The Regional and the Aggregate Effects of Bank Funding Shocks*

Shohini Kundu† Seongjin Park‡ Nishant Vats§

Abstract

How large is the aggregate effect of bank credit supply on economic growth, and how much of it can cross-sectional estimates recover? We construct granular bank funding shocks by interacting local disasters with banks' geographically concentrated deposit bases. Using the same variation, we estimate a regional credit-supply elasticity of 0.088 and measure the aggregate lending and output responses. The regional loan-quantity channel explains only 9% of the aggregate output response. The remaining 91% captures aggregate adjustment outside the channel identified by regional variation. Our results suggest that well-identified regional credit-supply estimates may capture only a small share of the aggregate response.

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†Anderson School of Management, UCLA and CEPR. Email: shohini.kundu@anderson.ucla.edu

‡Nanyang Business School, NTU Singapore. Email: seongjin.park@ntu.edu.sg

§Olin Business School, Washington University in St Louis. Email: vats@wustl.edu

1 Introduction

What do regional estimates of the real effects of bank credit supply imply for the aggregate effects of bank funding shocks? A large empirical literature uses shocks to banks to identify how changes in credit supply affect firms, borrowers, and local economic activity.[1] These studies compare regions, firms, or borrowers that differ in their exposure to lender-level shocks. This cross-sectional variation separates changes in credit supply from economic conditions common across units, identifying credible estimates of the causal effect of bank credit on local economic activity.

These well-identified cross-sectional estimates have fundamentally shaped our understanding of how shocks to banks transmit to the real economy. A natural question is what they imply for the economy as a whole: how does total output respond when a shock changes the funding capacity of the banking system? The challenge is inherent in the source of identification. Cross-sectional designs recover the effect of credit supply by comparing more exposed units with less exposed units and, therefore, difference out changes that are common across them. This common component is precisely what the cross-sectional comparison is designed to remove, but it remains part of the aggregate response to the underlying funding shock. The common component reflects equilibrium adjustments that occur throughout the economy as the funding shock is transmitted, including aggregate changes in wages and prices, adjustments in bank and borrower balance sheets, and substitution across sources of finance. To the extent that these responses are common across regions, they affect aggregate output without appearing in the cross-sectional estimate. This is the missing-intercept problem: a well-identified regional credit-supply elasticity need not recover the full aggregate response to the funding shock that generated the underlying variation (Nakamura and Steinsson, 2018; Chodorow-Reich, 2020; Guren et al., 2021a; Huber, 2023; Wolf, 2023; Sraer and Thesmar, 2018; Mian et al., 2023; Matthes et al., 2025).

This paper develops a framework that links regional estimates of bank credit supply to the aggregate effects of the underlying bank funding shock. The model provides a unified representation of the regional and aggregate responses and establishes how the effect identified from relative changes in local bank credit maps into the economy-wide response to the same funding disturbance.

At the regional level, bank credit affects output by financing production and influencing firms' employment decisions. Changes in bank lending, however, need not translate one for one into either

[1] See, for example, Peek and Rosengren (1997, 2000); Ashcraft (2005); Khwaja and Mian (2008); Paravisini (2008); Leary (2009); Loutskina and Strahan (2009, 2015); Ivashina and Scharfstein (2010); Chava and Purnanandam (2011); Cornett et al. (2011); Puri et al. (2011); Cetorelli and Goldberg (2012); Schnabl (2012); Jiménez et al. (2012); Gilje et al. (2016); Jiménez et al. (2017); De Haas and Van Horen (2013); Becker and Ivashina (2014); Iyer et al. (2014); Nanda and Nicholas (2014); Chodorow-Reich (2014); Ioannidou et al. (2015); Ivashina et al. (2015); Paravisini et al. (2015); Ramcharan et al. (2016); Cortés and Strahan (2017); Di Maggio and Kermani (2017); Jensen and Johannesen (2017); Berton et al. (2018); Huber (2018); Amiti and Weinstein (2018); Gropp et al. (2019); Cortés et al. (2020); Hale et al. (2020); Beck et al. (2021); Doerr and Schaz (2021); Favara et al. (2021); Di Giovanni et al. (2022); Xu (2022); Blattner et al. (2023); Paravisini et al. (2023); Bergman et al. (2025); Greenwald et al. (2025); Kundu and Vats (2026).

productive activity or employment. Firms can partially replace bank credit with retained earnings, equity, trade credit, and non-bank finance, while employment can adjust only partially to changes in credit conditions. The resulting regional credit-supply elasticity therefore measures how local output responds in equilibrium to a funding-induced change in bank lending.

Aggregating across regions then establishes what this regional elasticity predicts for the economy as a whole. The model decomposes the aggregate output response into two components: the response implied by applying the regional credit-supply elasticity to the aggregate change in bank lending, and the equilibrium adjustment that is common across regions and therefore absent from the regional comparison. The latter is the missing intercept.

The framework thus establishes the objects that must be estimated to connect regional evidence to the aggregate response. Doing so requires measuring the regional and aggregate responses to the same underlying funding disturbance. We accomplish this using a common source of bank funding variation. The regional design estimates how local output responds to funding-induced changes in local bank credit, while the aggregate design estimates how total bank lending and aggregate output respond to the same funding shock. The model then combines these estimates to recover the missing intercept.

