking business by acquiring Hibernia National Bank headquartered in New Orleans, Louisiana, with operations primarily concentrated in Louisiana and Texas. They reported 21% deposit share of the Louisiana market in 2005. This case study examines the impact of Hurricane Katrina – which struck Louisiana, Mississippi, and parts of Texas in August 2005 – on Hibernia Bank's deposits.

As a primer, Hibernia National Bank was founded in 1870 in New Orleans, Louisiana.

Over the years, Hibernia National Bank expanded its services and branches primarily through mergers and acquisitions. Notably, Hibernia merged with The New Orleans Bank in 1998, strengthening its regional presence and diversifying its services. It continued acquiring smaller banks and expanding its branch network across Louisiana and into markets like Texas, establishing itself as a leading financial institution in the region. In 2005, Capital One Financial Corporation acquired Hibernia Bank, marking Capital One's entry into the retail banking sector. The acquisition marked the end of Hibernia's operation as an independent entity, while its legacy continued under the Capital One brand.

Majority of deposits of Hibernia came from regions in Louisiana and parts of Texas. Appendix Figure F.4a presents the geographic distribution of bank deposits of Hibernia National Bank as of June 2005. The large deposit counties of Hibernia were severely affected by Hurricane Katrina. Specifically, Hibernia operated in 69 counties, 60 of which experienced some damage from Hurricane Katrina. Appendix Figure F.4b presents the geographic distribution of property damages per capita associated with Hurricane Katrina in counties where Hibernia collected deposits prior to 2005. Taken together, Appendix Figures F.4a and F.4b, indicate that the deposit counties of Hibernia were severely hit by the hurricane.

To quantify the effect of Hurricane Katrina on Hibernia, we combine the geographic concentration of deposits with property damages due to natural disaster to construct the bank-level deposit shock for Hibernia (and then Capital One). Appendix Figure F.5 presents the bank-level deposit shock over time. We present this shock using all counties (navy blue line) as well as the top five deposit counties (maroon line). Two key patterns emerge from this figure. First, the bank-level deposit shock has a large spike in 2005, coinciding with the timing of Hurricane Katrina. Second, the shock is predominantly concentrated among the top five counties by deposit share. This suggests that the bank experienced a negative deposit shock due to the hurricane.

To further examine the effect of Hurricane Katrina on bank deposits, we compare the deposits in counties that were affected by Hurricane Katrina as well as counties that were unaffected.[13] Appendix Figure F.6 presents the changes in deposits in affected, unaffected and all counties around Hurricane Katrina. Our results indicate that the affected counties experienced a substantial decline in bank deposits and this decline of deposits in those counties was somewhat permanent. Moreover, while the deposits in the unaffected counties did not decline, the total deposits declined for the Hibernia Bank. Note that the increase in bank

[13] Affected counties are defined as those experiencing per capita property damage at or above the 95th percentile in 2005, while unaffected counties include all other counties.

deposits in 2008 may have been driven by Capital One's new acquisitions, as well as the flight to safety that occurred during the Global Financial Crisis. Another point to note is that the deposits increased immediately in year of Hurricane Katrina. Our observed pattern of deposits in Hibernia after Hurricane Katrina align closely with statements in Capital One's 2005 annual report:

> ... Hibernia has experienced a significant increase in deposits since the Gulf Coast hurricanes, most likely as a result of customers receiving federal funds and insurance payments relating to the hurricanes. Currently, it is unclear what customers will do with these deposits on a long-term scale. It is possible that as rebuilding and reinvesting in the Gulf Coast area begins, the amount of these incremental deposits with Hibernia could decrease significantly.

This case study indicates that natural disasters can lead to a decline in bank deposits. Furthermore, the impact of these disasters on local bank deposits may be lasting.

4.4 Other Properties of Deposit Shocks

Lastly, we investigate whether various bank characteristics can predict bank deposit shocks in Appendix Table G.1. 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 Appendix Figure G.1. Appendix Figure G.1a presents the kernel density of the coefficients of an AR(1) process for each bank's $\Gamma_{b,t}$. A significant portion is concentrated around zero, with an average estimate of -0.03 (dashed red line), indicating low persistence among shocks. Appendix Figure G.1b presents 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.

5 Deposit Shocks & Aggregate Fluctuations

This section investigates the deposits channel of aggregate fluctuations – the relationship between deposit shocks and aggregate fluctuations – given by the following equation:

$$\frac{\Delta GDP_t}{GDP_{t-1}} = \alpha + \beta \times \Delta ln(Deposits)_{t-1} + \epsilon_t \tag{3}$$

where $\frac{\Delta GDP_t}{GDP_{t-1}}$ represents U.S. GDP growth in year t, and $\Delta ln(Deposits)_{t-1}$ denotes the growth in total deposits in the previous year. The coefficient of interest is β, which estimates the elasticity of economic growth with respect to deposit growth. However, directly estimating the coefficient β is likely to produce biased results due to endogeneity issues, such as unobserved latent factors that affect both deposit supply and demand, or due to reverse causality.

We address this issue by constructing granular deposit shocks that combine the geographic distribution of bank deposits with natural disasters. These shocks follow the framework of granular instrumental variables (GIV) proposed by Gabaix and Koijen (2024) due to the granular geographic distribution of bank deposits, as shown in section 3. Additionally, using natural disasters as local idiosyncratic shocks allows us to mitigate key endogeneity concerns, as they are unlikely to be correlated with either observed and unobserved latent factors. Specifically, we estimate the impact of these granular deposit shocks on aggregate fluctuations, under the identifying assumption that they are uncorrelated with preexisting innovations in GDP growth. This assumption is plausible given that the shocks are based on exogenous local natural disasters, which are unlikely to be influenced by macroeconomic conditions such as GDP growth.

5.1 Construction of Granular Deposit Shocks

This section describes the construction of aggregate and granular deposit shocks. To construct the granular deposit shocks, we first aggregate bank-level deposit shocks ($\Gamma_{b,t}$) into an economy-wide deposit shock (Γ_t) by averaging them. Specifically, we weight each bank's deposit shock by its relative importance in the economy, measured by its total assets, $A_{b,t-1}$, as shown in equation 4.

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

Figure 9a presents the time series plot of the aggregate deposit shocks. Based on a narrative analysis of the crests presented in Appendix Table G.2, 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 9b 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 by subtracting equal-weighted natural disaster–induced property damages per capita from the aggregate deposit shocks,

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

where N_b is the number of banks and N_c is the number of counties. Gabaix and Koijen (2024) 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. Intuitively, granular deposit shocks capture the idiosyncratic deposit growth of large banks following natural disasters. We validate in Appendix Table G.3 that these shocks are associated with a decline in aggregate deposit growth and can explain 10.26% of total variation in deposit growth. This makes granular shocks a suitable proxy for idiosyncratic shocks to deposit growth.

5.2 Granular Deposit Shocks and Aggregate Fluctuations

This section shows that granular deposit shocks can explain aggregate fluctuations. We investigate this relationship formally in Table 6, in which we regress GDP growth on the granular deposit shock. Column 1 does not include any fixed effects. In columns 2 through 6, we sequentially introduce lags of the granular deposit shock, allowing us the assess the impact over different time horizons. In column 7, we incorporate the granular deposit shock and five lags thereof. The estimates associated with the contemporaneous and one-period lag granular deposit shock remain robust to the inclusion of year fixed effects. Overall, the results indicate that granular deposit shocks negatively affect economic growth. Specifically, a granular deposit shock equivalent to the 90$^{\text{th}}$ (95$^{\text{th}}$) percentile reduces economic growth by 0.01 to 0.03 pp (0.06 to 0.16 pp), according to the estimates of columns 2 and 7. The R^2 associated with column 7 demonstrates that granular deposit shocks can explain 5.80% of variation in economic growth.

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 7 presents these results. There are two takeaways from the horse race. First, the effect of the granular deposit shocks on 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 uncertainty shocks, term spread, government expenditure shocks and the granular residual from Gabaix (2011).

Next, we study the long-run responses of GDP growth to the granular deposit shocks, using a vector autoregressive (VAR) model. To this end, we examine the orthogonalized impulse response function (OIRF) of GDP growth following granular deposit shocks based on VAR(1,1) and VAR(2,2) models in Figures 10a and 10b, respectively. The figures indicate that the effect of granular deposit shocks on GDP growth is immediate, however, transitory; i.e., the effect becomes statistically insignificant beyond the first quarter and gradually diminishes over the next eight quarters. This result contrasts with the finding of Figure 8, where we observe 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 in the short-run. Granular deposit shocks affect GDP growth in the short run when financial frictions are binding and acute. With time, firms and households may substitute towards other sources of external financing, leading the effect to dissipate in the long run. Moreover, banks may be able to identify alternative sources of funding.

5.3 Discussion of the Magnitude

In order to assess the quantitative role of the geography of bank deposits – whether the 5.80% 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 city-level house price volatility is between 2.5 and 3 times the size of aggregate house price volatility. For personal income, the volatility of aggregate growth is 0.027, whereas the size-weighted average volatility of county-level growth is 0.04, approximately 1.5 times higher. Let us aggressively calibrate our benchmark economy to have $\sigma_c = 3\sigma$ and $N \approx 3,000$. The aggregate volatility 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: 5.80% of variation in economic growth is explained by granular deposit shocks. Hence, the geography of bank deposits considerably affects aggregate economic fluctuations.

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. 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 0.99. This indicates that a 10 basis point decrease in the loan supply is associated with a decline of economic growth by 9.9 basis points. This effect represents a 8.71% change from the mean and 3.76% change from the standard deviation.

Our estimate for the deposit elasticity of economic growth is 1.49. The results indicate that a 10 basis point decrease in deposit growth results in a decline of economic growth by 14.89 basis points. This effect represents a 13.10% change from the mean and 5.66% change from the standard deviation. Further, the deposit elasticity of economic growth is almost 1.51 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 1.51 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 $1.26 lending.

5.4 Discussion on Identifying Assumption

The key identifying assumption of our analysis is that the interaction of deposit concentration with disasters does not serve as a proxy for correlated interactions. Specifically, if the granular distribution of bank deposits may be correlated with the granular distribution of economic activity, the disaster shocks in these areas may be transmitted into aggregate shocks through channels other than their effect on bank deposits. We provide three pieces of evidence in support of our identifying assumption.

First, we create alternative granular shock variables for each county in an attempt to account for the geographic distribution of correlated economic factors, including employment, GDP, population, and the number of establishments. The employment granular shock is calculated as the average property damage per capita, weighted by the county's share of national employment. Similarly, we create granular shocks for GDP, population, and establishments, which measure the average property damage per capita, weighted by the county's share of national GDP, population, and number of establishments, respectively. Table 9 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 remains negative and statistically significant. This indicates that the effects of deposit concentration are not driven by the fat-tailed distribution of measures of local economic activity that may be correlated with the distribution of bank deposits.

Second, we address the concern that bank deposit concentration may reflect the geographic concentration of other bank products, particularly credit. To examine this, we construct granular lending shock variables based on the geographic distribution of bank lending, weighting local disaster shocks by the share of bank loans in each region, rather than deposits as in our baseline granular shocks. These granular lending shocks serve as a placebo measure that mimics the granular deposit instrument, using geographic loan concentration instead of geographic deposit concentration. We create granular lending shocks using the geographic distribution of lending in mortgage markets, utilizing HMDA data ($\Gamma_{t-1}^{L,HMDA}$), and small business lending data from the CRA data ($\Gamma_{t-1}^{L,CRA}$), and an average of the two shocks ($\Gamma_{t-1}^{L,Total}$). Table 10 presents the results from using these placebo measures as well as running the horse race of these placebo measures against our granular deposit shock. Our results indicate that these granular lending shocks fail to explain fluctuations in GDP growth, accounting for only 0.02% of the variation, in contrast to the 0.92% variation explained by granular deposit shocks. Moreover, the placebo measures are statistically insignificant and economically small in magnitude. These findings suggest that the geographic distribution of deposits, rather than the geographic distribution of other banking products like credit, is a key driver of our results.

Third, we address the concern that our shocks may be capturing the direct effect of natural disasters on the aggregate economy 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 an OIRF analysis based on a VAR model. Figure 11 reports these results. Our results indicate that there is no statistically significant direct effect of disasters on economic growth. Moreover, we supplement this test with additional measures of natural disaster impact, using home- and business-related disaster losses reported in the SBA Disaster Loan Program dataset. Appendix Table G.4 reports the results from these alternative measures. As with the previous test, we find no statistically significant effect of disaster-related losses on aggregate economic growth. Further, these direct loss measures can only account for 0.3% of variation in economic growth. Taken together, these results indicate that the direct effect of natural disasters on the overall economy is likely to be limited. This is consistent with the findings of Strobl (2011) which documents that while natural disasters may negatively impact local economic activity, they do not directly affect national economic growth rates. This further lends credence to our main finding that our results are driven by idiosyncratic shocks to deposit growth.

Another key identifying assumption of our shocks is the importance of banks in the overall economy. We test this assumption through a placebo exercise that examines the role of large banks in explaining our baseline results. We measure each bank's relative importance in the economy using its book value of assets. Specifically, we construct a series of placebo shocks by systematically excluding the largest banks for each quarter. The intuition of this test is that if natural disasters impact deposits of small banks, the aggregate effect is likely to be muted. However, disasters affecting the deposits of large banks are expected to have a greater aggregate effect, as suggested by Gabaix (2011). Moreover, large banks are vital nodes in the lending network structure, making them more likely to transmit shocks across the country, consistent with the findings of Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012) and Corbae and D'Erasmo (2021).

To implement this test, we vary bank size by excluding banks with asset shares above the k^{th} percentile, where k ranges from the 95^{th} to the 20^{th} percentile in 5-point percentile steps. Figure 12 reports the point estimates (Panel 12a) and the model R^2 (Panel 12b) from the regression of these placebo shocks on GDP growth. On the x-axis, *All* represents the baseline granular shock using all banks, while subsequent labels indicate the percentile cutoff for bank size used in constructing the shocks. The figure shows that as we exclude systemically important banks from the shock construction, both the effect size and the model's ability to explain GDP growth variation gradually decline, eventually converging to zero. This indicates the importance of shocks to large banks in explaining aggregate fluctuations.

5.5 Robustness

Addressing Measurement Error: Next, we assess the extent to which measurement error may influence the relation between granular deposit shocks and aggregate fluctuations. We replicate our baseline regression specification in Table 6, adjusting our deposit concentration measure. Specifically, we account for potential error in the measurement of granular deposits shocks, which may arise from various factors discussed in Section 3.3.2. Table 11 presents the results indicating that the geographic mismeasurement issue is unlikely to explain our key finding.

We further corroborate the relationship between granular shocks and GDP growth by employing granular shocks that exploit the branch concentration instead of deposit concentration as discussed in Section 3.3.4. As noted earlier, this measure of geographic concentration of bank deposit activity is likely to be immune to measurement error associated with the geography of bank deposits. Table 12 presents the results. We note that granular shocks based on branch concentration negatively affect economic growth. This finding is consistent with the results shown in Table 6. These shocks explain 6.4% of the variation in GDP growth, compared to the 5.8% noted in Table 6. Overall, these results suggest that geographic measurement issues are unlikely to undermine the paper's central conclusions that granular deposit shocks are negatively associated with economic growth.

Historical SOD: Our analysis begins in 1994 primarily because this marks the start of the banking era following the Riegle-Neal Act, which eliminated restrictions on the geographic expansion of banks. In this section, we utilize historical deposit data to extend our analysis back to 1981, allowing us to assess the robustness of our findings over a longer time frame.[14]

Appendix Figure G.2 presents the geographic concentration of bank deposits using the historical data. We find that the geographic concentration of bank deposits remains a robust phenomenon even over an extended period. Notably, the concentration of bank deposits was significantly higher in the 1980s compared to the late 1990s. This higher concentration reflects the strict state regulations on bank geographic expansion prior to the Riegle-Neal Act. Furthermore, the data indicate that geographic concentration has been declining since the 1980s, and stabilizing around the late 1990s. This trend aligns with the gradual deregulation of bank geographic expansion by several states during the 1980s, culminating in the legislative changes introduced by the Riegle-Neal Act in 1994.

[14]We access the historical Summary fo Deposits data from Christa Bouwman's website. See here.

Next, we assess the robustness of our baseline effect of granular shocks on GDP growth, using this extended time series. Appendix Table G.5 replicates the baseline results with the extended dataset. Our analysis confirms that the key result holds when considering granular shocks derived from the longer historical timeline. Furthermore, columns 8, 9, 11, and 12 of the table split the regression samples into periods before and after 1994, the year the Riegle-Neal Act was enacted. We find that granular shocks accounted for approximately 15.7% of the total variation in economic growth prior to deregulation, compared to only 5.7% in the post-1994 period. This finding suggests that regulatory restrictions on the geographic expansion of banks contributed to increased financial fragility. The subsequent deregulation appears to have partially mitigated this fragility.

6 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.

6.1 Small Business Lending & Deposit Shocks

We begin by studying the relationship between small business lending growth and deposit shocks using specification 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, illiquid assets that are rarely securitized. As a result, lending in this market relies heavily 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 à 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 13 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. Economically, a one standard deviation deposit shock is associated with a decline of 0.60 to 1.10 percentage points in lending growth.[15] Additionally, columns 7 and 8 estimate equation 6 separately for counties unaffected and affected by disasters, respectively. 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 H.1 shows that the negative coefficients from the Jordà projection persist for several years following the disaster, with the results primarily driven by unaffected counties, as shown in Appendix Figure H.2. We further extend

[15]Our results are robust to the exclusion of credit card banks from the sample. See Appendix Table H.1.

the analysis to examine the effect of deposit shocks on mortgage lending and find similar results (see Appendix Figure H.3).

A necessary condition for idiosyncratic shocks to explain aggregate fluctuations is that the idiosyncratic shocks must affect the behavior of the large players in the market. Therefore, we 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, large, and systematically important banks. Small banks are defined as institutions with total assets of less than $2 billion. Medium banks have assets between $2 billion and $10 billion. Large banks are those with assets between $10 billion and $50 billion. Systemically important banks (SIBs) are defined as institutions with total assets of $50 billion or more, in line with the threshold established under Title I of the Dodd-Frank Act. Appendix Table B.1 reports the results for the estimation of equation 6 for small banks, medium banks, large banks, and SIBs separately. The results indicate that large banks and SIBs reduce their lending growth by a substantial margin following a deposit shock. This holds for lending in both the small business and the mortgage market segment as shown in Panels A and B, respectively.

6.2 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.

6.2.1 Bank Frictions and the Transmission of Idiosyncratic Shocks

Table 14 examines 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 that are more reliant on such deposits as a primary funding source are more likely to reduce lending. Column 2 examines the impact of banks' capital constraints on the transmission of deposit shocks. Regulatory constraints and balance sheet costs can impair banks' resilience to unanticipated shocks by pushing them closer to their limits, resulting in lending contractions after a deposit shock. Column 3 tests how informational (dis)advantages influence the transmission of deposit shocks across geographies. Specifically, we examine whether banks transmit shocks more to areas where they lack informational advantages, as indicated by the absence of a physical branch. The key estimate – the interaction term between bank constraints and deposit shocks – is statistically significant and negative across all measures of bank constraints.

Overall, these results suggest that banks facing greater constraints are more likely to amplify the impact of deposit shocks.[16]

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 × county × 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 × bank × 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 15 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, suggesting that the contraction in lending is more pronounced for loans that are more likely to be funded by deposits.

6.2.2 Borrower Constraints, Transmission of Idiosyncratic Shocks, and the Real Effects

This section examines the role of borrower constraints in the transmission of deposit shocks. We document that the firms which are more dependent on banks as a source of external financing drive the baseline response in lending growth to deposit shocks and are more likely to have real effects on the economy.

We begin by using CRA lending data and firm size as proxies for external finance dependence to identify firms that 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 ×

[16] We present the step-wise estimation of the results in Table 14 in Appendix Tables H.2, H.3, and H.4 where we sequentially add fixed effects. The estimates remain stable in magnitude. Additionally, Appendix Table H.5 reports results using a second classification scheme, where the core is defined by the above-median share of lending in a county-year. The results are robust to this alternative definition.

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 16 presents the estimates of the effect. The results indicate that contraction in lending is pronounced for small firms suggesting that the deposit shocks transmit more to constrained borrowers relative to unconstrained borrowers.

Next, we examine the effect of bank deposit shocks on real firm outcomes of younger firms using the Dealscan dataset. For each firm, we identify the lead banks using Dealscan data and aggregate the deposit shocks experienced by all lead banks of a firm. Furthermore, 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) documents 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 cross-sectional heterogeneity in the 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.

Table 17 reports the results examining the effect of bank-level deposit shocks on younger firms using a specification that includes firm and industry × young × year fixed effects. Columns 1-4 use the natural logarithm of total debt, book value of assets, employment, and capital expenditure as the key dependent variables, respectively. The estimate of interest associated with the interaction term of young and bank-level deposit shock 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 13% decline in debt, 9% decline in the book value of assets, 12% decline in employment, and a 20% 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.

7 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 deposits. While liquidity transformation is critical for financing long-term illiquid assets, it is also a key 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 – and provides estimates of the deposit elasticity of economic growth and the money multiplier.

We introduce a new fact on the geographic concentration of bank deposits. We document that at least 30% of bank deposits are concentrated within a single county. The geographic concentration of deposits within a bank is widespread across banks of all sizes, including the largest banks. We show that when counties with concentrated deposits experience disaster shocks, local bank deposits decline. These deposit shocks can, in turn, generate aggregate fluctuations, particularly, when large banks are affected. We document a negative relation between bank deposit shocks and lending activity – the key mechanism through which bank deposit shocks affect economic growth. Specifically, multi-market banks amplify these deposit shocks to other counties through their internal capital markets. This amplification is particularly pronounced in the presence of financial frictions which impede banks' ability to replace deposits and borrowers' ability to substitute funding from alternative sources. adams2020lending

Our paper introduces a previously undocumented source of financial fragility, with implications for both researchers and policymakers involved in 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. Our findings suggest that regulators should also consider the resulting concentration of deposits in merged institutions, given its potential impact on financial stability. Moreover, policies designed to mitigate the impacts of natural disasters or climate change should take into account the aggregate effects of local shocks, operating through the channels identified in this paper.