Our central finding is that the regional loan-quantity channel accounts for only a small share of the aggregate response. The regional credit-supply elasticity is precisely estimated and economically meaningful, but applying it to the aggregate contraction in bank lending accounts for only approximately 9 percent of the aggregate decline in output. The remaining 91 percent is the missing intercept, the component of the aggregate response not accounted for by the loan-quantity channel implied by the regional elasticity. Under the funding-specificity condition, this component captures equilibrium adjustment induced by the bank funding shock that is not recovered by the regional loan-quantity channel. Thus, establishing a causal effect of bank credit on local economic activity does not by itself establish that the same channel accounts for a quantitatively large share of the economy-wide response to the underlying shock.

Estimating both sides of this decomposition within a common empirical setting poses a particular identification challenge. Regional identification requires idiosyncratic shocks that generate differential exposure across locations, whereas aggregate estimation requires those same shocks to carry sufficient economic weight to move national outcomes. We obtain both from the interaction of natural disasters with the geography of bank deposits. Deposits are geographically concentrated within banks, so local disasters can generate meaningful bank-level funding shocks when they strike locations that are important to a bank's deposit base. The banking system is itself granular, hence, shocks to economically important banks need not wash out in the aggregate. These two layers of concentration allow the same local funding disturbances to generate both cross-sectional variation across counties and time-series variation in the

aggregate economy, following the granular logic of Gabaix (2011).

We begin by documenting the first ingredient, the geographic concentration of bank deposits. Using branch-level Summary of Deposits data from 1994 to 2019, we find that the single county providing the largest share of a bank's deposits accounts, on average, for approximately 30 percent of its deposit base. Geographic concentration is widespread and remains substantial among the largest U.S. banks, even though these institutions operate across many markets. This concentration makes banks differentially exposed to local economic conditions in the places from which they raise their funding. When a substantial fraction of a bank's deposits comes from a small set of locations, a shock to one of those locations can become a meaningful bank-level funding shock.

We examine the geographic measurement of deposits in detail. The concentration pattern remains after adjustments for headquarters and main-office reporting, tax-related deposit placement, mergers and acquisitions, non-local deposits, large operational branches, and counties in which banks have substantial lending operations. Deposits in banks' largest deposit counties are also distributed across multiple branches. A separate measure based on the geographic distribution of physical branches, which does not depend on the assignment of deposit balances across locations, displays similar concentration. These exercises establish geographic concentration as an economically meaningful feature of banks' funding bases.

The second ingredient is a source of local variation in that funding base. Natural disasters provide such variation. We find that disasters reduce local deposits substantially and persistently. A one-standard-deviation disaster shock is associated with a 0.09 to 0.11 percentage-point decline in county deposit growth, comparable to the 25th percentile of the deposit-growth distribution, and the effect remains negative for years after the initial event. The persistence of the response makes disaster exposure useful for studying changes in bank funding rather than transitory fluctuations in local liquidity.

The underlying economic responses are consistent with this funding channel. Disasters reduce local employment, establishments, and household income, thereby reducing resources available for deposit funding. Migration out of affected counties increases only modestly. At the bank level, institutions whose important deposit-supplying counties experience disasters suffer declines in total deposits, concentrated in savings and time deposits. Thus, local disaster exposure translates into a reduction in the total funding base of the banks that depend on the affected locations. The aggregate funding shock produces the same pattern, predicting a subsequent decline in aggregate deposit growth.

We combine these facts to construct bank-level funding shocks. For each bank, we weight county-level disaster damage by the county's lagged importance to the bank's deposit base. A disaster therefore generates a larger funding shock when it strikes a location supplying a larger share of the bank's deposits. Banks exposed to the same national sequence of disasters consequently experience different

funding shocks according to the predetermined geography of their deposit bases. The construction builds on the bank-shock approach of Amiti and Weinstein (2018); Galaasen et al. (2023); Kundu and Vats (2026) and the granular instrumental-variables methodology of Gabaix and Koijen (2024), while using disaster-induced deposit losses as the source of bank-specific funding variation.

We use these funding shocks in two complementary empirical designs. The regional design asks how credit supply and output respond in a county when the banks serving that county experience funding shocks elsewhere. We restrict the identifying disasters to locations outside the county's own state, weight each disaster by its importance to the bank's deposit base, and aggregate across banks according to their importance as lenders in the destination county. The resulting instrument therefore connects funding conditions at a county's lenders to local credit supply while geographically separating the origin of the funding shock from the destination economy. This transmission through multi-market banks builds on the internal-capital-market mechanism studied by Gilje et al. (2016).

We establish this transmission directly at the bank-county level. Multiple banks serve the same county in a given year, allowing us to compare lenders with different exposure to funding shocks while holding fixed local credit demand and economic conditions. Our specification exploits variation across banks within a county-year and controls for persistent bank-county relationships. Banks more exposed to out-of-state funding shocks subsequently reduce small-business lending in the same county. The response persists beyond the initial year and remains present in counties that do not themselves experience disasters. These estimates provide direct evidence that funding shocks originating elsewhere alter the supply of credit by multi-market banks.

The county-level first stage shows that this transmission survives aggregation across local lenders. Counties whose banks experience larger funding shocks outside the state subsequently experience slower loan growth. Instrumenting county loan growth with this variation yields a regional credit-supply elasticity of approximately 0.088. This estimate implies that a one-percentage-point increase in county loan growth induced by bank funding conditions raises county nominal GDP growth by about 0.09 percentage points.

Interpreting this regional estimate as a credit-supply effect requires an exclusion restriction, but not the strong assumption that disasters outside a county's state have no effect on that county. Counties are connected across state borders through trade, migration, production networks, and other economic and social linkages, so remote disasters may affect local activity through channels unrelated to bank funding. Instead, identification requires that counties more exposed to disasters through their lenders' funding networks are not also systematically more exposed to those same disasters through real-economic linkages. The restriction would be violated, for example, if counties tend to borrow from banks whose important deposit markets are also disproportionately important trading partners or otherwise

economically connected to those counties.

We evaluate this condition directly. The bank-county evidence provides one test: county-by-year fixed effects absorb local economic conditions common to all banks serving the same county and year, including demand effects transmitted through real-economic linkages, while identification comes from differences in banks' funding exposure. At the county level, we construct measures of exposure to the same out-of-state disasters using employment, GDP, population, establishments, trade, migration, geographic distance, and social connectedness rather than banks' deposit exposures, and include these measures in the regional specification. The regional credit-supply relationship remains stable after accounting for these alternative channels of disaster exposure. Together, these tests support the interpretation that the identifying variation operates through banks' funding networks rather than through counties' broader real-economic exposure to the underlying disasters.

Having identified the regional credit-supply response, we turn to the aggregate effect of the same underlying funding disturbances. We construct an aggregate granular funding shock from the same bank-level shocks, weighting them according to banks' lagged economic importance and removing their equal-weighted component, following Gabaix and Koijen (2024). The resulting shock is large when disasters affect important deposit-supplying counties of banks that themselves account for a large share of the banking system. The construction therefore combines two layers of concentration. Geographic concentration allows local shocks to generate meaningful funding shocks within banks, while concentration across banks allows shocks to economically important institutions to survive aggregation. This mechanism connects the paper to the literature on the granular origins of aggregate fluctuations (Gabaix, 2011; Acemoglu et al., 2012; Amiti and Weinstein, 2018).

The aggregate funding shock displays economically meaningful time-series variation. Its largest realizations coincide with major disaster episodes, including Hurricanes Katrina, Sandy, and Harvey, with the size of each realization determined by the importance of the affected locations to the deposit bases of large banks. A positive granular funding shock is followed by declines in aggregate deposits, aggregate commercial and industrial lending, and aggregate GDP. The estimated responses of aggregate lending and aggregate output are approximately equal in magnitude. A one-standard-deviation funding shock is associated with a decline in quarterly GDP growth of approximately 0.26 percentage points, equivalent to roughly 23 percent of mean quarterly growth. The negative output response is also robust to allowing for richer dynamics.

Interpreting these aggregate responses as the effects of bank funding shocks requires a different identifying condition from the regional design. The aggregate regressions estimate the total response of lending and output to the funding shock itself, including equilibrium responses operating through other channels. Therefore, they do not require the regional exclusion restriction that a county's banking-network

exposure to disasters be orthogonal to its residual exposure to those disasters through non-banking real-economy linkages. Instead, identification requires that innovations in the granular shock represent changes in the funding capacity of economically important banks rather than other aggregate disturbances correlated with output. We refer to this as the *funding-specificity condition*. The construction is designed to isolate this variation by combining idiosyncratic local disasters with predetermined deposit exposures and bank size and by removing the equal-weighted component of disaster exposure. In this respect, funding specificity is an application-specific analogue of the relevance and contemporaneous-exogeneity conditions for external instruments in macroeconomics: the constructed shock must covary with the targeted bank-funding innovation while not proxying for other contemporaneous structural disturbances that independently affect aggregate activity (Stock and Watson, 2018).

We first ask whether the granular funding shock is simply capturing other sources of aggregate fluctuations. The estimated GDP response remains stable after controlling separately and jointly for oil-supply shocks, monetary-policy surprises, economic-policy uncertainty, the term spread, government-expenditure shocks, and the firm-level granular residual of Gabaix (2011). The coefficient on the granular funding shock is essentially unchanged when all six controls are included jointly. Thus, the aggregate relationship is not absorbed by these prominent macroeconomic disturbances.

The granular construction generates a distinctive prediction about bank size. If idiosyncratic funding shocks survive aggregation because a relatively small number of banks account for a disproportionate share of the banking system, then removing those banks should progressively eliminate the aggregate relationship. We test this prediction by reconstructing the shock after successively excluding the largest banks. Both the estimated GDP response and the explanatory power of the shock fall sharply once the largest banks are excluded. The aggregate relationship is therefore concentrated among precisely the institutions whose economic weight allows idiosyncratic funding shocks to survive aggregation. The bank-county evidence reinforces this interpretation: the lending contraction following a funding shock is largest among systemically important banks, so the institutions responsible for granularity are also those for which the underlying funding shocks generate the strongest credit response.