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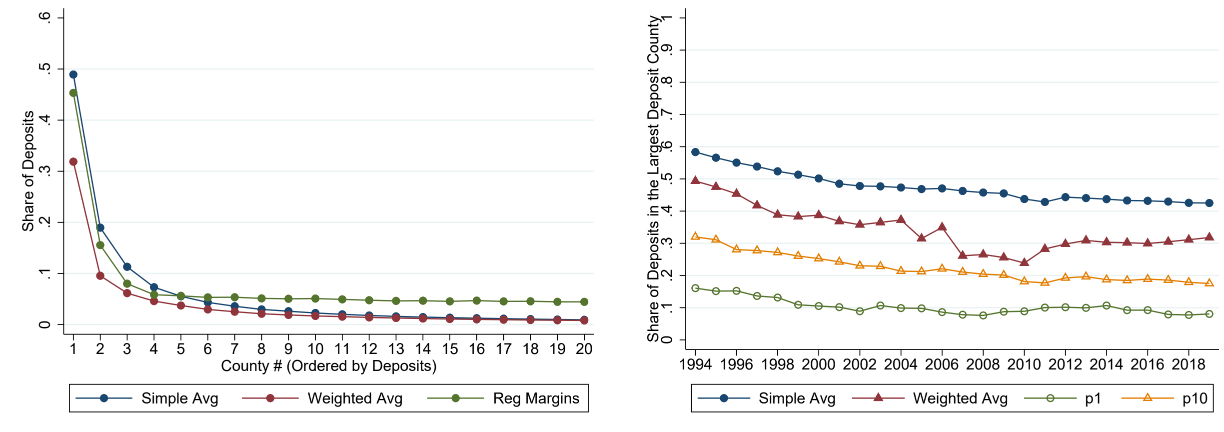
Figure 1: Geographic Concentration of Deposits

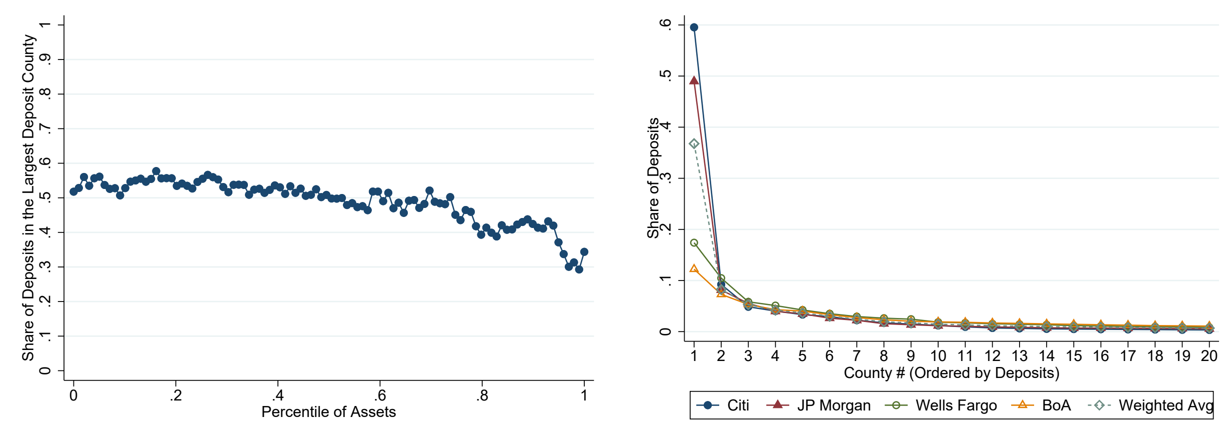


(a) Cross Section

(b) Time Series

This figure uses the Summary of Deposits (SOD) data from 1994 to 2019 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 raises 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 2019. The time series plots 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

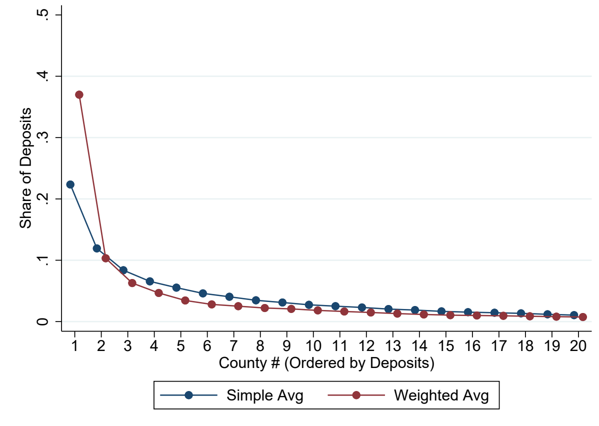


(a) Banks By Size

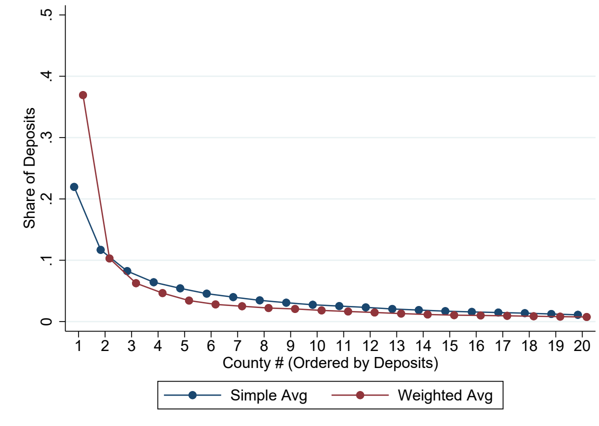
(b) Four Largest Banks

This figure uses the Summary of Deposits (SOD) data from 1994 to 2019 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 raises the largest amount of deposits for a given bank.

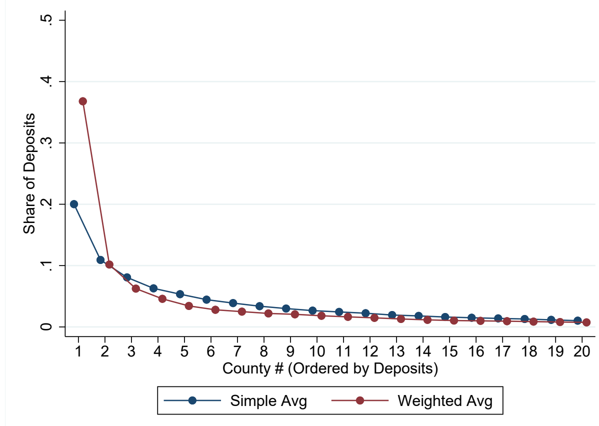
Figure 3: Deposit Concentration of Banks that Changed Headquarters



(a) Deposit-Weighted Distribution



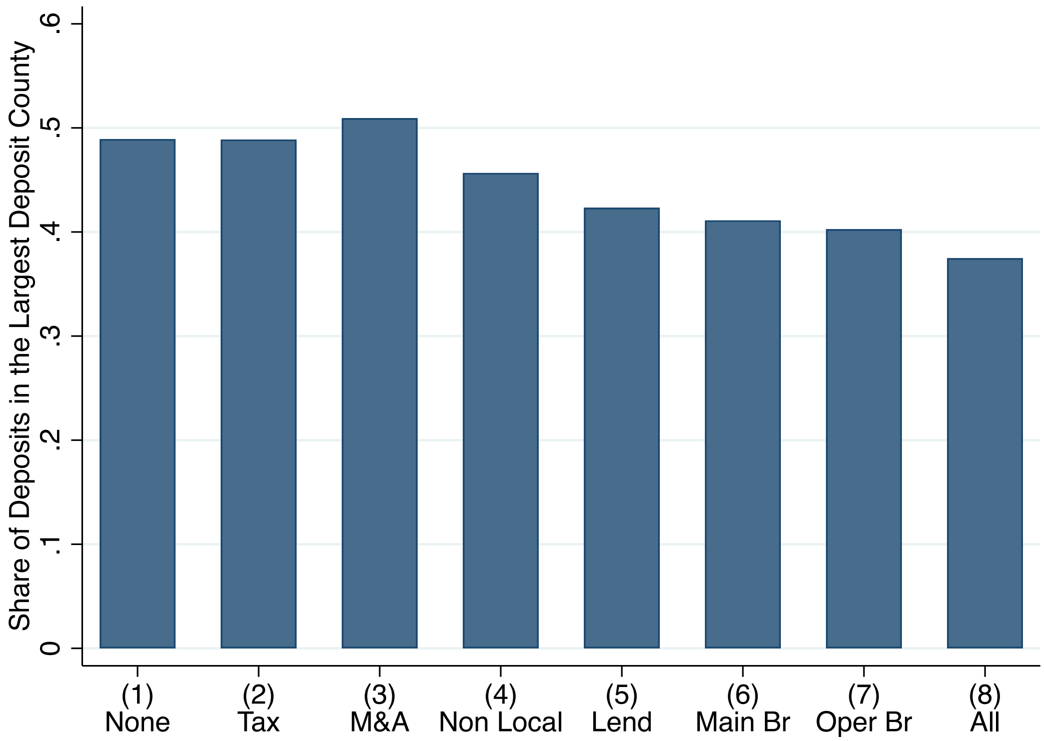
(b) Equal Distribution



(c) Omission

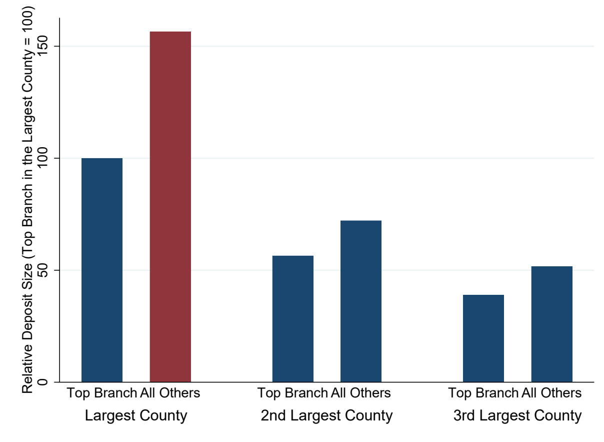
Note: This figure uses the Summary of Deposits (SOD) data and illustrates the geographic concentration of bank deposits for banks that changed headquarters in our sample period. The figure is plotted for the years in which the bank changed its headquarter (not all years). The y-axis represents the share 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 raises 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 3a 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 3b plots the deposit concentration after removing the change in deposits at the headquarter county and equally distributing this change across all counties. Figure 3c 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 4: Share of Deposits in Top County After Excluding Certain Counties/Branches

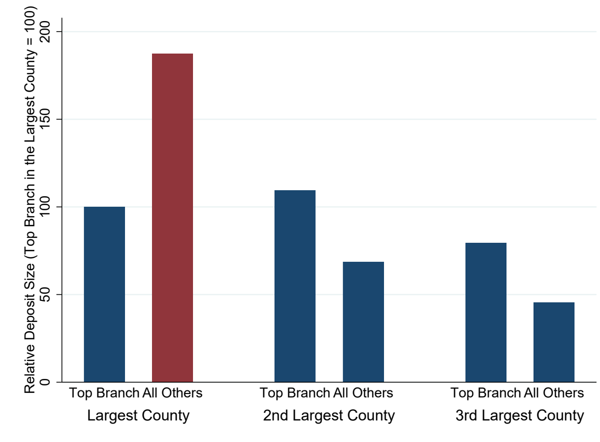


This figure illustrates the geography of a county with the largest deposit share for a given bank from 1994 to 2019. Each bar, except the first, presents the share of bank deposits from the top deposit county after excluding certain branches or counties. The first bar presents the average share of bank deposits from the top deposit county for all banks. The second bar presents the share of bank deposits from the top deposit county after excluding the nine states without state income taxes: Alaska, Florida, Nevada, New Hampshire, South Dakota, Tennessee, Texas, Washington, and Wyoming. The third bar presents the share of bank deposits from the top deposit county after excluding banks involved in mergers and acquisitions starting from the year of their first acquisition. The fourth bar presents the share of bank deposits from the top deposit county after excluding the total uninsured time-deposits and brokered deposits from total deposits reported at the main office. The fifth bar presents the share of bank deposits from the top deposit county after excluding the five largest counties for mortgage and small business lending for each bank. The sixth bar presents the share of bank deposits from the top deposit county after excluding the main office branch of the bank. The seventh bar presents the share of bank deposits from the top deposit county after excluding the largest branch in each state. The eighth or the last bar presents the share of bank deposits from the top deposit county after making all the exclusions made in bars 2-7.

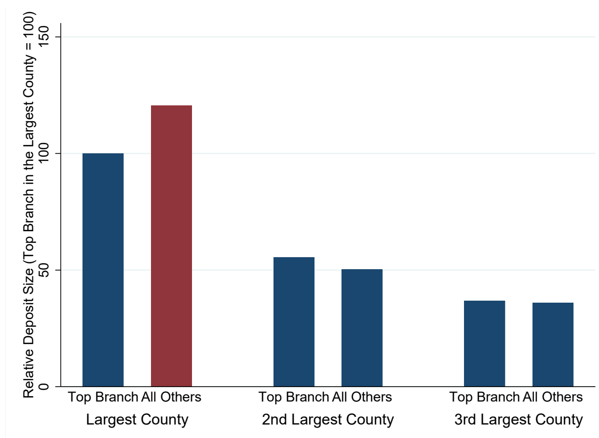
Figure 5: Within-County Distribution of Deposits



(a) All



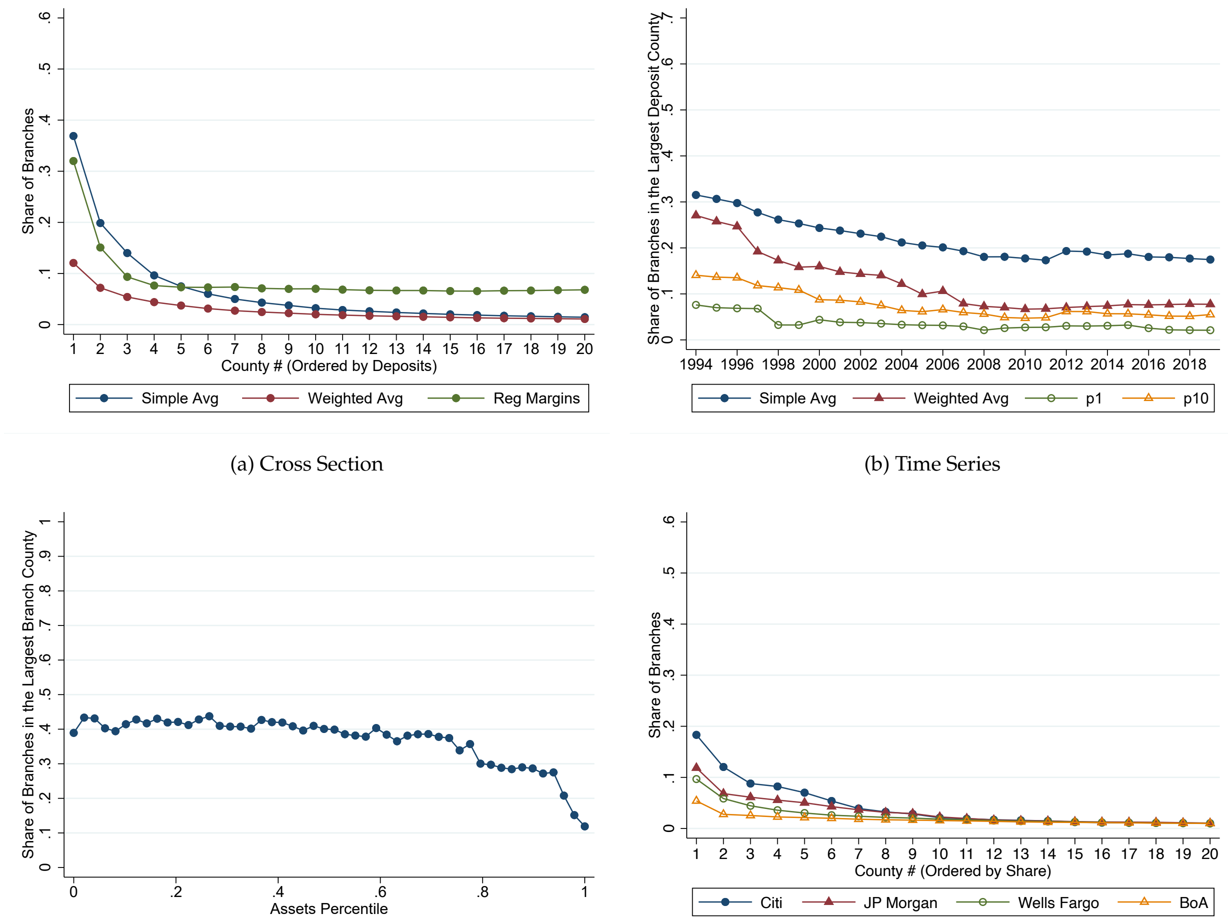
(b) Big 4



(c) Top 20

This figure uses the Summary of Deposits (SOD) data from 1994 to 2019 to compare the deposits held in the top branch of a county to all other branches in that county. First, we order 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 raises the greatest amount of deposits for a given bank.) Then, we order branches within a county by their deposit shares, i.e., the "top branch" is the branch that raises the greatest amount of deposits for a given bank in a given county. We compare the total deposits of all other branches (non-top branches) to the top branch. We scale the total deposits in the top branch of the largest county to 100 for ease of comparison. Figure 5a (Figure 5b and Figure 5c) reports the average relative deposits across all banks (Big 4 banks and Top 20 banks) for the three largest deposit counties. Big 4 banks include Bank of America, JP Morgan Chase, Wells Fargo, and Citibank and Top 20 banks, defined by total assets each year.

Figure 6: Branch Concentration



(a) Cross Section

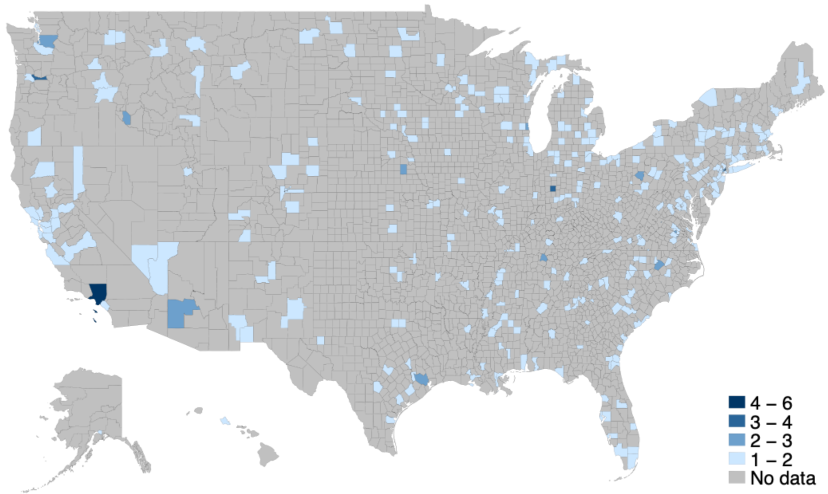
(b) Time Series

(c) Banks by Size

(d) Four Largest Banks

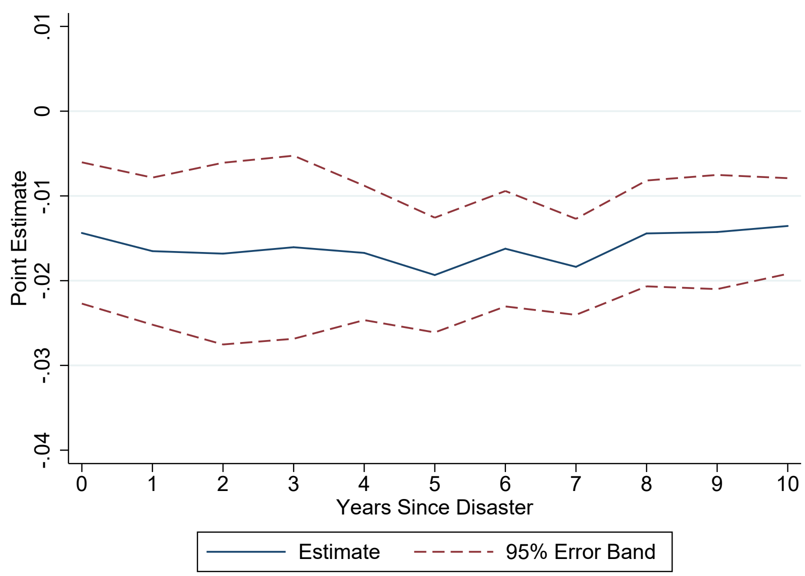
Note: This figure uses the Summary of Deposits (SOD) data from 1994 to 2019 and illustrates the geographic concentration of bank branches. Figure (a) orders counties by their branch shares for each bank (the county number refers to the rank of a county by the number of branches) and reports the average branch share of the top 20 counties. The blue line shows the simple average of the branch share, the red line shows the average branch share weighted by bank total assets, and the green line shows the average branch share controlling for bank-year and county-year fixed effects. Figure (b) reports the average branch share of the counties with the largest branch share (i.e., county #1) by year from 1994 to 2019. The time series plots the simple average, weighted average, first percentile, and tenth percentile of the share of branches in the largest branch county in blue, red, green, and yellow, respectively. Figure (c) sorts banks by their total assets and reports the average branch share of counties with the largest branch share against the percentile of the bank assets, i.e., average branch share in the largest brach counties corresponding to the percentile of bank assets, over the sample period. Figure (d) reports the branch 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 number of branches, i.e., county #1 refers to the county with the largest number of branches for a given bank.

Figure 7: Geography of Largest Deposit County



This figure shows the geographic distribution of counties where a bank held the largest deposit share during the period from 1994 to 2019. The intensity of the blue shading corresponds to the average number of banks over the entire sample period for which a county has the largest deposit share.