We further test the funding-specificity condition by distinguishing bank funding from other forms of geographic exposure to the same underlying disasters. Granular placebo shocks constructed from the geography of mortgage and small-business lending are economically small and statistically insignificant, while the deposit-based shock remains predictive of aggregate GDP. Granular shocks constructed from the same disasters but weighted by counties' national shares of employment, GDP, personal income, population, and establishments likewise do not absorb the funding-shock response. We obtain the same conclusion when we compare the response of GDP to aggregate disaster intensity and when we control directly for aggregate home and business losses. Finally, the relationship survives alternative treatments

of reported deposit geography, an independent construction based on the geographic distribution of bank branches, and an extension of the analysis to historical deposit data beginning in 1981. Together, these exercises support the interpretation of the aggregate variation as arising from the interaction of idiosyncratic local shocks, the geography of bank funding, and the economic importance of the affected banks.

The regional and aggregate estimates allow us to measure directly how much of the economy-wide response is captured by the regional credit-supply channel. The regional estimate tells us how much local output changes when bank credit moves because of a funding shock. The aggregate evidence tells us how much total lending and total output change following the same class of shock. Applying the regional elasticity to the aggregate contraction in bank lending gives the aggregate output response predicted by the loan-quantity channel. This channel accounts for approximately 9 percent of the observed aggregate output response. The remaining 91 percent is the missing intercept.

The decomposition has a particularly transparent interpretation in our setting because aggregate lending and aggregate output respond to the funding shock in approximately equal proportion. As a result, the regional elasticity approximately determines the share of the aggregate output response accounted for by the loan-quantity channel. For that channel to account for the entire aggregate response, local output would therefore have to respond nearly one for one to an instrument-induced change in bank credit. Such a response is unlikely when firms can substitute toward retained earnings, equity, trade credit, and non-bank finance and when employment adjusts only partially to financing conditions. Existing regional evidence likewise finds meaningful but incomplete responses of economic activity to bank credit. For example, Huber (2018) reports that firms fully dependent on Commerzbank held 20.5 percent less bank debt and had 5.3 percent lower employment after the lending cut, implying an employment-to-credit elasticity of approximately 0.26. Similarly, Berton et al. (2018) estimate an employment-to-credit-supply elasticity of approximately 0.36.

More generally, the decomposition provides a way to interpret regional credit-supply elasticities in aggregate terms. The share of the aggregate response attributable to the regional loan-quantity channel depends jointly on the regional elasticity and the relative aggregate responses of credit and output to the underlying shock. The near equality of these aggregate responses is specific to our setting; in other settings, both must be estimated to translate the regional elasticity into an aggregate prediction. The remaining difference is the missing intercept, which summarizes aggregate adjustment outside the regional loan-quantity channel. It can reflect common movements in wages and prices, adjustments in bank and borrower balance sheets, substitution across sources of finance, and other equilibrium responses not recovered by regional identification.

We then study the financial frictions that govern the propagation of the initial funding shock. The

evidence points to substitution frictions on both sides of the credit relationship. On the bank side, lending contracts more sharply when replacing lost funding or balance-sheet capacity is difficult. Banks that rely more heavily on deposits and banks with less capital reduce lending more following a funding shock. Banks also reallocate scarce lending capacity toward core relationships and away from non-core markets. In mortgage lending, jumbo originations, which are harder to move off balance sheet through the government-sponsored enterprises, contract more than conforming originations following the same funding shock.

The borrower evidence displays the corresponding pattern. Within the same bank and local market, lending contracts more to smaller businesses following a funding shock. Using bank-firm relationships, we further show that younger firms, which tend to have fewer financing alternatives, experience larger declines in debt, assets, employment, and capital expenditures when their lead banks are exposed to funding shocks. Transmission is therefore strongest where the relevant substitution margins are weakest, when banks have less capacity to replace funding and when borrowers have fewer alternatives to the credit those banks provide. These findings provide microeconomic evidence on the financial frictions that shape the propagation of bank funding shocks through the economy.

This paper makes two key contributions. First, we contribute to the literature connecting cross-sectional estimates of credit supply to aggregate outcomes. A large empirical literature uses differential exposure to lender shocks to identify the causal effects of bank credit supply on firms and local economic activity.[2] Within-borrower designs isolate partial-equilibrium lending effects by holding borrower demand fixed, while regional designs incorporate local general-equilibrium responses across firms and households. Our county-level specification belongs to the latter class. As emphasized by the missing-intercept literature, however, cross-sectional designs identify responses to differential exposure while absorbing the common component needed to recover aggregate effects (Nakamura and Steinsson, 2018; Chodorow-Reich, 2020; Guren et al., 2021a). The difference between regional and aggregate responses can reflect spillovers, their aggregation, and endogenous adjustment in national variables (Chodorow-Reich, 2020; Moll and Hanney, 2025). Existing approaches address this aggregation problem by imposing restrictions linking regional and aggregate responses (Wolf, 2023), combining cross-sectional exposure with time-series or factor variation (Gertler and Gilchrist, 2019; Sarto, 2024b; Matthes et al., 2025), or using regional decompositions, local multipliers, sufficient statistics, and structural models to

[2]See, for example, Peek and Rosengren (1997, 2000); Ashcraft (2005); Khwaja and Mian (2008); Paravisini (2008); Leary (2009); Loutskina and Strahan (2009, 2015); Ivashina and Scharfstein (2010); Chava and Purnanandam (2011); Cornett et al. (2011); Puri et al. (2011); Cetorelli and Goldberg (2012); Schnabl (2012); Jiménez et al. (2012); Gilje et al. (2016); Jiménez et al. (2017); De Haas and Van Horen (2013); Becker and Ivashina (2014); Iyer et al. (2014); Nanda and Nicholas (2014); Chodorow-Reich (2014); Ioannidou et al. (2015); Ivashina et al. (2015); Paravisini et al. (2015); Ramcharan et al. (2016); Cortés and Strahan (2017); Di Maggio and Kermani (2017); Jensen and Johannesen (2017); Berton et al. (2018); Huber (2018); Amiti and Weinstein (2018); Gropp et al. (2019); Cortés et al. (2020); Hale et al. (2020); Beck et al. (2021); Doerr and Schaz (2021); Favara et al. (2021); Di Giovanni et al. (2022); Xu (2022); Blattner et al. (2023); Paravisini et al. (2023); Bergman et al. (2025); Greenwald et al. (2025); Kundu and Vats (2026).

characterize propagation and map local estimates into aggregate counterfactuals (Guren et al., 2021a; Sraer and Thesmar, 2018, 2023b; Catherine et al., 2022; Mian et al., 2023; Sarto, 2024a).[3]

Our contribution is to provide a direct empirical bridge between the regional and aggregate effects of bank credit-supply shocks. Existing approaches typically recover an aggregate implication from regional variation by imposing an equivalence restriction, estimating a common component from separate time-series variation, decomposing regional propagation, or mapping local estimates into aggregate counterfactuals through a model. Our approach instead uses an explicit aggregation framework together with a common, observable source of bank-level funding variation. Disaster exposure in banks' out-of-market deposit bases generates differential changes in county credit supply for the regional design and, when aggregated across banks using their economic size, generates a corresponding national disturbance. This link allows the regional lending-output elasticity, the aggregate lending response, and the aggregate output response to be estimated on a common shock basis and tied together by the model's aggregation relationship. We can therefore quantify, rather than infer indirectly from auxiliary restrictions or a calibrated counterfactual, the extent to which the aggregate output response is explained by the lending channel identified in regional variation and the residual aggregate wedge that remains outside that channel.

Second, we contribute to the literature on the granular origins of aggregate fluctuations. A longstanding view in macroeconomics holds that idiosyncratic shocks average out across sufficiently many agents and therefore cannot account for aggregate fluctuations (Lucas, 1977). More recent work shows that this diversification logic can fail when economic activity is concentrated among a small number of large agents (Gabaix, 2011) or when economic linkages propagate shocks beyond the directly affected agents (Acemoglu et al., 2012). Our setting combines these two forces within the banking system and identifies the geography of bank liabilities as an underexplored source of financial fragility. Banks may diversify their lending across many locations while remaining dependent on a small number of markets for a substantial share of their deposits. A local shock to an important deposit market can therefore weaken a multi-market bank's overall funding position and induce lending contractions in geographically distant markets. Building on the bank-shock methodology of Amiti and Weinstein (2018) and the granular instrumental-variables approach of Gabaix and Koijen (2024), we construct these funding shocks from external, non-financial variation in disaster damage rather than from residual movements in lending or bank returns.[4] This construction makes the funding mechanism directly testable

[3] See Gertler and Gilchrist (2018) for a review of the gap between cross-sectional and aggregate evidence on financial shocks, and Sraer and Thesmar (2023a) for a review of approaches that use microeconomic evidence to discipline aggregate quantities and counterfactuals.

[4] More recently, Kundu and Vats (2021) and Galaasen et al. (2023) use granular instrumental-variables methods to construct bank-level shocks from granular exposure patterns. These approaches recover idiosyncratic shocks from residual or residualized variation in the underlying borrower-level or return processes. Our construction instead uses externally observed natural-disaster damage in banks' deposit markets to generate variation in bank funding conditions. This external source of variation reduces the concern that the measured

and generates regional and aggregate variation from the same underlying bank-level shocks, allowing us to link the local credit-supply response to its aggregate counterpart.

A key component of aggregation is the transmission of local funding shocks across locations through multi-market banks. A shock to an important deposit market can weaken a bank's overall funding position and reduce lending elsewhere. This transmission mechanism builds on a large literature showing that liquidity, funding, capital, monetary-policy, and regulatory shocks affect credit supply and real activity through integrated banks that reallocate funds across borrowers and locations (e.g., Khwaja and Mian, 2008; Cornett et al., 2011; Jiménez et al., 2012; Schnabl, 2012; Iyer et al., 2014; Ivashina et al., 2015; Gilje et al., 2016; Cortés and Strahan, 2017; Acharya et al., 2022). We show that geographic diversification in lending can coexist with substantial geographic concentration in funding. Local shocks to concentrated deposit markets can therefore propagate across the lending network of multi-market banks and, when the affected banks are economically large, contribute to aggregate fluctuations.[5]

Our setting is particularly related to Cortés and Strahan (2017), who study the reallocation of credit following natural disasters. They document a short-run increase in credit demand in affected areas, met primarily by smaller banks, with the effects dissipating within a year. We identify a distinct funding-supply channel whose effects persist beyond the first year. Disasters reduce local deposits as income, employment, business activity, and household wealth deteriorate. When affected locations are important sources of deposits for multi-market banks, these local losses weaken bank-wide funding conditions and reduce lending in other markets. The distinction therefore lies both in the source of the lending response and in the banks through which it is transmitted: Cortés and Strahan (2017) emphasize temporary credit-demand shocks and smaller banks, while our mechanism operates through persistent deposit losses and large, geographically diversified banks.