Figure 8: Long-Run Response of Deposit to Disaster Shocks

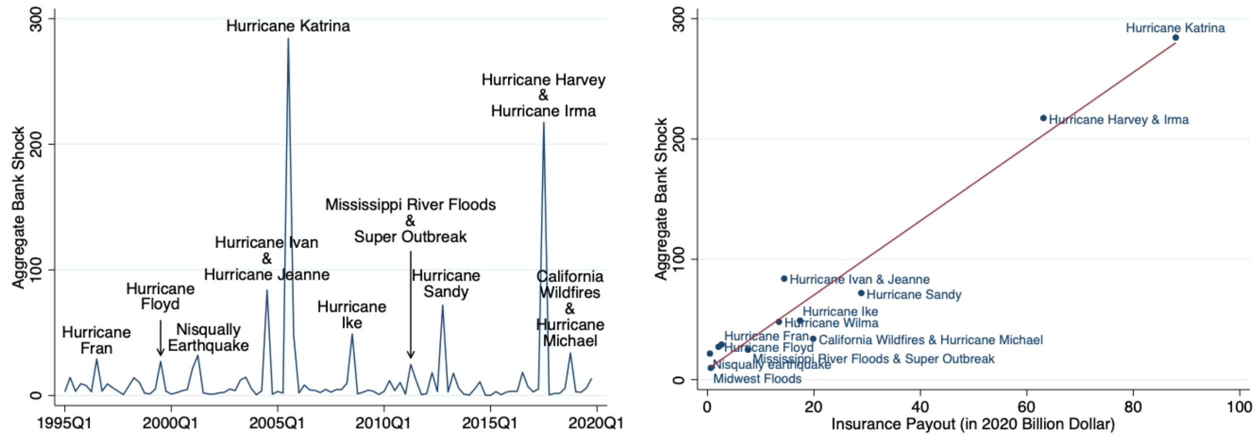


Note: This figure uses the Summary of Deposits (SOD) data matched with the Spatial Hazard Events and Losses Database for the United States (SHELDUS) and plots the estimated coefficient β_h's from the following specification:

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

The data span from 1994 to 2019. 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 9: Aggregate Bank Deposit Shock

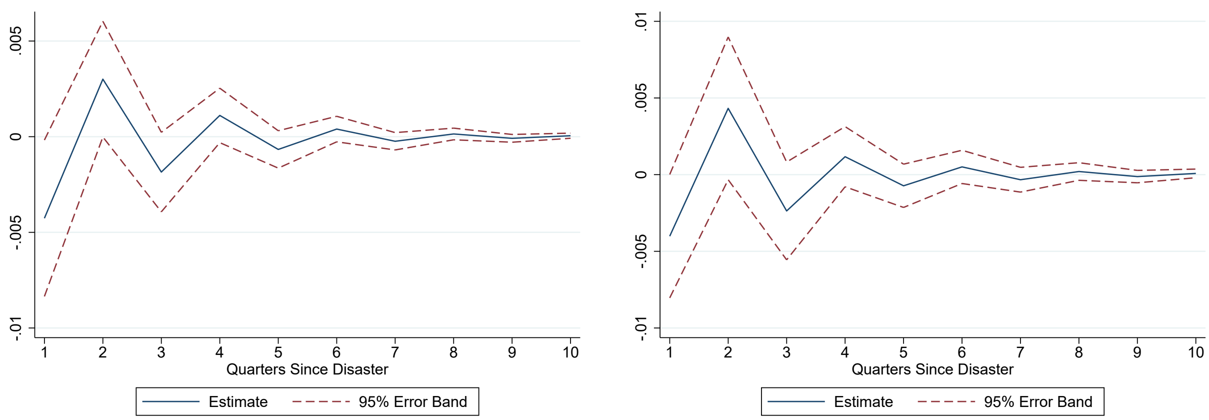


(a) Aggregate Shock over Time

(b) Aggregate Shock and Insurance Payout

Note: Figure 9a plots the aggregate bank deposit shock (Γ_t) from Q1-1995 until Q4-2019 and indicates major disasters at its notable peaks. Figure 9b plots the aggregate bank deposit shock against the insurance payout during the same period (blue dots) and illustrates the best-fit line (solid red line).

Figure 10: Long-Run Response of GDP Growth to Granular Deposit Shocks

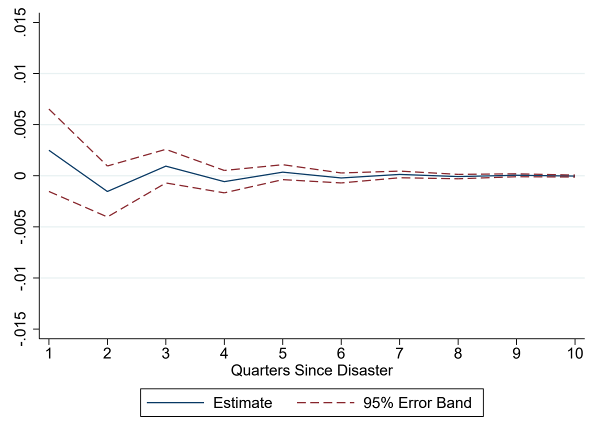


(a) Impulse Response Function from VAR(1,1)

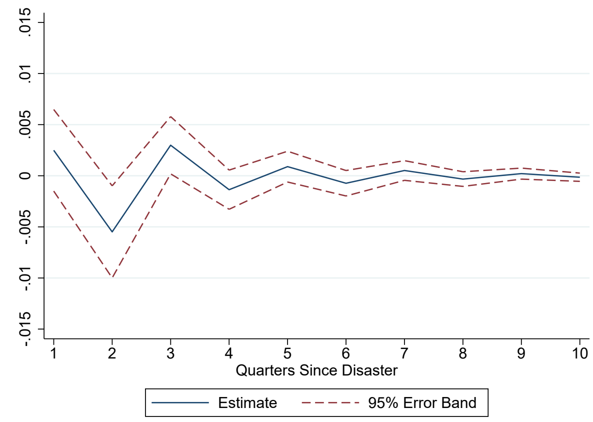
(b) Impulse Response Function from VAR(2,2)

Note: This figure uses the quarterly series of GDP growth from 1994Q3 to 2019Q4 using granular deposit shock as the key independent variable. The figure presents the orthogonalized impulse response functions (IRF) estimated using a VAR(1,1) model in Figure 10a and a VAR (2,2) model in Figure 10b with GDP growth and granular deposit shock. The IRF presents the changes in GDP growth following granular shocks. The solid blue line plots the IRF until 10 steps, and the dashed red line plots the 95% confidence interval for the IRF.

Figure 11: Long-Run Responses of GDP Growth to Aggregate Disaster Shock



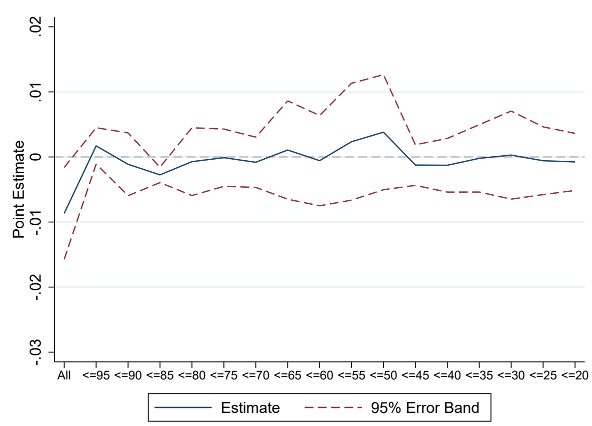
(a) Impulse Response Function from VAR(1,1)



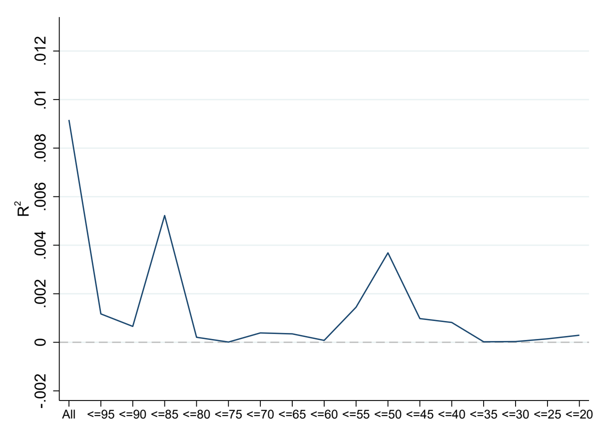
(b) Impulse Response Function from VAR(2,2)

Note: This figure uses the quarterly series of GDP growth from 1994Q3 to 2019Q4 using aggregate disaster shock as the key independent variable. Aggregate disaster shock is measured using total property damages, measured in $100K, due to disasters in the preceding quarter. The figure presents the orthogonalized impulse response functions (IRF) estimated using a VAR(1,1) model in Figure 11a and a VAR (2,2) model in Figure 11b with GDP growth and aggregate disaster shock. The IRF presents the changes in GDP growth following disaster shocks. The solid blue line plots the IRF until 10 steps, and the dashed red line plots the 95% confidence interval for the IRF.

Figure 12: Placebo Test: Salience of Large Banks



(a) Point Estimate



(b) Model R^2

Note: This figure examines the salience of large banks in explaining the baseline effect. We construct a series of placebo shocks by excluding the most significant banks – by asset share – for each quarter. Specifically, we exclude banks with asset share above the k^{th} percentile, with k ranging from the 95th to the 20th percentile in 5 percentile steps. We run the baseline regression of the GDP growth rate on the baseline and placebo granular shocks according to the following regression specification:

$$\frac{GDP_t - GDP_{t-1}}{GDP_{t-1}} \times 100 = \alpha_k + \beta_k \times \Gamma^{k*}_{t-1} + \varepsilon^k_t$$

Figure 12a presents the point estimates associated with the regression specification above on the Y-axis. Figure 12b presents the model R^2 associated with the regression specification above the Y-axis. On the X-axis, *All* indicates the coefficient and the model R^2 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 placebo shocks.

Table 1: Summary Statistics

	# Obs	Mean	SD	P26	P50	P75
Panel A: County × Year						
Deposit Growth (%)	79,884	3.21	6.32	0.03	2.97	6.12
Total Property Damage (in 2021 Thousand USD)	79,884	7,914.53	221,419.29	0.13	52.69	420.84
Total Property Damage per Capita (in 2021 USD)	79,884	125.38	2,455.58	0.01	1.66	14.13
Ln(Number of Establishments)	81,596	6.44	1.48	5.43	6.30	7.28
Ln(Number of Employees)	81,098	8.86	1.72	7.69	8.77	9.88
Migration: Outflow per Capita	78,321	7.40	2.28	5.92	7.03	8.41
Migration: Inflow per Capita	78,321	7.52	2.74	5.65	7.01	8.79
Migration: Net Outflow per Capita	78,321	-0.12	1.59	-0.82	0.02	0.71
Panel B: Bank × Year						
Γ_{bt}	18,428	82.13	907.08	1.00	5.17	22.79
Ln(Total Deposits)	14,568	13.58	1.67	12.37	13.28	14.54
Ln(Transaction Deposits)	14,501	11.85	1.59	10.77	11.51	12.63
Ln(Saving Deposits)	14,565	12.50	2.00	10.99	12.30	13.71
Ln(Time Deposits)	14,563	12.55	1.52	11.46	12.32	13.46
Panel C: County × Bank × Year						
Small Business Lending Growth (%)	613,931	0.05	1.10	-0.44	0.00	0.51
Mortgage Lending Growth (%)	1,363,681	0.02	2.58	-0.50	0.00	0.58
Panel D: Firm × Year						
Ln(Debt)	14,383	5.72	2.69	4.09	5.95	7.57
Ln(Assets)	15,043	7.12	2.31	5.49	7.07	8.71
Ln(Employment)	14,363	1.69	1.41	0.47	1.36	2.60
Ln(CapEx)	13,540	3.73	2.44	2.00	3.80	5.48
Panel E: Aggregate Level						
GDP Growth (%)	102	1.14	2.62	-0.48	1.76	3.39
Deposit Growth (%)	101	1.65	1.14	0.88	1.65	2.25
C&I Lending Growth (%)	101	1.32	2.42	0.16	1.87	2.88
Γ_t^*	102	-10.94	28.97	-12.44	-6.23	-1.56
$\Gamma_t^{*Branch}$	102	-7.31	27.57	-10.88	-4.86	-0.97

Note: This table reports summary statistics of key variables explored in this paper. Panel A presents county-year level variables, including total property damages from SHELDUS (1994–2019), the number of establishments and employees from CBP (1994–2019), and migration data from IRS (1994–2018). Panel B presents bank-year level variables, where Γ_{bt}, defined in Section 4, is constructed using branch-level deposit data from SOD and disaster damage data from SHELDUS. The other bank financials are from Call Reports (1994–2019). Panel C presents county-bank-year level variables, including small business lending data from CRA (1997–2019) and mortgage lending data from HMDA (1994–2019). Panel D presents firm-year level variables from Compustat (1994–2019). Panel E presents quarterly aggregate variables from 1994 to 2019, including GDP, deposits, and C&I lending data from FRED. Γ_t^* and $\Gamma_t^{*Branch}$ defined in Section 4, aggregate Γ_{bt} using bank size from Call Reports, where Γ_t^* is based on deposit shares and $\Gamma_t^{*Branch}$ is based on branch shares.

Table 2: Disaster Shock and Deposit Growth

Dep Var: $\Delta\ln(\text{Deposits})_{c,t}$	(1)	(2)	(3)	(4)	(5)	(6)
Disaster Shock$_{c,t-1}$	-0.0163***	-0.0179***	-0.0147***	-0.0163***	-0.0169***	-0.0144***
	(0.0044)	(0.0045)	(0.0045)	(0.0046)	(0.0043)	(0.0043)
Year FE		✓		✓		
County FE			✓	✓		✓
State × Year FE					✓	✓
# Obs	79,884	79,884	79,884	79,884	79,884	79,884
R^2	0.0003	0.0306	0.0686	0.099	0.1435	0.2031

Note: This table uses the Summary of Deposits (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 span from 1994 to 2019. 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 the outcome variable is 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: Economic Effects of Natural Disasters

	Panel A: Effect of Disasters on Business						
ln(# Establishment)$_{c,t}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Disaster Shock$_{c,t-1}$	-0.0204***	-0.0206***	-0.0188***	-0.0190***	-0.0201***	-0.0007*	-0.0006**
	(0.0068)	(0.0068)	(0.0066)	(0.0066)	(0.0069)	(0.0003)	(0.0003)
County FE						✓	✓
State FE			✓	✓			
Year FE		✓		✓		✓	
State × Year					✓		✓
# Obs	81,596	81,596	81,596	81,596	81,596	81,596	81,596
R^2	0.0002	0.0005	0.2660	0.2663	0.2670	0.9957	0.9963

	Panel B: Effect of Business on Deposits						
ln(Deposits)$_{c,t}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ln(# Establishments)$_{c,t-1}$	0.9902***	0.9891***	1.0059***	1.0044***	1.0042***	0.8830***	0.8211***
	(0.0052)	(0.0052)	(0.0055)	(0.0055)	(0.0056)	(0.0272)	(0.0284)
County FE						✓	✓
State FE			✓	✓			
Year FE		✓		✓		✓	
State × Year					✓		✓
# Obs	77,755	77,755	77,755	77,755	77,755	77,754	77,754
R^2	0.9106	0.9342	0.9276	0.9511	0.9522	0.9899	0.9910

	Panel C: Effect of Disasters on Employment						
ln(Employment)$_{c,t}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Disaster Shock$_{c,t-1}$	-0.0214***	-0.0216***	-0.0191***	-0.0193***	-0.0205***	-0.0014**	-0.0016***
	(0.0074)	(0.0074)	(0.0064)	(0.0064)	(0.0067)	(0.0006)	(0.0006)
County FE						✓	✓
State FE			✓	✓			
Year FE		✓		✓		✓	
State × Year					✓		✓
# Obs	81,098	81,098	81,098	81,098	81,098	81,098	81,098
R^2	0.0002	0.0008	0.2578	0.2584	0.2594	0.9931	0.9938

Note: This table uses annual data on establishments from the County Business Patterns series from 1994 to 2019 and reports the estimated coefficient β in the following specification:

$$Y_{c,t} = \beta \times X_{c,t-1} + \theta_c + \theta_t + \varepsilon_{c,t}$$

where c denotes the county and t indicates the year. The dependent variable in Panel A, *ln*(# Establishment), is the natural log of total number of establishments in county c in year t. The dependent variable in Panel B, *ln*(Deposits), is measured as the natural log of total deposits in county c in year t. The dependent variable in Panel C, *ln*(Employment), is the natural log of total employment in county c in year t. The independent variable in Panels A and C, Disaster Shock$^*_{c,t-1}$, is the dollar amount of property damage per capita from natural disasters in county c and year $t-1$, standardized to mean of zero and standard deviation of one. The independent variable in Panel B, *ln*(Establishment), is the natural log of total number of establishments in county c in year $t-1$. All outcome variables are 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 4: Disasters and Migration

	(1) Outflow	(2) Inflow	(3) Net Outflow
Disaster Shock	0.0636***	-0.0172***	0.0808***
	(0.0111)	(0.0053)	(0.0136)
County FE	✓	✓	✓
Year FE	✓	✓	✓
# Obs	78,321	78,321	78,321
R^2	0.8100	0.8079	0.4764

Note: This table uses IRS Statistics of Income (SOI) annual data on migration from 1994 to 2018 and reports the estimated coefficient β in the following specification:

$$Y_{c,t} = \beta \times \text{Disaster Shock}_{c,t-1} + \theta_c + \theta_t + \varepsilon_{c,t}$$

where c denotes the county and t indicates the year. Y is the outflow per capita in column 1, inflow per capita in column 2, and net outflow (outflow-inflow) in column 3. 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 $t-1$, standardized to a mean of zero and standard deviation of one. All outcome variables are 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 5: Deposits and Bank Deposit Shocks

$ln(\text{Deposits})_{b,t}$	(1) Total	(2) Transaction	(3) Savings	(4) Time
$\Gamma_{b,t-1}$	-0.0035*	0.0017	-0.0061**	-0.0037**
	(0.0020)	(0.0029)	(0.0024)	(0.0018)
Bank FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
# Obs	14,568	14,501	14,565	14,563
R^2	0.9655	0.9214	0.9565	0.9469

Note: This table reports the estimated coefficient β in the following specification:

$$Y_{b,t} = \beta \times \Gamma_{b,t-1} + \theta_b + \theta_t + \varepsilon_{b,t}$$

where b, and t indicate bank , and year, respectively. The data span from 1994 to 2019. The dependent variable $Y_{b,t}$ is the natural logarithm of the volume of deposits ($ln(Deposits)$) for various deposit accounts; total deposits in column 1; transaction deposits in column 2; non-transaction savings deposits in column 3; and time deposits in column 4. θ_b and θ_t are bank and 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. The independent variable used in this table is standardized to a mean of zero and a standard deviation of one. All outcome variables are 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 6: Granular Shock and Aggregate Fluctuations

Dep Var: GDP growth	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Γ^*_t	-0.0099**						-0.0096**	-0.0152*
	(0.0048)						(0.0039)	(0.0088)
Γ^*_{t-1}		-0.0087**					-0.0097***	-0.0164**
		(0.0036)					(0.0034)	(0.0075)
Γ^*_{t-2}			0.0129***				0.0112***	0.0032
			(0.0030)				(0.0028)	(0.0173)
Γ^*_{t-3}				0.0016			0.0011	-0.0072
				(0.0103)			(0.0092)	(0.0266)
Γ^*_{t-4}					-0.0021		-0.0034	-0.0115
					(0.0056)		(0.0049)	(0.0215)
Γ^*_{t-5}						-0.0107***	-0.0122***	-0.0203
						(0.0035)	(0.0040)	(0.0208)
Constant	1.0325***	1.0406***	1.2577***	1.1782***	1.1138***	1.0164***	0.8873***	
	(0.1298)	(0.1107)	(0.1374)	(0.1213)	(0.1443)	(0.1157)	(0.1034)	
Year FE								✓
# Obs	102	101	100	99	98	97	97	96
R^2	0.0121	0.0092	0.0205	0.0003	0.0006	0.0147	0.0580	0.0714

Note: This table uses quarterly GDP growth series from 1994Q3 to 2019Q4 and reports the estimated coefficient β_h in the following regression specification:

$$\frac{GDP_t - GDP_{t-1}}{GDP_{t-1}} \times 100 = \alpha + \beta_h \times \Gamma^*_{t-h} + \varepsilon_t$$

where t indicates quarter-year and h indicates the number of lags. $\frac{GDP_t - GDP_{t-1}}{GDP_{t-1}}$ is the quarterly GDP growth rate, and Γ^*_{t-h} denotes the granular deposit shock and its lags. Newey-West heteroskedasticity and autocorrelation (8 quarter lags) robust standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 7: Horse Race: Granular Shock & Other Macroeconomic Shocks

Dep Var: GDP growth	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Γ^*_{t-1}	-0.0098**	-0.0103***	-0.0091**	-0.0095**	-0.0098**	-0.0105***	-0.0100**	-0.0097**
	(0.0040)	(0.0037)	(0.0043)	(0.0041)	(0.0040)	(0.0040)	(0.0042)	(0.0041)
Oil Shock$_{t-1}$		0.3620						0.3250
		(0.3513)						(0.3283)
Monetary Shock$_{t-1}$			0.3795					0.3429
			(0.2879)					(0.2876)
Uncertainty Shock$_{t-1}$				-0.2399				-0.2135
				(0.2306)				(0.2434)
Term Spread$_{t-1}$					0.0114			-0.0512
					(0.1238)			(0.1137)
Gvt Exp Shock$_{t-1}$						-0.1377		-0.0658
						(0.2029)		(0.1898)
Γ^{Gabaix}_{t-1}							0.1112	0.0239
							(0.1237)	(0.1297)
Constant	1.0256***	1.0228***	1.0368***	1.0258***	1.0253***	1.0174***	1.0234***	1.0303***
	(0.1152)	(0.1135)	(0.1190)	(0.1036)	(0.1141)	(0.1243)	(0.1107)	(0.1144)
# Obs	97	97	97	97	97	97	97	97
R^2	0.0122	0.0313	0.0332	0.0205	0.0122	0.0149	0.0140	0.0573

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 regression specification:

$$\frac{GDP_t - GDP_{t-1}}{GDP_{t-1}} \times 100 = \alpha + \beta_1 \times \Gamma^*_{t-1} + \beta_2 \times \text{Macro-Shock}_{t-1} + \varepsilon_t$$

where t indicates quarter-year. $\frac{GDP_t - GDP_{t-1}}{GDP_{t-1}}$ is the quarterly GDP growth rate, Γ^*_t denotes the granular deposits shock, and Macro-Shock$_t$ denotes the vector of macroeconomic shocks. Column 2 uses oil shocks based on the quarterly average of the oil supply surprise series from Känzig (2021). Column 3 uses monetary shocks based on quarterly average of tight-window monetary policy shocks from Vats (2020). Column 4 uses uncertainty shocks based on the percentage change in the economic policy uncertainty index from Baker, Bloom, and Davis (2016). Column 5 uses the term spreads, defined as the difference between the market yield on US treasury securities at 5 year constant maturity and the market yield on US treasury securities at 3 month constant maturity. Column 6 uses government expenditure shocks, defined as the percentage change in the total government expenditure. Column 7 uses the granular residuals of Gabaix (2011), defined as the sum of the top 100 firms' idiosyncratic productivity shocks, weighted by the share of firms sales in GDP. The idiosyncratic productivity shock is computed by taking the log difference of sales per employee and controlling for industry-level mean productivity growth. The macroeconomic shocks are standardized to a mean of zero and standard deviation of one. Newey-West heteroskedasticity and autocorrelation (8 quarter lags) 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	1.4892**				1.5083*	
	(0.6948)				(0.8729)	
C&I Lending Growth			0.9873*			
			(0.5631)			
Γ^*_{t-1}		-0.0058*		-0.0088**		-0.0058*
		(0.0034)		(0.0037)		(0.0034)
# Obs	101	101	101	101	101	101
R^2	0.0092	0.0220	0.0092	0.0111	0.0111	0.0220

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 autocorrelation robust standard errors are reported in parentheses.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Granularity or Banking Transmission?