The two mechanisms can operate simultaneously. A disaster can raise immediate borrowing needs while reducing household wealth and savings over longer horizons. Small banks may therefore expand credit to meet the short-run needs of relationship borrowers, while persistent deposit losses lead larger banks to contract lending. This interpretation is consistent with evidence that small banks rely more heavily on relationship lending and may be better positioned to lend in environments with heightened informational frictions (Berger and Udell, 2002; Berger et al., 2005, 2017; DeYoung et al., 2015).[6]

shock is mechanically constructed from lending or return outcomes that may themselves respond to aggregate conditions or bank credit supply.

[5] Our focus on multi-market banks complements work emphasizing local banks' responses to localized shocks (e.g., Iyer et al. (2023)). Cortés (2014); Plosser (2014); Gilje et al. (2016); Gilje (2019), for example, document increased lending by local banks, often with limited access to capital markets, following natural disasters or energy booms. We show that local shocks also matter for large, multi-market banks because their deposit funding can remain geographically concentrated. Our findings also complement Doerr et al. (2024), who show that funding shocks arising from population aging affect risk-taking by large banks.

[6] Chavaz (2016) show that small banks originate a larger share of new mortgage and small-business loans in disaster-affected areas. Similar patterns are documented by Cortés (2014) for the United States, Koetter et al. (2020) for Germany, and Cramer et al. (2024) for India. This evidence is consistent with the role of small banks emphasized by Cortés and Strahan (2017).

Consistent with this interpretation, we find that larger banks reduce lending in disaster-affected counties, whereas the estimated response of smaller banks is positive. The two sets of findings can therefore be reconciled by differences in the timing, source, and bank-level transmission of disaster-induced credit responses. Appendix B provides a more detailed comparison.

The remainder of the paper proceeds as follows. Section 2 develops the framework linking regional and aggregate responses and formalizes the missing-intercept decomposition. Section 3 describes the data. Section 4 constructs and validates the bank funding shock. Section 5 estimates the regional credit-supply elasticity. Section 6 estimates the aggregate lending and output responses. Section 7 combines the regional and aggregate estimates to recover the missing intercept. Section 8 examines the financial frictions governing the transmission of funding shocks. Section 9 concludes.

2 The Model

The framework distinguishes between the response to a bank credit-supply shock that can be recovered from variation across regions and the response of the aggregate economy to the same underlying shock. A regional comparison identifies how output changes when bank credit changes in one region relative to another and therefore absorbs adjustments that are common across regions. The aggregate response includes both the effect operating through changes in bank lending and these common equilibrium adjustments. The two responses need not coincide, and the purpose of the framework is to provide a mapping between them.

We formalize this distinction in a simple production and banking framework. Regional output depends on bank credit through its effects on productive inputs and employment, giving rise to a regional credit-supply elasticity, χ. A common bank funding shock also changes aggregate bank lending and aggregate output. We denote these aggregate responses by ϕ and θ, respectively. Combining the regional elasticity with the aggregate lending response gives the component of the aggregate output response implied by the regional loan-quantity channel. The difference between this prediction and the total aggregate output response is the *missing intercept*, δ. The resulting decomposition, $\theta = \chi\phi + \delta$, organizes the empirical analysis that follows.

The model develops this relationship in three steps. A regional block describes production, employment, and the response of local output to bank credit and delivers the structural elasticity χ. A banking block describes how disruptions to deposit funding affect banks' balance-sheet capacity and the supply of credit across the markets they serve. Finally, the aggregation step shows how the regional credit-supply response maps into the aggregate economy and derives the missing-intercept decomposition. The framework thereby establishes the economic objects that the subsequent empirical

analysis measures. Appendix Section A provides additional microfoundations, derivations, and tests of the aggregation assumptions used below.

2.1 Regional Economy

Counties are indexed by $c \in [0, 1]$ and time by t. Appendix Table A.1 collects the notation introduced below.

Aggregation. County output aggregates to national output through a constant-elasticity-of-substitution aggregator with elasticity of substitution $\sigma > 1$:

$$Y_t = \left(\int_0^1 Y_{c,t}^{\frac{\sigma-1}{\sigma}} \, dc \right)^{\frac{\sigma}{\sigma-1}}. \tag{1}$$

A first-order log-linearization around a symmetric steady state gives

$$g_t \equiv \Delta \ln Y_t \approx \int_0^1 \omega_c g_{c,t} \, dc, \tag{2}$$

where $g_{c,t} \equiv \Delta \ln Y_{c,t}$ and ω_c is county c's steady-state expenditure share. This approximation abstracts from higher-order terms associated with changes in the cross-county dispersion of output. Section 2.6 states the condition under which those terms can be ignored for the decomposition, and Appendix Section A.4 evaluates it empirically.