Dep Var: GDP growth	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Γ^*_{t-1}	-0.0087**	-0.0091**	-0.0071**	-0.0093**	-0.0092**	-0.0078**	-0.0046**
	(0.0036)	(0.0040)	(0.0029)	(0.0040)	(0.0039)	(0.0034)	(0.0022)
Γ^{Emp}_{t-1}		-0.0066				0.1369*	0.1872
		(0.0122)				(0.0767)	(0.1584)
Γ^{GDP}_{t-1}			-0.0054				0.0067
			(0.0119)				(0.1193)
Γ^{Pop}_{t-1}				-0.0085		-0.0968	-0.1381*
				(0.0115)		(0.0810)	(0.0817)
Γ^{Est}_{t-1}					-0.0094	-0.0328	-0.0393
					(0.0123)	(0.0640)	(0.0828)
Constant	1.0406***	1.0935***	1.0617***	1.1190***	1.1233***	1.1146***	1.0844***
	(0.1107)	(0.1314)	(0.1711)	(0.1419)	(0.1414)	(0.1269)	(0.1926)
# Obs	101	101	71	101	101	101	71
R^2	0.0092	0.0110	0.0105	0.0132	0.0133	0.0316	0.0583

Note: This table uses quarterly GDP series from 1998Q1 to 2019Q4 and reports the estimated coefficient, βs, in the following specification:

$$\frac{GDP_t - GDP_{t-1}}{GDP_{t-1}} \times 100 = \alpha + \beta \times \Gamma^*_{t-1} + \beta_1 \times \Gamma^{Emp}_{t-1} + \beta_2 \times \Gamma^{GDP}_{t-1} + \beta_3 \times \Gamma^{Pop}_{t-1} + \beta_4 \times \Gamma^{Est}_{t-1} + \varepsilon_t$$

where t indicates quarter-year. $\frac{GDP_t - GDP_{t-1}}{GDP_{t-1}} \times 100$ is the quarterly GDP growth rate, 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}, Γ^{Pop}_{t-1}, Γ^{Est}_{t-1} as the average of county-level property damages per capita weighted by the county's share of US GDP, population, and number of establishments respectively. The granular shocks are winsorized at the 1% level. Newey-West heteroskedasticity and autocorrelation (8 quarter lags) robust standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 10: Granular Bank Lending Shock and Aggregate Fluctuations

Dep Var: GDP growth	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Γ^{*}_{t-1}	-0.0079**		-0.0116**		-0.0113**		-0.0114**
	(0.0032)		(0.0057)		(0.0056)		(0.0057)
$\Gamma^{L,CRA}_{t-1}$		-0.0001	-0.0005				
		(0.0005)	(0.0007)				
$\Gamma^{L,HMDA}_{t-1}$				-0.0001	-0.0005		
				(0.0005)	(0.0007)		
$\Gamma^{L,Total}_{t-1}$						-0.0001	-0.0005
						(0.0005)	(0.0007)
Constant	1.0389***	1.1443***	1.1047***	1.1418***	1.1011***	1.1431***	1.1030***
	(0.1302)	(0.1743)	(0.1642)	(0.1718)	(0.1623)	(0.1731)	(0.1633)
# Obs	87	87	87	87	87	87	87
R^2	0.0092	0.0002	0.0146	0.0002	0.0141	0.0002	0.0144

Note: This table uses quarterly GDP series from 1994Q3 to 2019Q4 and reports the estimated coefficient β in the following specification:

$$\frac{GDP_t - GDP_{t-1}}{GDP_{t-1}} \times 100 = \alpha + \beta_1 \times \Gamma^{*}_{t-1} + \beta_2 \times \Gamma^{C}_{t-1} + \varepsilon_t$$

where t indicates quarter-year. $\frac{GDP_t - GDP_{t-1}}{GDP_{t-1}} \times 100$ is the quarterly GDP growth rate, Γ^{*}_{t} is the granular deposit shock, and Γ^{L}_{t} is the granular bank lending shock. The bank lending shock is constructed by taking a weighted average of county-level disaster shocks. The weights are based on the proportion of each bank's mortgage and small business lending in each county. We create granular lending shocks using the geographic distribution of lending in mortgage markets, utilizing HMDA data ($\Gamma^{L,HMDA}_{t-1}$), and small business lending data from the CRA data ($\Gamma^{L,CRA}_{t-1}$), and an average of the two shocks ($\Gamma^{L,Total}_{t-1}$). To compare the relative magnitude of the coefficient on the granular bank lending shock to the granular deposit shock, we divide the bank lending shock by one-hundred. Newey-West heteroskedasticity and autocorrelation (8 quarter lags) robust standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 11: Granular Shock and Aggregate Fluctuation – Shock Adjusted for Plausible Measurement Error

Dep Var: GDP growth	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Γ^*_{t-1}	-0.0097**	-0.0063**	-0.0079**	-0.0093**	-0.0082**	-0.0072*	-0.0037***	-0.0045*
	(0.0048)	(0.0028)	(0.0033)	(0.0039)	(0.0035)	(0.0038)	(0.0012)	(0.0027)
Constant	1.0114***	1.0494***	1.0492***	1.0368***	1.0568***	1.0695***	1.0843***	
	(0.1144)	(0.1059)	(0.1122)	(0.1193)	(0.1168)	(0.1201)	(0.1108)	
Year FE								Yes
# Obs	101	101	101	101	101	101	101	100
R^2	0.0158	0.0058	0.0090	0.0100	0.0116	0.0081	0.0062	0.0074
Shock Constructed After Dropping	Tax State	M&A Banks	Non-Local Deposits	HQ	Operating Branch	Lending County	All	All

Note: This table uses quarterly GDP series from 1994Q3 to 2019Q4 and reports the estimated coefficient β_h in the following specification:

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

where t indicates quarter-year and h indicates the number of lags. $\%\Delta GDP_t$ is the quarterly GDP growth rate, and Γ^*_{t-1} denotes the granular deposit shock in the prior quarter. Column 1 reports results using granular shocks constructed after excluding the nine states without state income taxes: Alaska, Florida, Nevada, New Hampshire, South Dakota, Tennessee, Texas, Washington, and Wyoming. Column 2 excludes banks involved in mergers and acquisitions during the sample period. Column 3 excludes uninsured time deposits and brokered deposits from the total deposits reported at the main office. Column 4 excludes the bank's main office branch. Column 5 excludes the largest branches in each state. Column 6 excludes counties that represent the bank's largest lending locations. Column 7 incorporates all exclusions from columns 1 through 6 simultaneously. Column 8 presents results using year fixed effects and granular shocks constructed with all the exclusions made in columns 1 through 6. Newey-West heteroskedasticity and autocorrelation (8 quarter lags) robust standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 12: Branch-Based Granular Shock and Aggregate Fluctuations

Dep Var: GDP growth	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Γ^*_t	-0.0090**						-0.0095***	-0.0161**
	(0.0039)						(0.0035)	(0.0075)
Γ^*_{t-1}		-0.0108**					-0.0127***	-0.0211***
		(0.0048)					(0.0042)	(0.0067)
Γ^*_{t-2}			0.0080*				0.0073**	0.0023
			(0.0048)				(0.0036)	(0.0130)
Γ^*_{t-3}				0.0088			0.0083	0.0046
				(0.0128)			(0.0118)	(0.0246)
Γ^*_{t-4}					-0.0009		-0.0020	-0.0056
					(0.0050)		(0.0044)	(0.0158)
Γ^*_{t-5}						-0.0135**	-0.0153***	-0.0191
						(0.0054)	(0.0056)	(0.0174)
Constant	1.0757***	1.0572***	1.1724***	1.2260***	1.1305***	1.0358***	0.9624***	
	(0.1188)	(0.1132)	(0.1373)	(0.1151)	(0.1299)	(0.1186)	(0.0972)	
Year FE								✓
# Obs	102	101	100	99	98	97	97	96
R^2	0.0089	0.0129	0.0072	0.0089	0.0001	0.0212	0.0642	0.0803

Note: This table uses quarterly GDP growth series from 1994Q3 to 2019Q4 and reports the estimated coefficient β_h in the following regression specification:

$$\frac{GDP_t - GDP_{t-1}}{GDP_{t-1}} \times 100 = \alpha + \beta_h \times \Gamma^*_{t-h} + \varepsilon_t$$

where t indicates quarter-year and h indicates the number of lags. $\frac{GDP_t - GDP_{t-1}}{GDP_{t-1}}$ is the quarterly GDP growth rate, and Γ^*_{t-h} denotes the granular deposit shock and its lags. Newey-West heteroskedasticity and autocorrelation (8 quarter lags) robust standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 13: Small Business Lending and Deposit Shocks

Dep Var: $\Delta ln(Lending)_{b,c,t}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Gamma_{b,t-1}$	-0.0072***	-0.0090***	-0.0079***	-0.0110***	-0.0060***	-0.0100***	-0.0206***	-0.0089***
	(0.0017)	(0.0017)	(0.0018)	(0.0020)	(0.0018)	(0.0021)	(0.0077)	(0.0022)
County FE		✓	✓					
Year FE		✓	✓					
County × Year FE				✓		✓	✓	✓
Bank × County FE					✓	✓	✓	✓
Bank FE			✓					
# Obs	613,931	613,931	613,931	613,931	613,931	613,931	120,432	471,785
R^2	0.0000	0.0098	0.0161	0.1178	0.0728	0.1901	0.3103	0.2038
Sample	All Counties	All Counties	All Counties	All Counties	All Counties	All Counties	Unaffected Counties	Affected Counties

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 span from 1997 to 2019. 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, standardized to mean zero and standard deviation of one. All outcome variables are winsorized at the 1% level. Standard errors clustered at the bank-county level are reported in parentheses. Columns 1-6 report results using the full sample. Column 7 restricts the sample to the counties that were not affected by any disaster in year $t-1$, and column 8 restricts the sample to counties that were affected by a disaster in year $t-1$. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 14: Small Business Lending and Deposit Shocks by Bank Characteristics

Dep Var: $\Delta ln(Lending)_{b,c,t}$	(1)	(2)	(3)
High Sh. $CD_{b,t-1} \times \Gamma_{b,t-1}$	-0.0227***		
	(0.0039)		
High Sh. $CD_{b,t-1}$	0.0593***		
	(0.0042)		
Low Tier 1 $Ratio_{b,t-1} \times \Gamma_{b,t-1}$		-0.1663***	
		(0.0125)	
Low Tier 1 $Ratio_{b,t-1}$		-0.0224***	
		(0.0047)	
$NC_{b,c,t-1} \times \Gamma_{b,t-1}$			-0.0094***
			(0.0035)
$NC_{b,c,t-1}$			0.3831***
			(0.0090)
$\Gamma_{b,t-1}$	-0.0040	-0.0063***	-0.0028
	(0.0024)	(0.0020)	(0.0022)
County × Year FE	✓	✓	✓
County × Bank FE	✓	✓	✓
# Obs	593,600	593,600	593,600
R^2	0.1932	0.1932	0.1959

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 span from 1997 to 2019. 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, standardized to mean zero and standard deviation of one. 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 outcome variables used in this table are winsorized at the 1% level. Standard errors clustered at the bank-county level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 15: Jumbo vs Non-Jumbo Mortgage Loans and Deposit Shocks

Dep Var: $\Delta ln(Lending)_{b,c,t,j}$	(1)	(2)	(3)	(4)
Jumbo$_j$ $\times \Gamma_{b,t-1}$	-0.0344***	-0.0344***	-0.0344***	-0.0360***
	(0.0043)	(0.0043)	(0.0043)	(0.0046)
Jumbo$_j$	0.0156***	0.0156***	0.0156***	
	(0.0013)	(0.0013)	(0.0013)	
$\Gamma_{b,t-1}$	0.0225***	0.0102***		
	(0.0030)	(0.0033)		
County × Year FE		✓		
County × Bank FE		✓		
County × Bank × Year FE			✓	✓
County × Bank × Jumbo FE				✓
# Obs	2,731,356	2,731,356	2,731,356	2,731,356
R^2	0.0000	0.0576	0.5301	0.5484

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 span from 1995 to 2019. 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, standardized to a mean of zero and standard deviation of one. $Jumbo_j$ 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 outcome variables are winsorized at the 1% level. Standard errors clustered at the bank-county level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 16: Small vs Large Recipients of Small Business Loans and Deposit Shocks

Dep Var: $\Delta ln(Lending)_{b,c,t,s}$	(1)	(2)	(3)	(4)
$\text{Small}_s \times \Gamma_{b,t-1}$	-0.0111***	-0.0111***	-0.0111***	-0.0076**
	(0.0032)	(0.0034)	(0.0032)	(0.0036)
Small_s	-0.0096***	-0.0096***	-0.0096***	
	(0.0015)	(0.0016)	(0.0015)	
$\Gamma_{b,t-1}$	0.0056**	0.0034		
	(0.0027)	(0.0028)		
County × Year FE		✓		
County × Bank FE		✓		
County × Bank × Year FE			✓	✓
Small × County × Bank FE				✓
# Obs	608,648	608,648	608,648	608,648
R^2	0.0000	0.1637	0.5348	0.5671

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 span from 1997 to 2019. 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, standardized to a mean of zero and standard deviation of one. $Small_s$ 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 outcome variables are winsorized at the 1% level. Standard errors clustered at the bank-county level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 17: Bank-Borrower Lending Relationship and Real Effects

	(1)	(2)	(3)	(4)
	Debt	Size	Employment	CapEx
$\text{Young}_f \times \sum_b \Gamma_{b,t-1}$	-0.1328*	-0.0995**	-0.1216**	-0.2023**
	(0.0734)	(0.0503)	(0.0568)	(0.0858)
$\sum_b \Gamma_{b,t-1}$	-0.0070	-0.0019	-0.0005	0.0016
	(0.0044)	(0.0027)	(0.0023)	(0.0032)
Firm FE	✓	✓	✓	✓
Industry × Young × Year FE	✓	✓	✓	✓
# Obs	11,537	12,156	11,530	10,794
R^2	0.9317	0.9722	0.9711	0.9518

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, standardized to a mean of zero and standard deviation of one. $\sum_b \Gamma_{b,t-1}$ refers to the sum of bank deposit shocks for lead banks of firm f identified using the Dealscan database. We standardize this to a mean of zero and a standard deviation of one. $\theta_{i,g,t}$ and θ_f are industry-young-year and firm fixed effects, respectively. Industries refer to the 38 Fama-French industries. All outcome variables used in this table are 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 Fluctuations

Contents

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, Miller, Petersen, Rajan, and Stein (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.

A.1 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:

$$\mathbb{E}_t(\frac{\Delta D_{b,c,t}}{\sum_b D_{b,c,t-1}}) = \frac{D_{b,c,t-1}}{\sum_b D_{b,c,t-1}} \times \epsilon_{c,t} \tag{A.6}$$

$$\Rightarrow \mathbb{E}_t(\Delta D_{b,c,t}) = D_{b,c,t-1} \times \epsilon_{c,t} \tag{A.7}$$

Dividing both sides of equation A.7 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.

$$\mathbb{E}_t(\frac{\Delta D_{b,c,t}}{\sum_c D_{b,c,t-1}}) = \frac{D_{b,c,t-1}}{\sum_c D_{b,c,t-1}} \times \epsilon_{c,t} \tag{A.8}$$

Aggregating equation A.8 across all counties for a bank b gives us the relationship between shocks to bank deposit growth and disaster shocks as follows:

$$\sum_c \frac{\mathbb{E}_t(\Delta D_{b,c,t})}{\sum_c D_{b,c,t-1}} = \sum_c \frac{D_{b,c,t-1}}{\sum_c D_{b,c,t-1}} \times \epsilon_{c,t} \tag{A.9}$$

Equation A.9 allows us to define bank shocks as follows:

$$\Gamma_{b,t} := \sum_{c} \{ \frac{D_{b,c,t-1}}{\sum_c D_{b,c,t-1}} \times \varepsilon_{c,t} \} \tag{A.10}$$

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

$$\Gamma_t := \sum_{b} \Gamma_{b,t} = \sum_{b} \left(\sum_{c} \{ \frac{D_{b,c,t-1}}{\sum_c D_{b,c,t-1}} \times \varepsilon_{c,t} \} \right) \tag{A.11}$$

Appendix B Comparison to Existing Empirical Literature

This section relates our findings to empirical work documenting the response of bank lending to natural disaster shocks in the US, particularly Cortés and Strahan (2017). In this section, we argue that our results do not contradict their results but the two results can co-exist. Specifically, we note that both sets of findings are not only compatible but also mutually reinforcing, once one accounts for heterogeneity in bank characteristics and behavior.

Cortés and Strahan (2017) emphasize the short-lived nature of demand-side shocks following natural disasters. Specifically, the authors find that natural disasters temporarily increase credit demand in affected areas, leading to a short-term increase in lending by small banks. However, these effects typically dissipate within a year.

In contrast, our paper focuses on the supply side and highlights the persistent effects of disasters on local deposits. We show that natural disasters can reduce household income, employment, and business activity in affected counties, leading to a sustained decline in bank deposits. These negative income effects may be long-lasting, resulting in persistent deposit outflows. When the affected counties serve as key deposit bases—particularly for larger banks—these localized shocks can translate into broader bank-level declines and explain aggregate fluctuations.

What are the key differences? Our results differ from those in Cortés and Strahan (2017) in both the nature of the effect and the key economic agents driving the response to the same underlying events – namely, natural disasters.

1. Cortés and Strahan (2017) focus on the response of banks to local credit demand shocks, whereas our findings focus on a deposit supply shock that constrains banks' liquidity creation capacity.

2. The primary agents in Cortés and Strahan (2017) are **small banks**, which respond to increased local credit demand by expanding lending. In contrast, our results highlight the role of **large banks**, which can contribute to aggregate fluctuations through aggregation of idiosyncratic disaster shocks.

Can the two results co-exist?: At the face of it, our findings may appear to conflict with those of Cortés and Strahan (2017). However, the two sets of results can coexist for the following reasons:

1. **Disasters can increase short-run credit demand as well as impair long-run depositor wealth:** Natural disasters can simultaneously generate a short-term increase in borrowing needs – such as for repairs, replacement of assets, or to bridge temporary income gaps – and impair long-term household wealth and income. In the short run, this can raise credit demand in affected counties, prompting an increase in localized lending by small banks, as documented in Cortés and Strahan (2017). Over the longer horizon, however, if disasters lead to permanent income losses and business disruptions, they can cause a persistent decline in household savings and deposit levels. These deposit outflows weaken bank funding capacity, particularly for banks with concentrated geographic exposure to affected areas. This structural funding loss, especially if not offset through external finance, can reduce banks' ability to lend more broadly, beyond the disaster-affected markets.

We observe this dual effect in our case study: deposits often rise immediately following a disaster – potentially due to insurance payouts, relief funding, or precautionary savings – but decline sharply in subsequent years as the longer-term economic fallout takes hold. Thus, initial credit expansions can coexist with longer-run funding constraints. This is also consistent with the Thakor and Yu (2024) who argue that damage caused by natural disasters increases the demand for investment, loans and cash withdrawal, so they create the possibility of diminished deposit inflows occurring at the same time as elevated loan demand.

2. **Small and large banks respond differently to the same event:** Another reason to believe that our findings can co-exist with those of Cortés and Strahan (2017) lies in the fundamental differences in how large and small banks respond to shocks, particularly in their lending behavior.

   Small banks are typically more locally embedded and are more likely to engage in relationship lending. This form of lending, characterized by long-standing, trust-based interactions with borrowers, allows small banks to better assess creditworthiness, especially when standard metrics may be compromised by shocks like natural disasters. In contrast, large banks generally operate with more transactional, arm's-length lending models. They lend at greater distances, form less exclusive and shorter-duration relationships, and are less inclined to invest in acquiring and processing soft information. The idea that small banks are better equipped to collect and use soft information traces back to the seminal work of Berger, Miller, Petersen, Rajan, and Stein (2005), along with a broader literature showing that larger banks are generally less inclined to serve informationally difficult or marginal borrowers. Large idiosyncratic shocks, like natural disasters, heighten informational frictions and make it harder to assess borrower risk, thus, disproportionately deterring large-bank lending.