Local production. County c produces using employment $N_{c,t}$ and an effective productive input $X_{c,t}$:

$$Y_{c,t} = A_{c,t} X_{c,t}^{\alpha} N_{c,t}^{1-\alpha}, \qquad 0 < \alpha < 1, \tag{3}$$

where $A_{c,t}$ denotes local productivity. Log-linearizing gives

$$g_{c,t} = a_{c,t} + \alpha \, \Delta \ln X_{c,t} + (1 - \alpha) \, \Delta \ln N_{c,t}, \qquad a_{c,t} \equiv \Delta \ln A_{c,t}. \tag{4}$$

The effective productive input is not identified with bank credit itself. Instead, $X_{c,t} = \mathcal{G}(B_{c,t}, H_{c,t})$, where $B_{c,t}$ denotes bank credit and $H_{c,t}$ collects other sources of finance available to firms, including retained earnings, equity, and trade credit. Log-linearizing,

$$\Delta \ln X_{c,t} = e_B \, \Delta \ln B_{c,t} + e_H \, \Delta \ln H_{c,t}, \qquad 0 \leq e_B \leq 1. \tag{5}$$

The distinction between $X_{c,t}$ and $B_{c,t}$ is important. Bank credit finances productive activity but is not

itself a productive input. A change in bank credit, therefore, need not translate one for one into productive capacity. The elasticity e_B captures this pass-through from bank credit to the effective productive input.

Labor market. Local labor demand and labor supply jointly determine employment. We summarize the resulting equilibrium relationship in log-linear form as

$$\Delta \ln N_{c,t} = \psi_B \, \ell_{c,t} - \psi_W \, \Delta \ln W_{c,t} + \psi_D \, \Delta \ln D_{c,t} + \psi_A \, \Delta \ln A_{c,t}, \tag{6}$$

where $\ell_{c,t} \equiv \Delta \ln B_{c,t}$ is county loan growth, $W_{c,t}$ is the local wage, $D_{c,t}$ is a local demand shifter, and $A_{c,t}$ is county productivity. The coefficient ψ_B captures the equilibrium response of employment to local credit conditions, while the remaining terms capture adjustment through wages, demand, and productivity.

Bank credit can therefore affect county output along two margins: through the effective productive input and through employment. Substituting equations (5) and (6) into equation (4) gives

$$g_{c,t} = \chi \, \ell_{c,t} - \kappa \, \Delta \ln W_{c,t} + \tau \, \Delta \ln D_{c,t} + q_{c,t}, \tag{7}$$

where

$$\chi \equiv \alpha e_B + (1-\alpha)\psi_B, \qquad \kappa \equiv (1-\alpha)\psi_W, \qquad \tau \equiv (1-\alpha)\psi_D, \tag{8}$$

$$q_{c,t} \equiv \left[1 + (1-\alpha)\psi_A\right] a_{c,t} + \alpha e_H \Delta \ln H_{c,t}. \tag{9}$$

The coefficient χ is the composite regional elasticity of output with respect to bank credit. It combines the direct response of the effective productive input to bank credit, αe_B, with the response operating through employment, $(1-\alpha)\psi_B$. There is no reason for this composite elasticity to be close to one. Bank credit is only one source of financing for local production. Firms can respond to a contraction in bank lending by drawing on retained earnings, issuing equity, using trade credit, borrowing from non-bank intermediaries, or adjusting other sources of external finance. Consequently, a one-percent change in bank credit need not produce a one-percent change in the effective productive input, which is captured by $e_B < 1$. Nor need employment move one for one with bank credit. Firms can adjust inventories, hours, utilization, investment, and other margins before changing employment, while equilibrium wage adjustment can further dampen the employment response to a change in local financing conditions.

For χ to approach one, the combined responses of productive inputs and employment to bank credit would therefore have to be unusually strong. Bank credit would need to be difficult to substitute

with other sources of finance, and changes in financing conditions would need to pass through strongly to firms' employment decisions. In an economy with multiple sources of finance and several margins of firm and labor-market adjustment, a regional credit-supply elasticity substantially below one is therefore economically natural. The magnitude of χ measures precisely how strongly a change in bank credit passes through these local adjustment margins into output.

2.2 Real-Economy Linkages

Counties are connected through channels unrelated to banking. Let $M = [m_{cc'}]$ summarize these connections, where $m_{cc'}$ measures county c's exposure to county c' through trade, production networks, commuting, migration, or related real-economy linkages. Local demand evolves according to

$$\Delta \ln D_{c,t} = d^0_{c,t} + \rho \int_0^1 m_{cc'} g_{c't}\, dc', \tag{10}$$

where $d^0_{c,t}$ is an idiosyncratic local demand component and ρ governs the strength of propagation across counties.

Substituting equation (10) into equation (7) yields

$$g_{c,t} = \chi \ell_{c,t} - \kappa \Delta \ln W_{c,t} + \tau d^0_{c,t} + \tau\rho \int_0^1 m_{cc'} g_{c't}\, dc' + q_{c,t}. \tag{11}$$

Equation (11) makes clear why identification of χ requires more than an exogenous shift in bank lending. County output may change because loan supply changes, but also because wages, productivity, non-bank finance, local demand, or economic conditions in connected counties change. The regional instrument identifies χ only if its variation is orthogonal to these other determinants of county output after the fixed effects and controls used in the empirical design.