   Using monthly survey data from 1993 to 2012 on small business managerial perceptions, Berger, Bouwman, and Kim (2017) provide evidence that small banks have comparative advantages in alleviating information frictions. Moreover, they show that small banks possess comparative advantages in overcoming these information frictions. They also show that small banks are more effective at providing liquidity insurance to small business customers, particularly when those customers' primary banks – often larger institutions – face liquidity constraints. Similarly, relationship lending enables small banks to continue supplying credit during turbulent times by smoothing through temporary shocks à la Petersen and Rajan (1994) and Berger and Udell (2002).

   Supporting this pattern of specialization, Chavaz (2016) find that in disaster-affected areas, small banks originate a greater share of new mortgage and small business loans, suggesting that these institutions are better equipped—or more incentivized—to lend in distressed markets. Cortés (2014) document similar behavior in US disaster contexts, while Koetter, Noth, and Rehbein (2020) and Celil, Oh, and Selvam (2022) provide comparable evidence from Germany and China, respectively. These findings reinforce the idea that small banks actively step in to support local economies during crises, in line with the mechanisms highlighted by Cortés and Strahan (2017).

   Moreover, DeYoung, Gron, Torna, and Winton (2015) provide evidence that banks relying on relationship lending are better able to maintain stable loan portfolios during times of stress. This helps explain why small banks may expand lending following natural disasters (as observed by Cortés and Strahan (2017)), while large banks – facing persistent deposit outflows and heightened informational frictions – may contract credit over a longer horizon (as we document). Thus, both sets of findings are not only compatible but also mutually reinforcing, once one accounts for heterogeneity in bank characteristics and behavior.

Lastly, we directly document the heterogeneity in the response of small and large banks in small business lending and mortgage lending. Specifically, Table B.1 shows that large banks, specifically, systematically important banks (SIBs), respond to natural disasters by reducing credit in areas affected by natural disasters. In contrast, the estimate associated with small banks (same definition as Cortés and Strahan (2017)) is positive.

Table B.1: Bank Lending and Deposit Shocks by Bank Size

	(1)	(2)	(3)	(4)
Panel A: Small Business Lending				
Dep Var: $\Delta ln(Lending)_{b,c,t}$	Small	Medium	Large	SIB
$\Gamma_{b,t-1}$	0.0194	-0.0081**	-0.0103	-0.0362***
	(0.0222)	(0.0036)	(0.0068)	(0.0087)
County × Year FE	✓	✓	✓	✓
County × Bank FE	✓	✓	✓	✓
# Obs	40,377	84,393	88,375	300,815
R^2	0.4556	0.4065	0.4031	0.2670
Panel B: Mortgage Lending				
Dep Var: $\Delta ln(Lending)_{b,c,t}$	(1) Small	(2) Medium	(3) Large	(4) SIB
$\Gamma_{b,t-1}$	0.0114	0.0229***	-0.0218**	-0.1096***
	(0.0181)	(0.0066)	(0.0096)	(0.0130)
County × Year FE	✓	✓	✓	✓
County × Bank FE	✓	✓	✓	✓
# Obs	123,327	158,298	255,195	501,742
R^2	0.3558	0.3636	0.3002	0.1872

Note: This table uses small business lending data collected under the Community Reinvestment Act (CRA) in Panel A and mortgage lending data collected under the Home Mortgage Disclosure Act (HMDA) in Panel B, matched with bank call report data and reports the estimated coefficient β in the following specification:

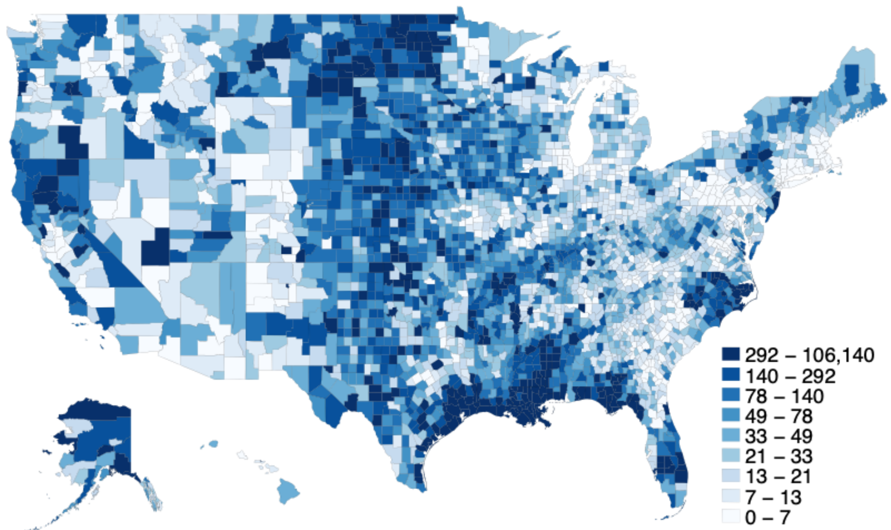
$$\Delta ln(Lending)_{b,c,t} = \beta \times \Gamma_{b,t-1} + \theta_{c,t} + \theta_{b,c} + \varepsilon_{b,c,t}$$

where b, c and t indicate bank, county, and year, respectively. The data span from 1997 to 2019. 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, standardized to mean zero and standard deviation of one. Small refers to banks with total assets less than \$2 billion (column 1), Medium refers to banks with total assets greater than or equal to \$2 billion but less than \$10 billion (column 2), Large refers to banks with total assets greater than or equal to \$10 billion but less than \$50 billion (column 3) and SIB or systematically important banks refers to banks with total assets greater than or equal to \$55 billion (column 4). We define small and medium banks based on cutoffs in DeYoung, Gron, Torna, and Winton (2015) and Cortés and Strahan (2017). We define SIBs based on \$50 billion cutoff for the definition of systematically important banks as per Title I of the Dodd-Frank Act. All remaining banks which are larger than medium banks but smaller than SIBs are classified as large banks. All outcome variables are winsorized at the 1% level. Standard errors clustered at the bank-county level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Appendix C Data

C.1 Descriptive Statistics of Disaster Data

Figure C.1: Property Damage Per Capita across Counties from 1994 to 2019



Notes: This figure illustrates the average annual natural disaster-induced property damage per capita across counties from 1994 to 2019. The intensity of the blue shading represents the dollar amount of property damage from natural disasters.

Table C.1: Property Damage from Natural Disasters

Hazard Type	Number of Affected Counties	Total Damage (in 2021 Billion $)	Property Damage Distribution (in 2021 Million $) P25	P50	P75	P95	P99
Flooding	25,408	253.54	0.01	0.08	0.51	8.68	66.80
Hurricane	3,062	199.28	0.03	0.38	3.98	144.34	1,393.51
Tornado	12,804	44.92	0.02	0.09	0.44	6.06	55.53
Earthquake	34	40.00	0.11	15.54	20.49	990.91	35,524.24
Wildfire	2,010	36.91	0.00	0.06	0.85	11.18	158.70
Hail	12,631	35.01	0.00	0.02	0.09	1.90	37.38
Wind	51,947	21.71	0.01	0.02	0.07	0.58	3.55
Winter Weather	16,817	16.90	0.01	0.04	0.22	2.75	19.68
Severe Storm	45,702	14.90	0.00	0.02	0.05	0.34	2.03
Landslide	871	5.34	0.00	0.01	0.14	10.23	67.55
Drought	2,922	3.23	-	-	-	1.61	18.10
Lightning	10,484	1.34	0.00	0.02	0.08	0.51	1.74
Coastal	1,104	0.42	-	-	-	0.33	8.89
Tsunami	57	0.13	0.01	0.03	0.10	16.62	44.41
Heat	2,733	0.05	-	-	-	0.08	0.17
Fog	387	0.05	0.00	0.02	0.12	0.61	2.13
Volcano	17	0.02	0.06	0.06	0.06	16.12	16.12
Avalanche	818	0.01	-	-	0.00	0.02	0.40
All Hazard Types	189,808	673.79	0.00	0.02	0.11	1.90	21.96

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 2019.

C.2 Definitions of Key Bank-Level Variables

We list the names of the variables from the Drechsler, Savov, and Schnabl (2017) dataset in italics, followed by the corresponding Call Report variable names in parentheses.

- **Assets**: *assets* (RCFD2170 from 1976Q1)
- **Loan**: *qavgloans* (RCON3360 from 1976Q1)
- **Equity**: *equity* (RCFD3210 from 1976Q1)
- **Cash**: *cash* (RCFD0010 from 1976Q1 – sparsely reported after 2015 – ; RCFD0071+RCFD0081 from 1984Q1 – used to fill missing values)
- **Deposits**: *deposits* (RCON2200 from 1976Q1)
- **Hedge**: *nethedging*; Hedge refers to the net hedging calculated as the difference between the value of interest rate swaps where the bank has agreed to pay a fixed rate and the value of the floating interest rate swaps (RCFDA589 -(RCFD3450-RCFDA589) from 1997Q1)
- **Dividend**: *dividendoncommonstock* (RIAD4460 from 1983Q1)
- **Operating Income**: *operinc* (RIAD4000 from 1983Q1; RIAD4079+RIAD4107 from 1984Q1)

C.3 Descriptive Statistics of Bank-Level Variables & Other Aggregate Shocks

Table C.2: Summary Statistics: Bank$_{l}evel Variables \& Other Aggregate Shocks$

	# Obs	Mean	SD	P25	P50	P75
Panel A: Bank × Year						
Ln(Assets)	10,894	14.05	1.75	12.74	13.71	15.06
Loan/Assets (%)	10,894	64.01	13.19	56.36	65.44	73.32
Equity/Assets (%)	10,894	10.09	2.84	8.20	9.61	11.36
Cash/Assets (%)	10,894	5.16	4.20	2.61	3.84	6.06
Deposits/Assets (%)	10,894	78.85	9.83	74.37	80.97	85.96
Hedge/Assets (%)	10,894	-4.63	37.74	0.00	0.00	0.00
Dividend/Assets (%)	10,894	0.20	0.31	0.00	0.11	0.25
Operating Income/Assets (%)	10,894	1.67	0.55	1.26	1.62	1.99
Panel B: Aggregate Level						
Oil Shock	97	0.01	0.82	-0.24	0.00	0.32
Monetary Shock	97	-0.01	0.03	-0.01	-0.00	0.00
Uncertainty Shock	97	0.01	0.16	-0.10	0.01	0.11
Term Spread	97	1.12	0.75	0.61	1.10	1.58
Government Expenditure Shock	97	4.38	2.50	2.97	4.23	6.17
Γ_t^{Gabaix}	97	-0.00	0.01	-0.00	0.00	0.00
Γ_t^{Emp}	101	8.85	17.30	1.38	3.23	8.73
Γ_t^{GDP}	71	9.84	21.54	1.76	3.26	9.04
Γ_t^{Pop}	101	10.00	19.82	1.77	3.96	10.13
Γ_t^{Est}	101	9.39	18.05	1.50	3.66	10.23
$\Gamma_t^{L,CRA}$	87	201.66	423.81	27.42	75.90	205.09
$\Gamma_t^{L,HMDA}$	87	205.98	431.35	28.35	77.49	206.46
$\Gamma_t^{L,Total}$	87	197.35	416.37	26.99	74.31	203.66
Ln(Total Home Loss)	75	21.14	1.22	20.15	21.25	21.86
Ln(Total Business Loss)	75	20.26	1.42	18.93	19.98	21.24

Note: This table reports summary statistics of control variables explored in this paper. Panel A presents bank-year level variables, where bank financial data are from Call Reports (1994–2018) – see Section C.2 for definitions. Panel B presents quarterly aggregate variables. Oil shocks based on the quarterly average of the oil supply surprise series from Känzig (2021). Monetary shocks based on quarterly average of tight-window monetary policy shocks from Vats (2020). Uncertainty shocks based on the percentage change in the economic policy uncertainty index from Baker, Bloom, and Davis (2016). Term spreads, defined as the difference between the market yield on US treasury securities at 5 year constant maturity and the market yield on US treasury securities at 3 month constant maturity. Government expenditure shocks, defined as the percentage change in the total government expenditure. Granular residuals (γ_t^{Gabaix}) constructed as in Gabaix (2011). In addition, Γ_t^{Emp}, Γ_t^{GDP}, Γ_t^{Pop}, and Γ_t^{Est} are property damage per capita weighted by county-level employment, GDP, population, and the number of establishments, respectively. $\Gamma_t^{L,CRA}$ and $\Gamma_t^{L,HMDA}$ are granular bank lending shocks constructed based on banks' small business lending (CRA) and mortgage lending (HMDA), and $\Gamma_t^{L,Total}$ is the average of the two. Total home and business losses are the estimated dollar losses based on insurance payouts sourced from the SBA.

Appendix D How do Banks Report in the SOD Database?

This section outlines the common reporting practices banks use to assign deposits to branches, based on our understanding of the Federal Deposit Insurance Corporation's (FDIC) guidelines (see the SOD Reporting Instructions for the 2024 guidelines) and conversations with bankers on how these guidelines are typically applied in practice.

D.1 What is Summary of Deposits (SOD)?

The Summary of Deposits (SOD) is an annual survey conducted by the Federal Deposit Insurance Corporation (FDIC) to collect data on branch office deposits as of June 30 for all FDIC-insured institutions. The SOD requires institutions to report the deposits assigned to each office location.

D.2 How do Banks Decide on the Branch Location of Deposits?

Banks decide to attribute the deposits to a specific branch based on three-overarching principles:

1. Bank branch that is closest to the reported address of the account holder.
2. Bank branch that is closest to the location where the account is most active.
3. Bank branch where the account was physically opened.

Banks typically assign deposits based on either the location where the account was opened or the branch closest to the account holder's reported address. During the account opening process, banks collect the account holder's address as part of their Know Your Customer (KYC) procedures, which are updated when the account holder changes their address.

Additionally, some banks may tie deposits to a branch for the purpose of branch manager compensation or similar incentives. This practice often occurs when a customer opens an account in person at a branch, and the bank continues to report those deposits under that branch to assess the manager's performance.

It is important to note that while the Summary of Deposits (SOD) guidelines permit banks to allocate deposits to the nearest branch based on where account activity occurs, implementing this in practice can be challenging. Accurately tracking the locations of check cashing, point-of-sale (POS) transactions, and ATM usage requires continuous monitoring. Although advancements in technology have simplified this process, it remains a costly endeavor for banks to consistently report on all depositors.

D.3 Deposit Recording in Practice

When a customer opens an account in person, their deposits are assigned to the branch where the account was established. In contrast, if the account is opened online, deposits are allocated to the branch nearest to the customer's reported address. However, if there is no physical branch in the customer's county, the deposits may be assigned to either the main office or the bank's headquarters.

If an existing customer changes their address, the bank may adjust the allocation of their deposits in one of three ways:

1. The bank may choose to continue attributing the deposits to the branch where their deposits were last assigned.

2. The bank may reallocate the deposits to the branch closest to the customer's new address.

3. If no physical branch exists in the new county, the bank has the option to assign the deposits to either the main branch or the headquarter branch.

If a bank branch closes, deposits from that branch can be consolidated into another branch within the same county. If no other branches are available in that county, the deposits may be attributed to the main branch or the headquarters.

Finally, an existing customer may request a bank to change their branch location because of relocation, convenience, tax considerations, impending closure of a bank branch, among other reasons.

D.4 How Common is Consolidation of Deposits?

As noted earlier, recording bank deposits may involve the consolidation of deposits from multiple branches within a single branch in a county. This consolidation can occur either due to the closure of existing branches or, as permitted by SOD guidelines, for operational efficiency. Furthermore, SOD reporting mandates that banks indicate when a branch serves as a consolidating entity for other branches within the same county. This designation is noted in the publicly accessible SOD database under the variable name *brcenm*, marked with an indicator *C*.

We exploit this information to assess the prevalence of such practices within our sample. We find that only two banks reported a consolidating branch over our sample from 1994 to 2019. The two banks that have a consolidated branch are: US Metro Bank and the First Security Bank of New Mexico, NA (currently inactive). This indicates that such practices are rarely employed, and banks are more likely to report these deposits at the main office or headquarter branches.

D.5 Recording of Other Deposit Types

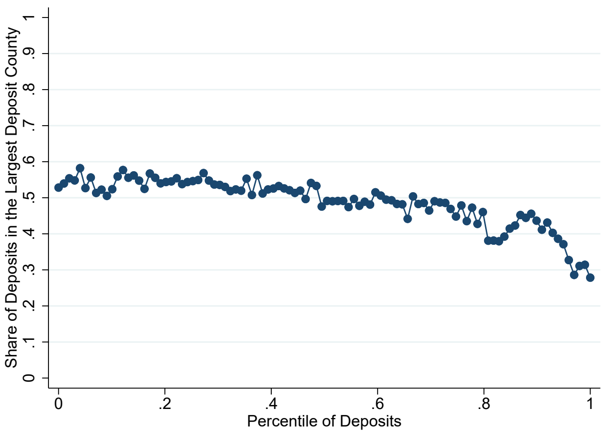
Certain types of deposits, such as brokered deposits, reciprocal deposits, or deposits placed through a listing service, do not have a clearly defined geographic footprint. For instance, in the SOD data, brokered deposits – funds acquired through a third party known as a deposit broker – are generally assigned to the institution's headquarters or main office. This allocation is consistent with the centralized nature of acquiring brokered deposits. A similar reporting approach is applied to other special types of deposits that also lack a well-defined geographic basis.

Lastly, some U.S. banks may collect deposits through branches located outside the United States. According to SOD reporting guidelines, these deposits must not be attributed to any U.S. location, regardless of whether they are insured. This requirement is enforced by ensuring that the total deposits reported in the SOD must exactly match with the "Deposits in domestic offices" reported on Schedule RC of the Call Reports, or the "Total deposits and credit balances, excluding International Banking Facility (IBF) deposits liabilities" reported in Schedule E of the Report of Assets and Liabilities.

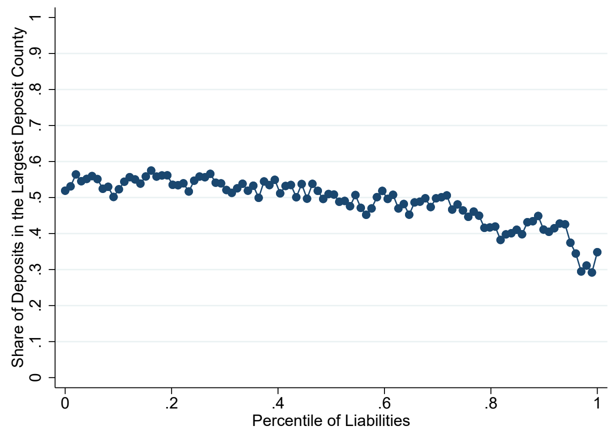
Appendix E Measurement of Geography of Deposits

E.1 Measurement Error: Full Sample

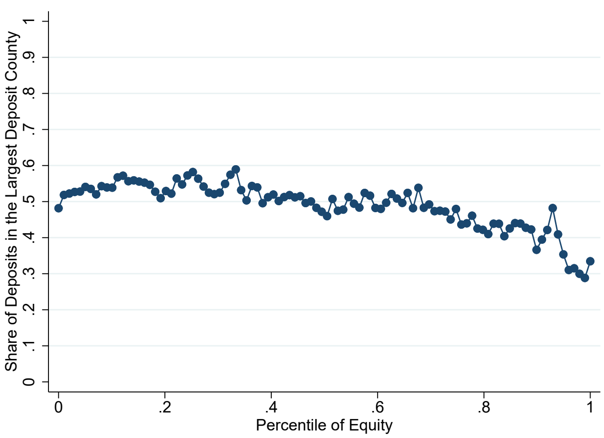
Figure E.1: Geographic Concentration Across Bank Characteristics



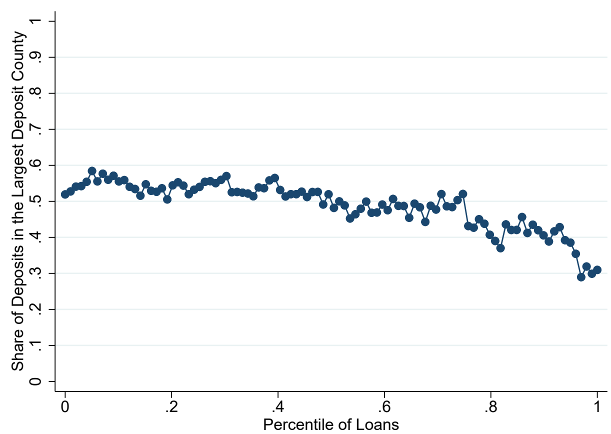
(a) Deposits



(b) Liabilities



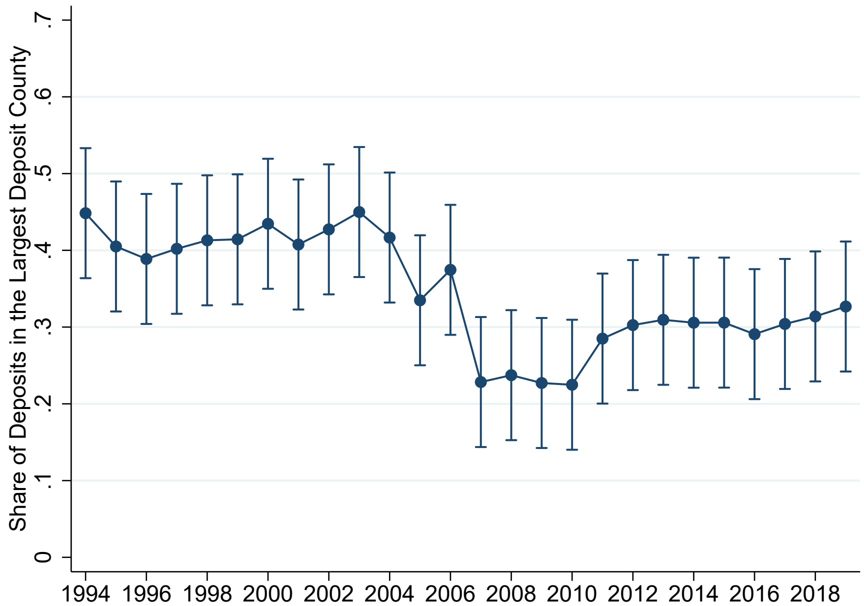
(c) Equity



(d) Loans

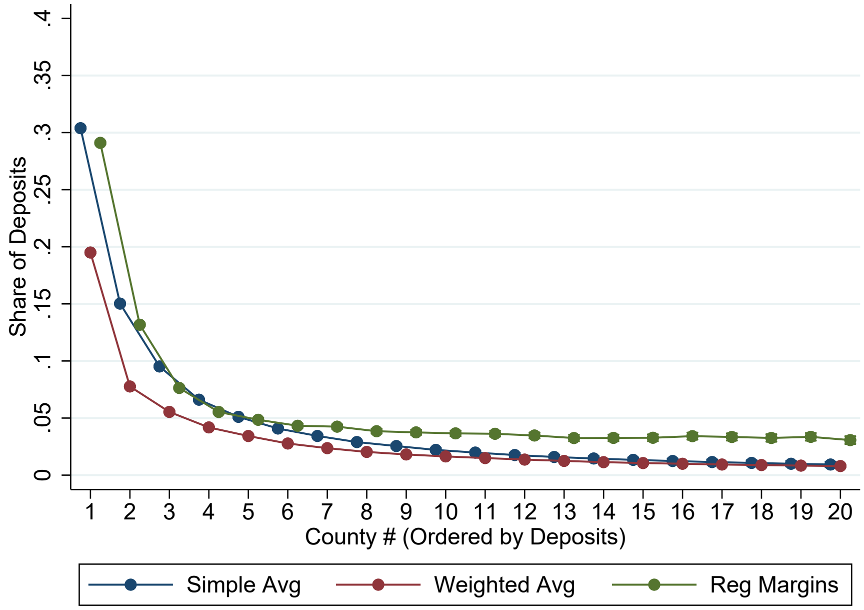
Note: This figure uses the Summary of Deposits (SOD) data from 1994 to 2019 and illustrates the relation between the geographic concentration of deposits (Figure E.1a), liabilities (Figure E.1b), equity (Figure E.1c), and loans (Figure E.1d). Each figure sorts banks by their deposits, total liabilities, book value of equity, and loans in figures E.1a, E.1b, E.1c, and E.1d, 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 E.2: Time Series of Deposit Concentration for Big 4 Banks

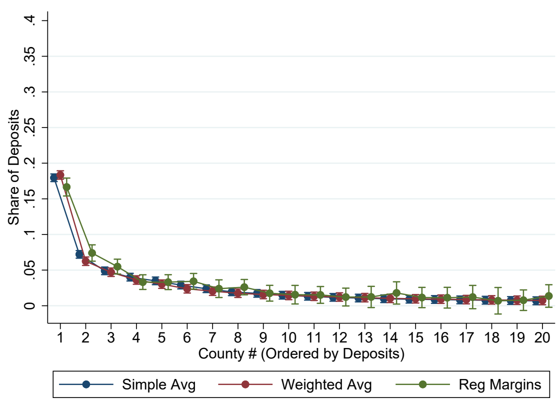


This figure uses the Summary of Deposits (SOD) data from 1994 to 2019 and illustrates the geographic concentration of bank deposits over time. The figure reports the share of deposits in the largest deposit county for the Big 4 banks over time. The Big 4 banks are Citibank, JP Morgan, Wells Fargo, and Bank of America.

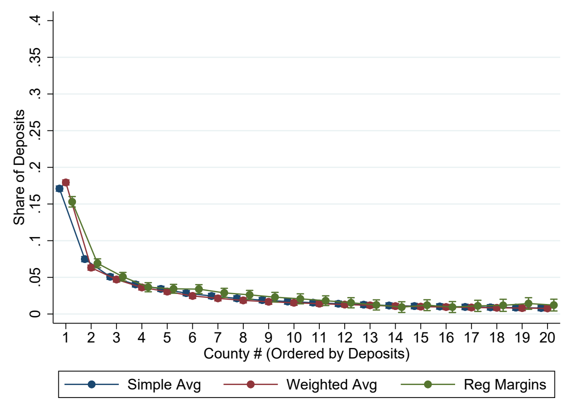
Figure E.3: Geographic Concentration of Deposits after Excluding the HQ Branch



(a) All Banks



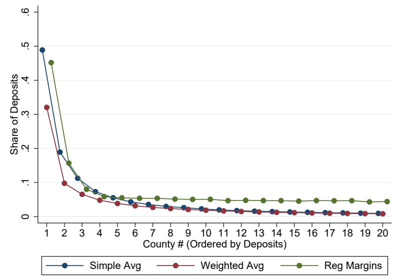
(b) Big 4



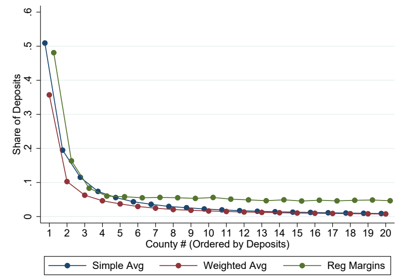
(c) Top 20

This figure uses the Summary of Deposits (SOD) data from 1994 to 2019 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 raises 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. Appendix Figure E.3a presents the results for the full sample of all banks, Appendix Figure E.3b presents the results for the Big 4 banks which includes Bank of America, JP Morgan Chase, Wells Fargo, and Citibank, and Appendix Figure E.3c presents the results for the top 20 banks, defined by total assets each year.

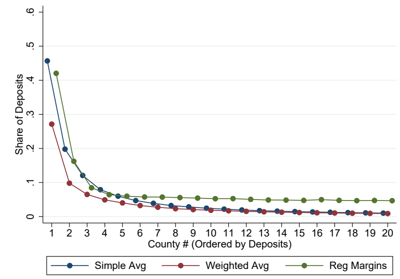
Figure E.4: Deposit Concentration after Addressing Confounding Factors



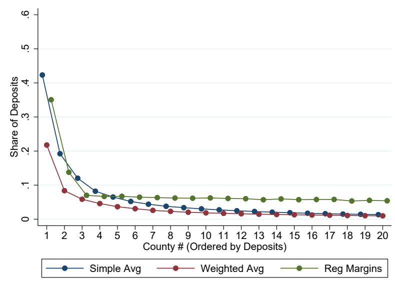
(a) Exclusion of Tax States



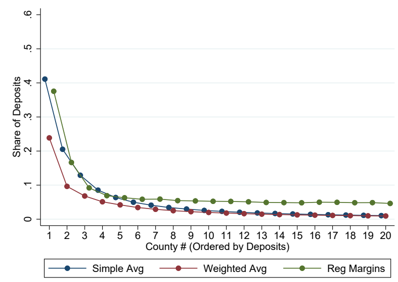
(b) Exclusion of Banks with M&A



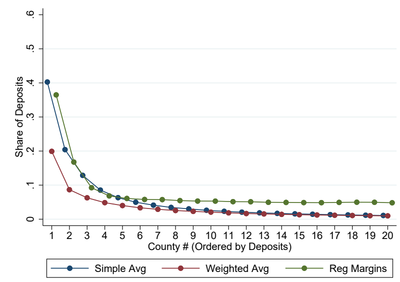
(c) Exclusion of Non-Local Deposits



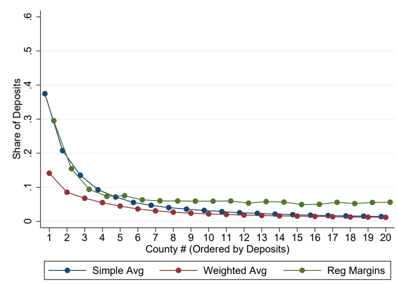
(d) Exclusion of Large Lending Counties



(e) Exclusion of Main Offices



(f) Exclusion of Operational Branches

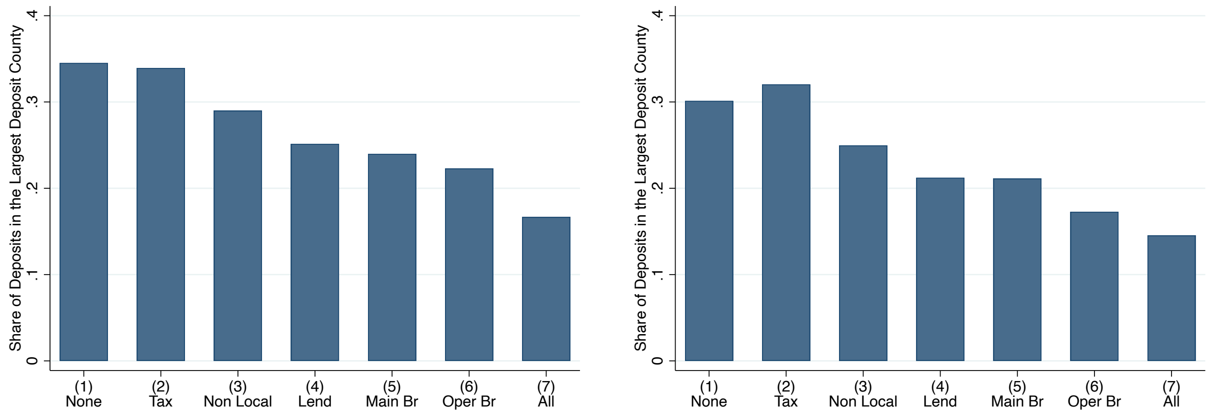


(g) All Adjustment

Note: This figure uses the Summary of Deposits (SOD) data from 1994 to 2019 and illustrates the geographic concentration of bank deposits. All figures order 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 raises the greatest amount of deposits for a given bank) and report 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. Each panel presents the share of bank deposits from the top deposit county after excluding certain branches or counties. Panel A presents the share of bank deposits after excluding the nine states without state income taxes: Alaska, Florida, Nevada, New Hampshire, South Dakota, Tennessee, Texas, Washington, and Wyoming. Panel B presents the share of bank deposits after excluding banks involved in mergers and acquisitions starting from the year of their first acquisition. Panel C presents the share of bank deposits after excluding the total uninsured time deposits and online deposits from total deposits reported at the main office. Panel D presents the share of bank deposits after excluding the five largest counties for mortgage and small business lending for each bank. Panel E presents the share of bank deposits after excluding the main office branch of each bank. Panel F presents the share of bank deposits after excluding the largest branches in each state. Panel G presents the share of bank deposits after making all the exclusions made in Panels A-F.

E.2 Measurement Error: Large Banks

Figure E.5: Share of Deposits in Top County After Excluding Certain Counties: Big 4 & Top 20

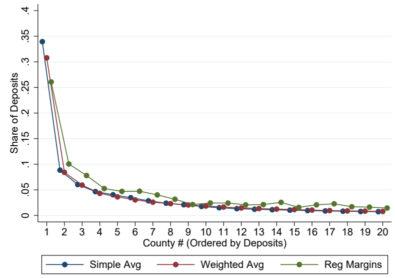


(a) Big 4 Banks

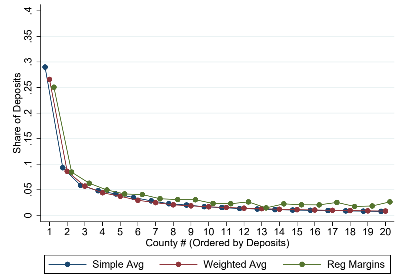
(b) Top 20 banks

This figure illustrates the geography of a county with the largest deposit share for a given bank from 1994 to 2019. Appendix Figure E.5a reports the results for the Big 4 banks, which includes Bank of America, JP Morgan Chase, Wells Fargo, and Citibank. Appendix Figure E.5b presents the results for the top 20 banks, defined by total assets each year. Each bar, except the first, presents the share of bank deposits from the top deposit county after excluding certain branches or counties. The first bar presents the average share of bank deposits from the top deposit county for all banks. The second bar presents the share of bank deposits from the top deposit county after excluding the nine states without state income taxes: Alaska, Florida, Nevada, New Hampshire, South Dakota, Tennessee, Texas, Washington, and Wyoming. The third bar presents the share of bank deposits from the top deposit county after excluding the total uninsured time-deposits and brokered deposits from total deposits reported at the main office. The fourth bar presents the share of bank deposits from the top deposit county after excluding the five largest counties for mortgage and small business lending for each bank. The fifth bar presents the share of bank deposits from the top deposit county after excluding the main office branch of the bank. The sixth bar presents the share of bank deposits from the top deposit county after excluding the largest branch in each state. The seventh or the last bar presents the share of bank deposits from the top deposit county after making all the exclusions made in bars 2-7. Note that we do not present the bar for M&A in this figure as all large banks have been involved in at least one mergers and acquisitions activity during our sample period.

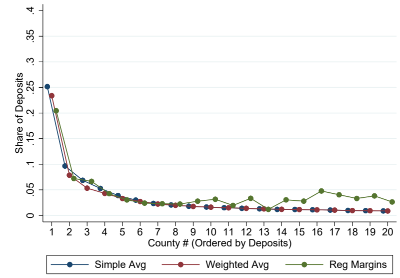
Figure E.6: Deposit Concentration after Addressing Confounding Factors, Big 4



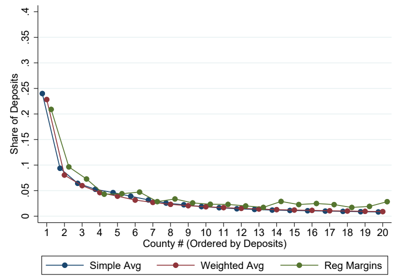
(a) Exclusion of Tax States



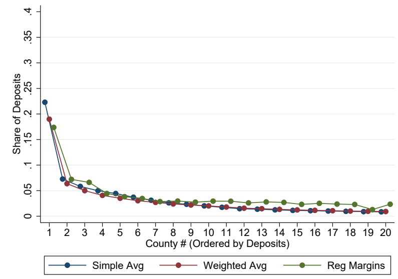
(b) Exclusion of Non-Local Deposits



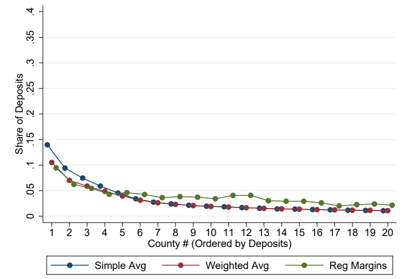
(c) Exclusion of Large Lending Counties



(d) Exclusion of Main Offices



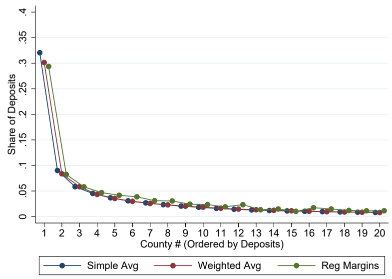
(e) Exclusion of Operational Branches



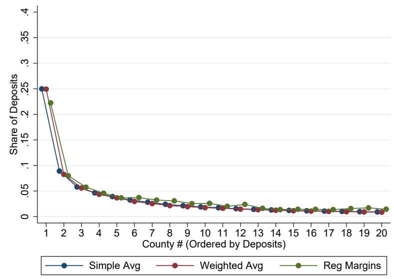
(f) All Adjustment

Note: This figure uses the Summary of Deposits (SOD) data from 1994 to 2019 and illustrates the geographic concentration of bank deposits. All figures order 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 raises the greatest amount of deposits for a given bank) and report 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. Each panel presents the share of bank deposits from the top deposit county after excluding certain branches or counties. Panel A presents the share of bank deposits after excluding the nine states without state income taxes: Alaska, Florida, Nevada, New Hampshire, South Dakota, Tennessee, Texas, Washington, and Wyoming. Panel B presents the share of bank deposits after excluding the total uninsured time deposits and online deposits from total deposits reported at the main office. Panel C presents the share of bank deposits after excluding the five largest counties for mortgage and small business lending for each bank. Panel D presents the share of bank deposits after excluding the main office branch of each bank. Panel E presents the share of bank deposits after excluding the largest branches in each state. Panel F presents the share of bank deposits after making all the exclusions made in Panels A-E. Note that we do present the panel for M&A in this figure as all large banks have been involved in at least one mergers and acquisitions activity during our sample period.

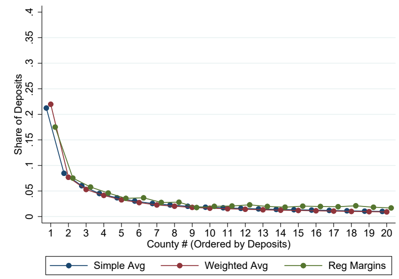
Figure E.7: Deposit Concentration after Addressing Confounding Factors, Top 20



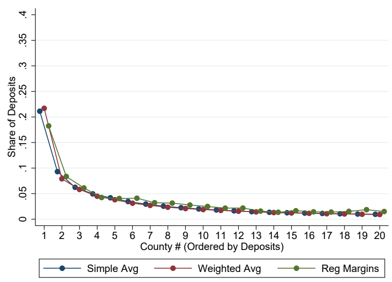
(a) Exclusion of Tax States



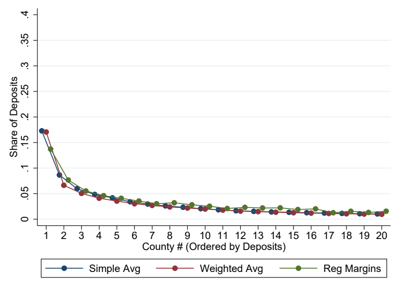
(b) Exclusion of Non-Local Deposits



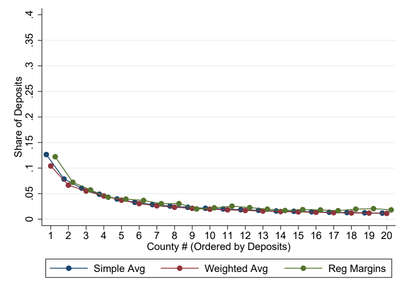
(c) Exclusion of Large Lending Counties



(d) Exclusion of Main Offices



(e) Exclusion of Operational Branches

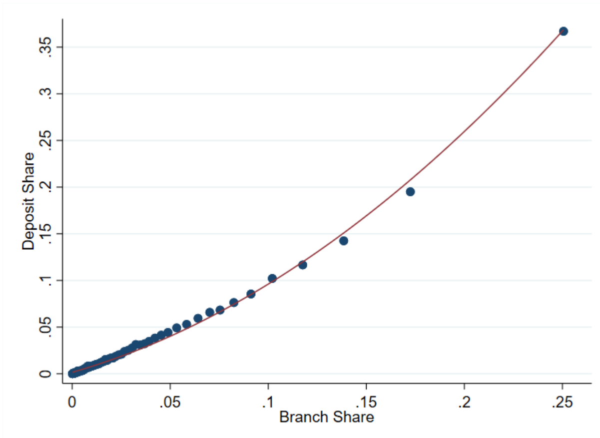


(f) All Adjustment

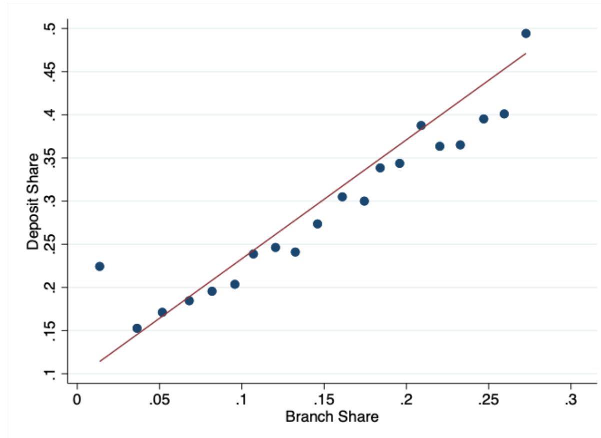
Note: This figure uses the Summary of Deposits (SOD) data from 1994 to 2019 and illustrates the geographic concentration of bank deposits. All figures order counties by their deposit shares for each bank (the county number refers to the rank of a county by the amount of deposits it raises, i.e., county #1 refers to the county that raises the greatest amount of deposits for a given bank) and report 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. Each panel presents the share of bank deposits from the top deposit county after excluding certain branches or counties. Panel A presents the share of bank deposits after excluding the nine states without state income taxes: Alaska, Florida, Nevada, New Hampshire, South Dakota, Tennessee, Texas, Washington, and Wyoming. Panel B presents the share of bank deposits after excluding the total uninsured time deposits and online deposits from total deposits reported at the main office. Panel C presents the share of bank deposits after excluding the five largest counties for mortgage and small business lending for each bank. Panel D presents the share of bank deposits after excluding the main office branch of each bank. Panel E presents the share of bank deposits after excluding the largest branches in each state. Panel F presents the share of bank deposits after making all the exclusions made in Panels A-E. Note that we do present the panel for M&A in this figure as all large banks have been involved in at least one mergers and acquisitions activity during our sample period

E.3 Branch Based Measure of Concentration

Figure E.8: Relationship between Deposit Share & Branch Share



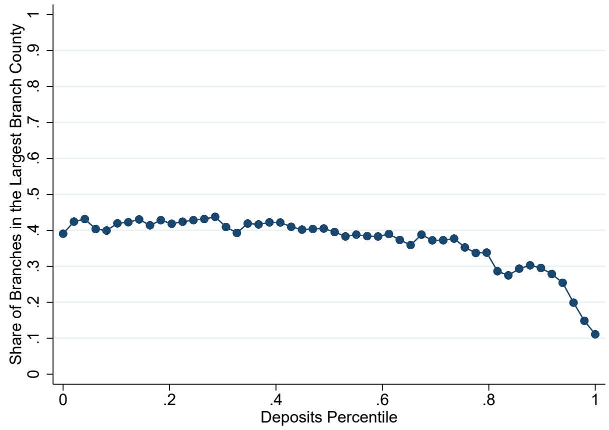
(a) All Counties



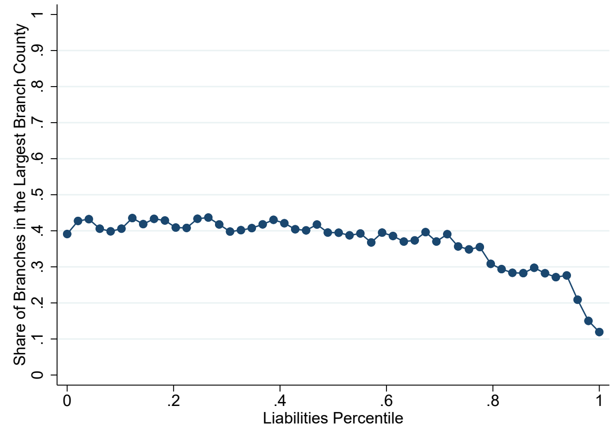
(b) Largest Deposit Counties

Note: This figure compares each county's share of deposits within a bank to its share of branches. Appendix Figure E.8a includes all counties, while Appendix Figure E.8b focuses on the counties with the largest amount of deposits for each bank. These shares are calculated using the Summary of Deposits (SOD) data from 1994 to 2019.

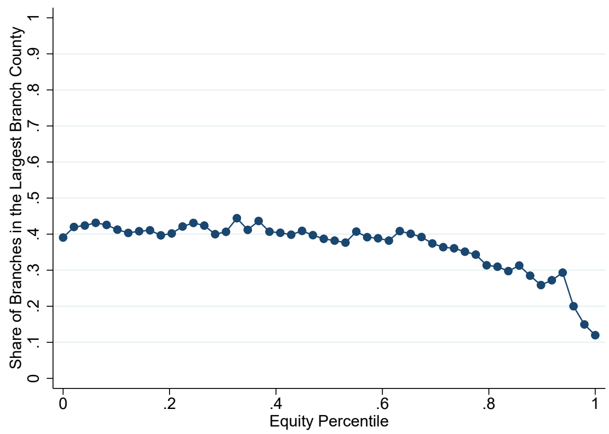
Figure E.9: Geographic Concentration of Branches Across Bank Characteristics



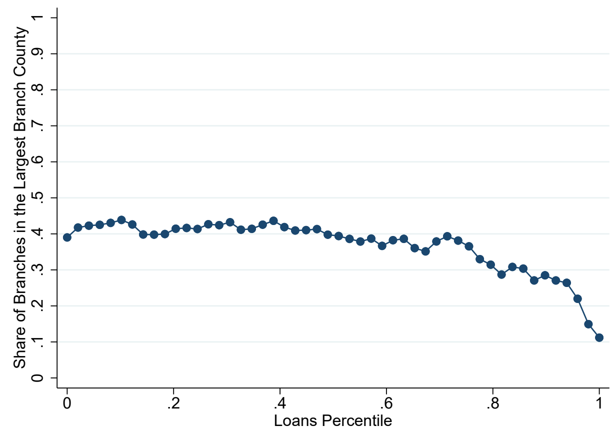
(a) Deposits



(b) Liabilities



(c) Equity



(d) Loans

Note: This figure uses the Summary of Deposits (SOD) data from 1994 to 2019 and illustrates the relation between the geographic concentration of deposits (Figure E.9a), liabilities (Figure E.9b), equity (Figure E.9c), and loans (Figure E.9d). Each figure sorts banks by their deposits, total liabilities, book value of equity, and loans in figures E.9a, E.9b, E.9c, and E.9d, 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.

Appendix F Disasters & Deposit Growth

F.1 Robustness

Table F.1: Disaster Shock and Deposit Growth with Control of Lagged Shocks

$\Delta ln(Deposits)_{c,t}$	(1)	(2)	(3)
Disaster Shock$_{c,t-1}$	-0.0144***	-0.0150***	-0.0153***
	(0.0043)	(0.0044)	(0.0045)
Disaster Shock$_{c,t-2}$		-0.0152***	-0.0156***
		(0.0046)	(0.0048)
Disaster Shock$_{c,t-3}$			-0.0085
			(0.0052)
County FE	✓	✓	✓
State-Year FE	✓	✓	✓
# Obs	79,884	79,884	79,884
R^2	0.2031	0.2034	0.2034

Note: This table uses the Summary of Deposits (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 span from 1998 to 2019. 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.

F.2 How Do Natural Disasters Affect Bank Deposits?

Table F.2: Disasters and Household Income

HH Income	(1)	(2)	(3)	(4)
Damage per Capita	-0.0306***	-0.0172***	-0.0030*	-0.0037*
	(0.0020)	(0.0021)	(0.0018)	(0.0019)
Household FE			✓	✓
Year FE		✓		✓
# Obs	251,088	251,088	251,088	251,088
Pseudo R^2	0.0015	0.0430	0.8637	0.8640

Note: This table uses annual survey data on household family income from the Community Population Survey from 1994 to 2019 and reports the estimated coefficient β in the following specification:

$$\text{HH Income}_{h,s,t} = \beta \times \text{Disaster Shock}_{s,t-1} + \theta_h + \theta_t + \varepsilon_{h,s,t}$$

where h denotes the household, s denotes the state and t indicates the year. HH Income is the total family income for household h in state s in year t. The independent variable, Disaster Shock$^*_{s,t-1}$, is the dollar amount of property damage per capita from natural disasters in state s and year $t-1$ standardized to a mean of zero and standard deviation of one. The outcome variable is winsorized at 1% level. The results are from a Poisson regression by pseudo maximum likelihood. Standard errors clustered at the county level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

F.3 Case Study: Long-Term Economic Effects of Hurricane Katrina

Figure F.1: Hurricane Katrina and Six Flags New Orleans

(a) Before

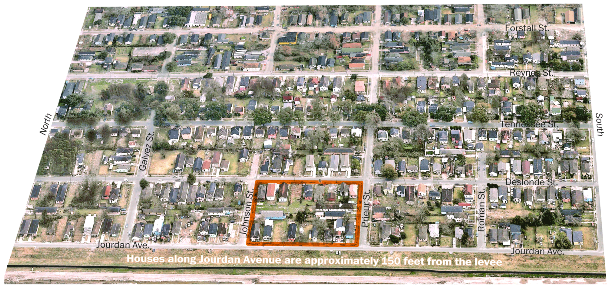
(b) After

(c) Before

(d) After

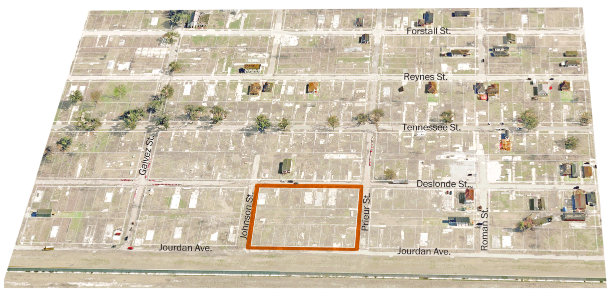
Note: This figure displays images of the Six Flags New Orleans, before and after Hurricane Katrina. Panels (a) and (c) present photos before the hurricane. Panels (b) and (d) present photos after the hurricane. The images in panel (a), (b), and (c) are reproduced from the New Orleans Advocate. The image in panel (d) is from Yahoo News. (Source: The New Orleans Advocate; Yahoo! News).

Figure F.2: Hurricane Katrina and the Lower Ninth Ward, New Orleans



(a) November 2, 2004

(b) September 9, 2005



(c) January 20, 2008

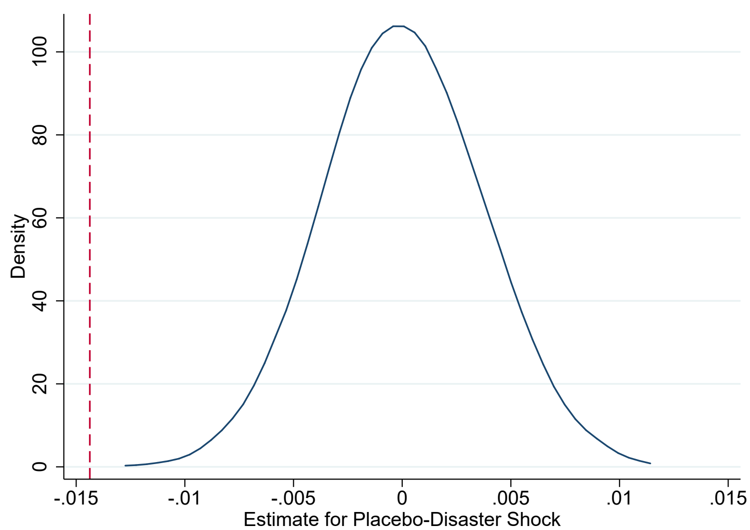
(d) January 31, 2015

Note: This figure displays aerial images of the Lower Ninth Ward in New Orleans following Hurricane Katrina's impact on the neighborhood in August 2005. Panels (a), (b), (c) and (d) show images of the same area on November 2, 2004; September 9, 2005; January 20, 2008; and January 31, 2015, respectively. Within the red rectangle, there were 18 structures before Katrina. The hurricane destroyed all of these structures in 2005, and 8 structures were rebuilt over the following 10 years. These images are reproduced from the Washington Post. (Source: The Washington Post).

F.4 Placebo Test: Disaster Shocks and Deposit Growth

We conduct a placebo test to validate that the relationship between disaster shocks and deposit growth is not spurious. We estimate equation 2, 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 F.3 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 -0.0112 to 0.0099 with a standard deviation of 0.0034. The dashed red line denotes the location of the coefficient of the interaction term from column 6 of Appendix Table 2. None of the 1,000 simulated placebo β values lie to the left of the dashed red line. Therefore, 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 F.3: Disaster Shock and Deposit Growth: Placebo Test



Min	p1	p5	p25	p50	p75	p95	p99	Max	Mean	St Dev
-0.0112	-0.0077	-0.0057	-0.0022	-0.0001	0.0024	0.0056	0.0082	0.0099	0.0000	0.0034

Notes: This figure uses the Summary of Deposits (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:

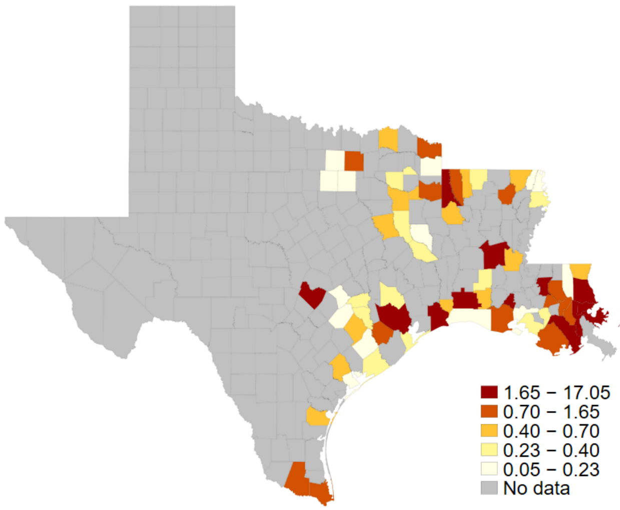
$$\Delta ln(Deposit)_{c,t} = \beta \times \text{Placebo Disaster Shock}_{c,t-1} + \theta_c + \theta_{s(c \in s),t} + \varepsilon_{c,t}$$

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 2019. 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 Table 2.

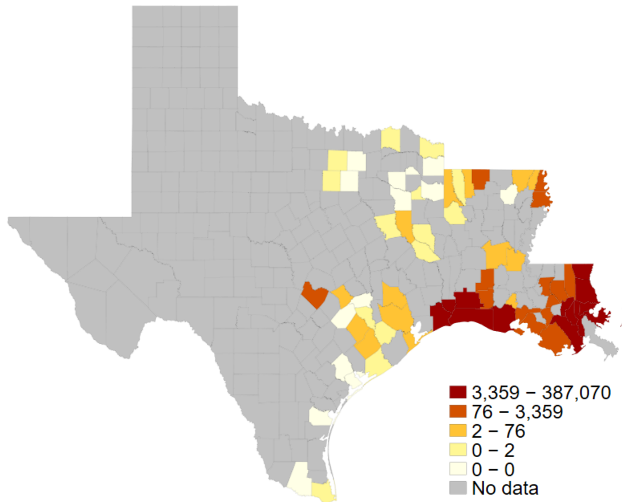
F.5 Case Study: Capital One (erstwhile Hibernia) & Hurricane Katrina

Figure F.4: Capital One Deposit Share and Damages Per Capita in 2005

(a) Deposit Share

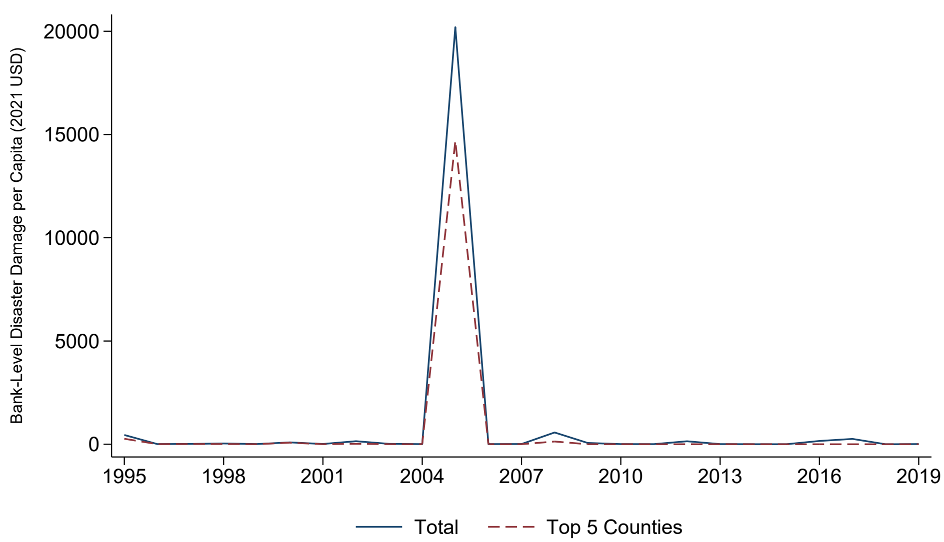


(b) Damage per Capita



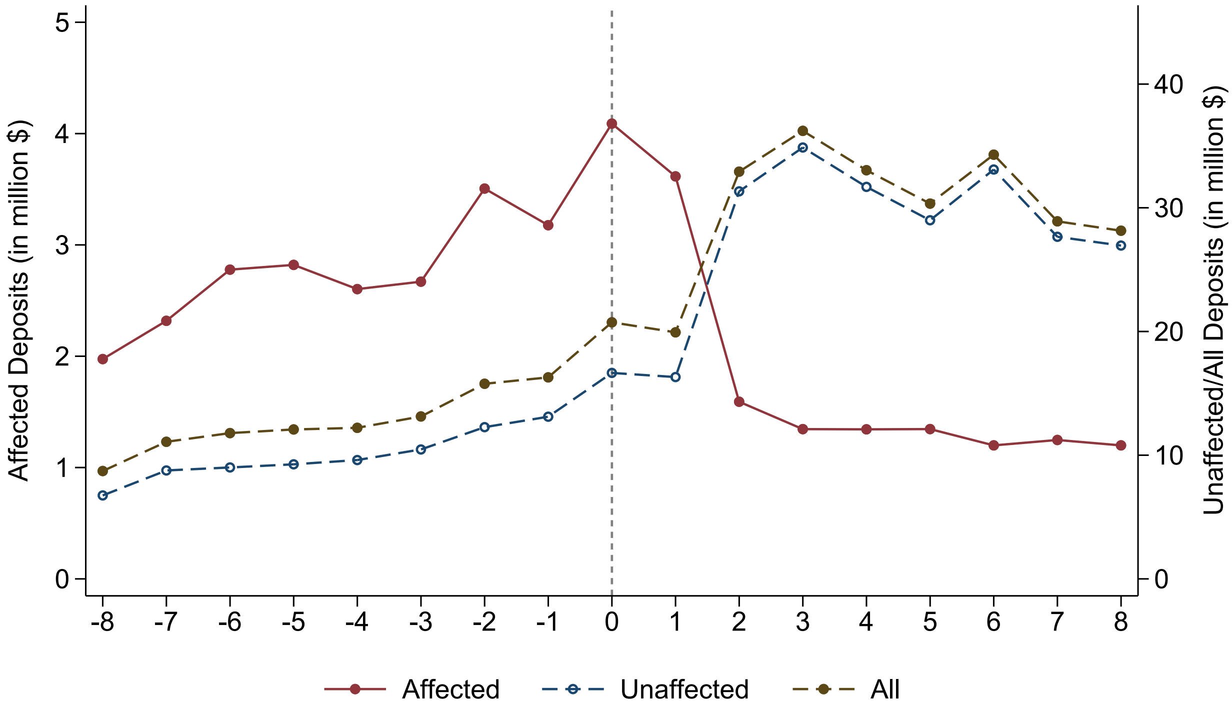
The figure presents the county heatmap for Capital One's deposit share (Figure F.4a) and the county heatmap for property damages per capita in 2021 USD (Figure F.4b). "No data" in the legend indicates that Hibernia did not operate in that area in 2005. Capital One Bank was known as Hibernia National Bank before 2006.

Figure F.5: Time-Series Bank-Level Shock for Capital One



This figure compares the total bank-level shock in 2005 to the bank-level shock constructed from the top 5 counties. Capital One Bank was known as Hibernia National Bank before 2006.

Figure F.6: Capital One Deposit Growth for Affected and Unaffected Counties

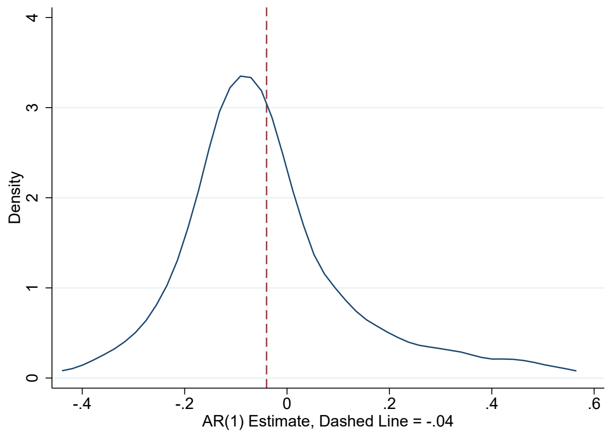


The figure shows Capital One's total deposits (millions of $) from 2000 to 2014. We use the *uninumbr* identifier from the FDIC Summary of Deposits Data to identify the unique branch number. We restrict our sample to all Capital One (erstwhile Hibernia) branches reported between 1994 and 2005. We first compute the total deposits by county in each year. We then identify "affected" and "unaffected" counties. Affected counties are defined as those experiencing per capita property damage at or above the 95th percentile in 2005, while unaffected counties include all other counties. Capital One was known as Hibernia National Bank before 2006.

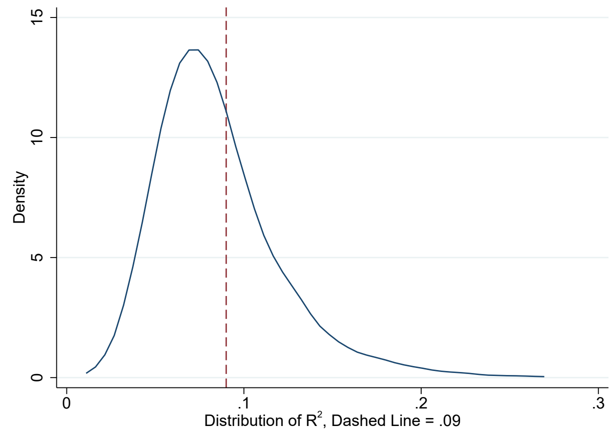
Appendix G Granular Shocks & Aggregate Fluctuations

G.1 Properties of Granular Shock

Figure G.1: 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 G.1a plots the kernel density of AR(1) coefficient for each bank's disaster shock. Figure G.1b 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 G.1a) and R^2 (Figure G.1b).

Table G.1: Orthogonality of Bank Characteristics to Bank-Level Disaster Shock

Dep Var: $\Gamma_{b,t}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\ln(\text{Assets})_{b,t-1}$	-0.0107								-0.0078	-0.1013
	(0.0085)								(0.0142)	(0.0700)
$\text{Loan/Assets}_{b,t-1}$		-0.0149*							-0.0200**	0.0239
		(0.0088)							(0.0096)	(0.0202)
$\text{Equity/Assets}_{b,t-1}$			0.0004						0.0020	-0.0015
			(0.0115)						(0.0110)	(0.0199)
$\text{Cash/Assets}_{b,t-1}$				-0.0043					-0.0091*	-0.0015
				(0.0047)					(0.0054)	(0.0116)
$\text{Deposits/Assets}_{b,t-1}$					0.0055				0.0043	0.0036
					(0.0095)				(0.0146)	(0.0125)
$\text{Hedge/Assets}_{b,t-1}$						0.0062***			0.0045	-0.0033
						(0.0016)			(0.0033)	(0.0024)
$\text{Div/Assets}_{b,t-1}$							-0.0072		-0.0093	-0.0181**
							(0.0068)		(0.0073)	(0.0090)
$\text{Income/Assets}_{b,t-1}$								0.0053	0.0090	0.0154
								(0.0067)	(0.0076)	(0.0146)
Bank FE										✓
Year FE										✓
# Obs	10,894	10,894	10,894	10,894	10,894	10,894	10,894	10,894	10,894	10,894
R^2	0.0001	0.0002	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0005	0.0677

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 span from 1997 to 2019. The dependent variable is the bank-level disaster shock $\Gamma_{b,t}$. The independent variables $\text{Bank-Characteristics}_{b,t}$ 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). Columns 9 and 10 use all the bank characteristics mentioned above. All variables are standardized to a mean of zero and standard deviation of one. All explanatory variables are 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 G.2: Aggregate Shock and Major Disasters

Quarter	Major Disaster #1	Affected States	Major Disaster #2	Affected States	Aggregate Bank Shock (Γ_t)	Insurance Payout (2020 Billion $)
1996Q3	Hurricane Fran	NC			29.07	2.63
1999Q3	Hurricane Floyd	NC			27.17	2.05
2001Q1	Nisqually earthquake	WA			21.57	0.44
2004Q3	Hurricane Ivan	FL, AL	Hurricane Jeanne	FL	83.88	14.40
2005Q3	Hurricane Katrina	LA, MS			284.34	87.96
2005Q4	Hurricane Wilma	FL			47.98	13.42
2008Q2	June 2008 Midwest floods	IN, IA, WI			9.67	0.60
2008Q3	Hurricane Ike	LA, TX			48.99	17.36
2011Q2	Mississippi River floods	MS, MO	Super Outbreak (Tornado)	AL, MS, TN	24.76	7.60
2012Q4	Hurricane Sandy	NJ			71.89	28.88
2017Q3	Hurricane Harvey	TX			217.38	63.11
2018Q4	California wildfires	CA	Hurricane Michael	FL	33.89	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 9a. The table reports the natural disasters, states affected by the disasters and the insurance payout associated with these disasters.

G.2 Granular Shocks & Deposit Growth

Table G.3: Granular Shock and Deposit Growth

Dep Var: Deposit growth	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Γ^*_t	0.0026						0.0024	0.0029
	(0.0037)						(0.0036)	(0.0045)
Γ^*_{t-1}		-0.0058*					-0.0068**	-0.0057*
		(0.0034)					(0.0029)	(0.0032)
Γ^*_{t-2}			-0.0018				-0.0020	0.0070
			(0.0022)				(0.0020)	(0.0089)
Γ^*_{t-3}				0.0020			0.0006	0.0114
				(0.0023)			(0.0017)	(0.0109)
Γ^*_{t-4}					0.0018		0.0010	0.0118
					(0.0018)		(0.0017)	(0.0118)
Γ^*_{t-5}						-0.0095***	-0.0101***	0.0000
						(0.0027)	(0.0027)	(0.0102)
Constant	1.6633***	1.5815***	1.6248***	1.6955***	1.6914***	1.5656***	1.5044***	
	(0.1201)	(0.1266)	(0.1175)	(0.1098)	(0.1194)	(0.1061)	(0.1393)	
Year FE								✓
# Obs	102	101	100	99	98	97	97	96
R^2	0.0044	0.0220	0.0021	0.0028	0.0021	0.0622	0.1026	0.1217

Note: This table uses quarterly deposit growth growth series from 1994Q3 to 2019Q4 and reports the estimated coefficient β_h in the following regression specification:

$$\frac{Dep_t - Dep_{t-1}}{Dep_{t-1}} \times 100 = \alpha + \beta_h \times \Gamma^*_{t-h} + \varepsilon_t$$

where t indicates quarter-year and h indicates the number of lags. $\frac{Dep_t - Dep_{t-1}}{Dep_{t-1}}$ is the quarterly deposit growth rate, and Γ^*_{t-h} denotes the granular deposit shock and its lags. Newey-West heteroskedasticity and autocorrelation (8 quarter lags) robust standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

G.3 Direct Effect of Natural Disasters

Table G.4: Granular Deposit Shock, Loss due to Disasters, and Aggregate Fluctuations

Dep Var: GDP growth	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Γ^*_{t-1}	-0.0065**		-0.0061**		-0.0061**		-0.0061**
	(0.0027)		(0.0027)		(0.0027)		(0.0027)
ln(Total Home Loss)$_{t-1}$		0.1147	0.0983			0.0107	0.0181
		(0.1458)	(0.1436)			(0.5204)	(0.5213)
ln(Total Business Loss)$_{t-1}$				0.1019	0.0869	0.0931	0.0719
				(0.1261)	(0.1247)	(0.4506)	(0.4544)
Constant	0.9988***	-1.3560	-1.0764	-0.9956	-0.7569	-1.0422	-0.8357
	(0.1347)	(3.0933)	(3.0501)	(2.5575)	(2.5331)	(3.4188)	(3.3595)
# Obs	75	75	75	75	75	75	75
R^2	0.0075	0.0032	0.0098	0.0034	0.0099	0.0034	0.0099

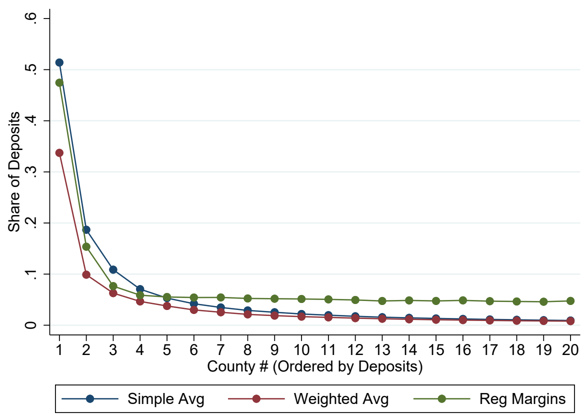
Note: This table uses quarterly GDP series from 2001Q1 to 2019Q4 and reports the estimated coefficient β in the following specification:

$$\frac{GDP_t - GDP_{t-1}}{GDP_{t-1}} \times 100 = \alpha + \beta_1 \times \Gamma^*_{t-1} + \beta_2 \times ln(\text{Total Home Loss})_{t-1} + \beta_3 \times ln(\text{Total Business Loss})_{t-1} + \varepsilon_t$$

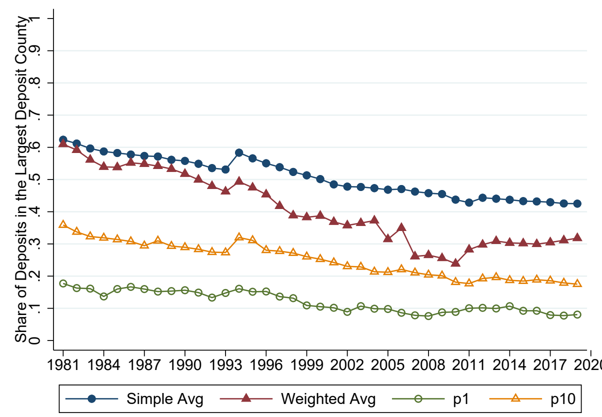
where t indicates quarter-year. $\frac{GDP_t - GDP_{t-1}}{GDP_{t-1}} \times 100$ is the quarterly GDP growth rate, Γ^*_t is the granular deposit shock. ln(Total Home Loss) and ln(Total Business Loss) are the natural logarithm transformed total dollar amount of home and business losses verified by the Small Business Administration, respectively. These variables are identified in the US Small Business Administration (SBA) Disaster Loan Program. Newey-West heteroskedasticity and autocorrelation (8 quarter lags) robust standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

G.4 Extending Baseline to Historical Data

Figure G.2: Geographic Concentration of Deposits: 1981-2019



(a) Cross Section



(b) Time Series

This figure uses the Summary of Deposits (SOD) data from 1981 to 2019 and illustrates the geographic concentration of bank deposits. Figure G.2a 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 raises 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 G.2b reports the average deposit share of the counties with the largest deposit share (i.e., county #1) by year from 1994 to 2019. The time series plots 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.

Table G.5: Granular Shock and Aggregate Fluctuations: 1981-2019

Dep Var: GDP growth	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
				All				<1994	>1994	All	<1994	>1994
Γ^*_t	-0.0080*						-0.0075**	0.0008	-0.0110**	-0.0135**	-0.0035	-0.0169*
	(0.0044)						(0.0035)	(0.0020)	(0.0045)	(0.0066)	(0.0045)	(0.0096)
Γ^*_{t-1}		-0.0077**					-0.0083**	-0.0145**	-0.0090***	-0.0144***	-0.0178**	-0.0158**
		(0.0039)					(0.0038)	(0.0058)	(0.0033)	(0.0048)	(0.0080)	(0.0072)
Γ^*_{t-2}			0.0158***				0.0155***	0.0224***	0.0108***	0.0057	0.0090	0.0017
			(0.0035)				(0.0035)	(0.0027)	(0.0027)	(0.0086)	(0.0295)	(0.0103)
Γ^*_{t-3}				-0.0014			-0.0016	-0.0076***	0.0005	-0.0122	-0.0222	-0.0085
				(0.0057)			(0.0051)	(0.0020)	(0.0094)	(0.0104)	(0.0295)	(0.0196)
Γ^*_{t-4}					-0.0045		-0.0049	-0.0019	-0.0083	-0.0147*	-0.0159	-0.0171
					(0.0054)		(0.0045)	(0.0032)	(0.0081)	(0.0088)	(0.0303)	(0.0125)
Γ^*_{t-5}						-0.0095***	-0.0100***	-0.0111**	-0.0074	-0.0200**	-0.0253	-0.0163
						(0.0036)	(0.0034)	(0.0054)	(0.0051)	(0.0088)	(0.0316)	(0.0123)
Constant	1.2346***	1.2288***	1.4442***	1.3139***	1.2682***	1.2264***	1.1551***	1.6269***	0.8695***			
	(0.1145)	(0.1140)	(0.1246)	(0.1106)	(0.1194)	(0.1217)	(0.1140)	(0.2211)	(0.1113)			
Year FE										✓	✓	✓
# Obs	154	153	152	151	150	149	149	45	100	148	44	100
R^2	0.0093	0.0085	0.0360	0.0003	0.0031	0.0135	0.0741	0.1570	0.0574	0.0911	0.1772	0.0754

Note: This table uses quarterly GDP growth series from 1981 through 2019 and reports the estimated coefficient β_h in the following regression specification:

$$\frac{GDP_t - GDP_{t-1}}{GDP_{t-1}} \times 100 = \alpha + \beta_h \times \Gamma^*_{t-h} + \varepsilon_t$$

where t indicates quarter-year and h indicates the number of lags. $\frac{GDP_t - GDP_{t-1}}{GDP_{t-1}}$ is the quarterly GDP growth rate, and Γ^*_{t-h} denotes the granular deposit shock and its lags. Newey-West heteroskedasticity and autocorrelation (8 quarter lags) robust standard errors are reported in parentheses. Column 8 presents the coefficients from estimating the sample for the period 1981 to 1993, prior to the passage of the Riegle-Neale Banking Branching Efficiency Act. Column 9 shows the coefficients from estimating the sample post-1994. Columns 10 through 12 replicate columns 7 through 9 with year fixed effects included. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Appendix H Mechanism

H.1 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. Appendix Table H.1 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 (2023). 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).

Table H.1: Small Business Lending and Deposit Shocks: Exclusion of Credit Card Banks

Dep Var: $\Delta ln(Lending)_{b,c,t}$	(1)	(2)
$\Gamma_{b,t-1}$	-0.0082***	-0.0100***
	(0.0022)	(0.0021)
County × Year FE	✓	✓
Bank × County FE	✓	✓
# Obs	529,644	613,600
R^2	0.2053	0.1902

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 span from 1997 to 2019. 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, standardized to a mean of zero and standard deviation of one. 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 (2023). 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 outcome variables used in this table are winsorized at the 1% level. Standard errors clustered at the bank-county level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

H.2 Bank Frictions and the Transmission of Idiosyncratic Shocks

Table H.2: 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. $CD_{b,t-1} \times \Gamma_{b,t-1}$	-0.0145***	-0.0179***	-0.0161***	-0.0234***	-0.0118***	-0.0227***
	(0.0034)	(0.0035)	(0.0036)	(0.0037)	(0.0037)	(0.0039)
High Sh. $CD_{b,t-1}$	0.0156***	0.0183***	0.0567***	0.0204***	0.0578***	0.0593***
	(0.0022)	(0.0022)	(0.0037)	(0.0023)	(0.0040)	(0.0042)
$\Gamma_{b,t-1}$	-0.0028	-0.0033	-0.0033	-0.0043*	-0.0029	-0.0040
	(0.0021)	(0.0021)	(0.0022)	(0.0023)	(0.0022)	(0.0024)
County FE		✓	✓			
Year FE		✓	✓			
County × Year FE				✓		✓
County × Bank FE					✓	✓
Bank FE			✓			
# Obs	593,600	593,600	593,600	593,600	593,600	593,600
R^2	0.0001	0.0102	0.0165	0.1217	0.0720	0.1932

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 span from 1998 to 2019. 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, standardized to a mean of zero and standard deviation of one. 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 outcome variables are winsorized at the 1% level. Standard errors clustered at the bank-county level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table H.3: 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$_{b,t-1} \times \Gamma_{b,t-1}$	-0.1349***	-0.1730***	-0.1577***	-0.1813***	-0.1232***	-0.1663***
	(0.0106)	(0.0113)	(0.0120)	(0.0118)	(0.0117)	(0.0130)
Low Tier 1 Ratio$_{b,t-1}$	0.0001	-0.0011	-0.0232***	-0.0028	-0.0140***	-0.0224***
	(0.0022)	(0.0022)	(0.0041)	(0.0023)	(0.0045)	(0.0047)
$\Gamma_{b,t-1}$	-0.0039**	-0.0048***	-0.0045**	-0.0067***	-0.0032*	-0.0063***
	(0.0017)	(0.0017)	(0.0018)	(0.0019)	(0.0018)	(0.0020)
County FE		✓	✓			
Year FE		✓	✓			
County × Year FE				✓		✓
County × Bank FE					✓	✓
Bank FE			✓			
# Obs	593,600	593,600	593,600	593,600	593,600	593,600
R^2	0.0003	0.0106	0.0166	0.1220	0.0719	0.1932

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 span from 1998 to 2019. 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, standardized to a mean of zero and standard deviation of one. $\lambda_{b,t-1}$ 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 outcome variables are winsorized at the 1% level. Standard errors clustered at the bank-county level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table H.4: Core vs Non-Core Markets by the Presence of Branch

Dep Var: $\Delta ln(Lending)_{b,c,t}$	(1)	(2)	(3)	(4)	(5)	(6)
$NC_{b,c,t-1} \times \Gamma_{b,t-1}$	-0.0095***	-0.0099***	-0.0105***	-0.0091***	-0.0087***	-0.0094***
	(0.0028)	(0.0028)	(0.0028)	(0.0033)	(0.0030)	(0.0034)
$NC_{b,c,t-1}$	0.0911***	0.1004***	0.1024***	0.0977***	0.4062***	0.3831***
	(0.0017)	(0.0018)	(0.0020)	(0.0019)	(0.0078)	(0.0084)
$\Gamma_{b,t-1}$	-0.0003	-0.0014	-0.0001	-0.0038*	0.0000	-0.0028
	(0.0016)	(0.0016)	(0.0016)	(0.0023)	(0.0017)	(0.0023)
County FE		✓	✓			
Year FE		✓	✓			
Bank FE			✓			
County × Year FE				✓		✓
County × Bank FE					✓	✓
# Obs	593,600	593,600	593,600	593,600	593,600	593,600
R^2	0.0015	0.0117	0.0177	0.1230	0.0761	0.1959

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 span from 1998 to 2019. 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, standardized to a mean of zero and standard deviation of one.. $NC_{b,c,t-1}$ 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 outcome variables are winsorized at the 1% level. Standard errors clustered at the bank-county level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table H.5: Core vs Non-Core Markets by the Share of Lending

Dep Var: $\Delta ln(Lending)_{b,c,t}$	(1)	(2)	(3)	(4)	(5)	(6)
$NC_{b,c,t-1} \times \Gamma_{b,t-1}$	-0.0086**	-0.0105***	-0.0121***	-0.0088**	-0.0096**	-0.0110***
	(0.0037)	(0.0038)	(0.0038)	(0.0040)	(0.0041)	(0.0043)
$NC_{b,c,t-1}$	0.5321***	0.5350***	0.6072***	0.5337***	1.0869***	1.1499***
	(0.0030)	(0.0031)	(0.0034)	(0.0031)	(0.0053)	(0.0052)
$\Gamma_{b,t-1}$	-0.0021	-0.0035**	-0.0015	-0.0056***	-0.0022	-0.0034*
	(0.0016)	(0.0016)	(0.0017)	(0.0020)	(0.0016)	(0.0020)
County FE		✓	✓			
Year FE		✓	✓			
Bank FE			✓			
County × Year FE				✓		✓
County × Bank FE					✓	✓
# Obs	593,600	593,600	593,600	593,600	593,600	593,600
R^2	0.0575	0.0678	0.0808	0.1766	0.1802	0.3003

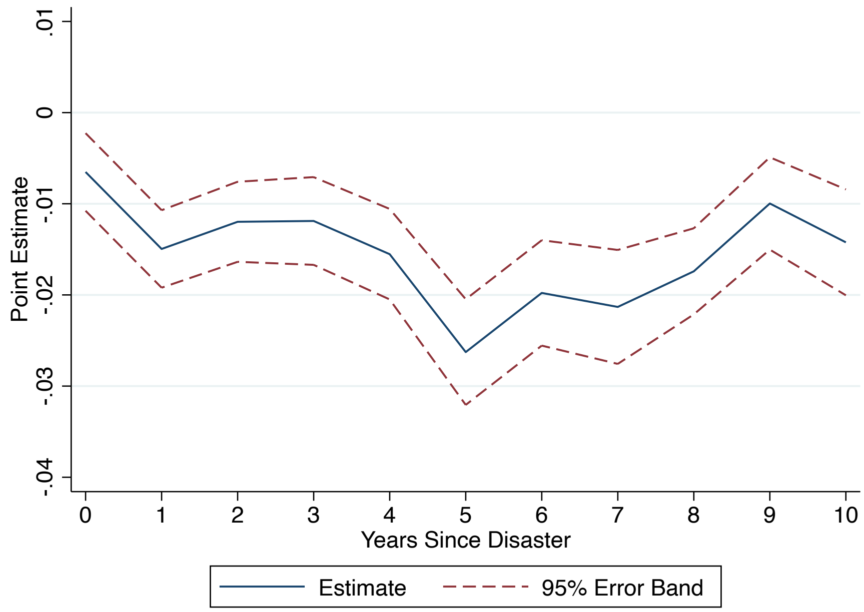
Note: This table uses small business lending data collected under the Community Reinvestment Act (CRA) and reports the estimated coefficient β's in the following specification:

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

where b, c and t indicate bank, county, and year, respectively. The data span from 1997 to 2019. 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, standardized to a mean of zero and standard deviation of one. $NC_{b,c,t-1}$ 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 outcome variables are winsorized at the 1% level. Standard errors clustered at the bank-county level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

H.3 Long-Run Responses to Deposit Shocks

Figure H.1: Long-Run Response of Small Business Lending to Disaster Shocks

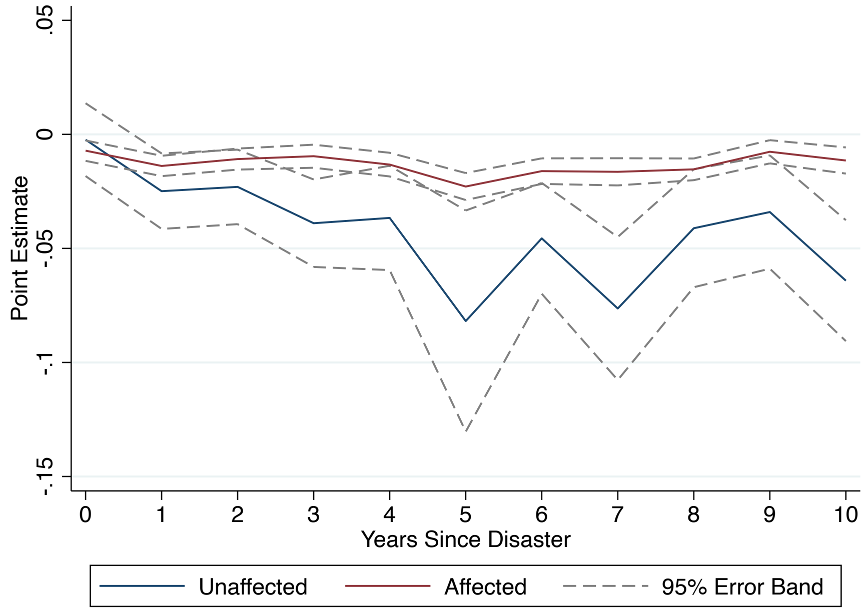


Note: This figure uses small business lending data collected under the Community Reinvestment Act (CRA) and plots the estimated coefficient β^h's in the following specification:

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

where b, c and t indicate bank, county, and year, respectively. The data span from 1997 to 2019. 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 confidence interval is computed from standard errors clustered by bank-county. 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.

Figure H.2: Disaster Affected and Unaffected Counties

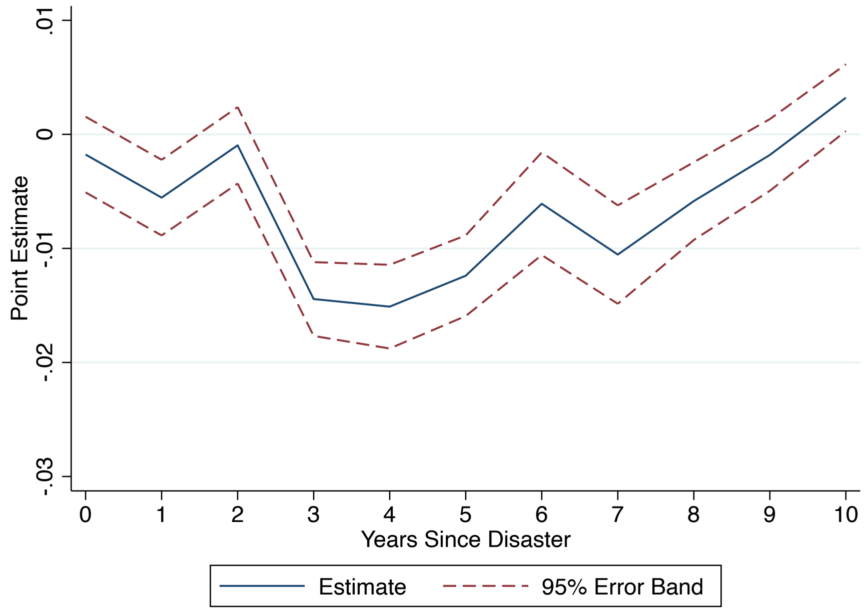


Note: This figure uses small business lending data collected under the Community Reinvestment Act (CRA) to plot the estimated coefficient β^h's in the following specification for disaster affected and unaffected counties:

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

where b, c and t indicate bank, county, and year, respectively. The CRA and HMDA data span from 1997 to 2019, and from 1995 to 2019, respectively. 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 $\times$ county and county $\times$ year fixed effects, respectively. All variables are standardized to mean zero and standard deviation of one and winsorized at the 1% level. The confidence interval is computed from standard errors clustered by bank-county. 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.

Figure H.3: 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 span from 1995 to 2019. $\Delta ln(Lending)_{b,c,t}$ 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 confidence interval is computed from standard errors clustered at the bank-county level. The dashed red line plots the 95% confidence interval for the point estimate β_h's.