2.3 From Disasters to Bank Funding Shocks

The empirical construction exploits the fact that banks raise deposits across many geographically dispersed counties. Disasters reduce local income, employment, business activity, and household wealth and thereby reduce deposit growth in affected locations. A disaster therefore has a larger effect on a bank's funding when it occurs in a county that supplies a large share of that bank's deposits. Appendix Section A.3 provides a microfoundation linking local deposit losses to this deposit-weighted bank funding shock.

Let $\omega^D_{b,c,t-1}$ denote the lagged share of bank b's deposits sourced from county c, and let $\text{Dmg}_{c,t}$

denote the disaster shock in county c. The bank's deposit-weighted disaster exposure is

$$\Gamma_{b,t} = \sum_{c} \omega^{D}_{b,c,t-1} \text{Dmg}_{c,t}. \tag{12}$$

The exposure is large when disasters strike locations that are important sources of funding for the bank.

We distinguish this empirical exposure from the bank's realized funding shock. Let

$$s_{b,t} = \theta^{\text{fund}} \Gamma_{b,t} + \xi^{\text{fund}}_{b,t}, \tag{13}$$

where $\xi^{\text{fund}}_{b,t}$ captures changes in funding conditions not generated by the deposit geography used in the empirical construction. The bank optimization problem below is written in terms of this underlying bank-level funding shock.

For the aggregate design, bank funding shocks are aggregated using lagged bank asset shares,

$$\Gamma_t = \sum_{b} \omega^{A}_{b,t-1} s_{b,t}, \tag{14}$$

and the equal-weighted component is removed following the granular instrumental-variables logic of Gabaix and Koijen (2024):

$$\Gamma^{*}_{t} \equiv \Gamma_t - \frac{1}{N_{b,t-1}} \sum_{b} s_{b,t}. \tag{15}$$

Under approximately common loadings on aggregate factors, this subtraction removes the common component of bank funding conditions and retains the idiosyncratic shocks whose aggregate importance depends on the granularity of the banking system.

The regional design uses the same underlying source of funding variation but constructs exposure at the bank-county level. For a bank b lending in county c, define

$$\Gamma^{\setminus s(c)}_{b,c,t} = \sum_{c \notin s(c)} \omega^{D}_{b,c,t-1} \text{Dmg}_{c,t}, \tag{16}$$

where $s(c)$ denotes the state containing county c. Thus, $\Gamma^{\setminus s(c)}_{b,c,t}$ uses only disasters occurring outside the destination county's state.

The economic funding shock remains a bank-level object. The bank-county index in equation (16) arises because the empirical exposure removes a different set of disaster locations depending on the county in which the bank's lending is observed. The same bank can therefore have different out-of-state

exposure across destination counties in a given period even though its underlying balance sheet is common across those counties. This distinction allows the empirical design to isolate the component of the bank's funding shock that originates outside the state of the local lending market.

Let $s^{\setminus s(c)}_{b,c,t}$ denote the corresponding out-of-state funding exposure after applying the same residualization used in the empirical construction. The county-level regional instrument is

$$z_{c,t} = \sum_{b} \omega^{L}_{b,c,t-1} s^{\setminus s(c)}_{b,c,t}, \tag{17}$$

where $\omega^{L}_{b,c,t-1}$ is bank b's lagged share of lending in county c. The regional instrument is therefore the lending-share-weighted aggregation of bank-county out-of-state funding exposures.

Excluding same-state disasters removes the most direct geographic connection between the source of the funding shock and economic conditions in the destination county. It does not, however, eliminate the possibility that disasters outside the state affect county c through trade, migration, or other real-economy networks. Section 2.5 states the additional exclusion restriction required for identification.

2.4 Bank Optimization and County Loan Supply

At the beginning of period t, bank b holds equity $E_{b,t}$, deposits $D_{b,t}$, and wholesale funding $F_{b,t}$ and chooses loans $\{L_{b,c,t}\}$ to maximize

$$\max_{\{L_{b,c,t}\}} \sum_{c} \left[(r_{b,c,t} - r^{f}_{t}) L_{b,c,t} - \frac{1}{2} \varphi_{c} L^{2}_{b,c,t} \right] \tag{18}$$

subject to

$$\sum_{c} L_{b,c,t} \leq E_{b,t} + D_{b,t} + F_{b,t}, \qquad \sum_{c} \omega^{R}_{b,c} L_{b,c,t} \leq \kappa^{\text{lev}} E_{b,t}, \tag{19}$$

where $r_{b,c,t}$ is the loan rate in county c, r^{f}_{t} is the marginal cost of funds, $\varphi_{c} > 0$ governs increasing marginal costs of lending, $\omega^{R}_{b,c}$ denotes regulatory risk weights, and κ^{lev} is a leverage parameter.

Let $\mu_{b,t}$ and $\eta_{b,t}$ denote the multipliers on the funding and capital constraints. The first-order condition for lending in county c is

$$(r_{b,c,t} - r^{f}_{t}) - \varphi_{c} L_{b,c,t} - \mu_{b,t} - \eta_{b,t} \omega^{R}_{b,c} = 0, \tag{20}$$

so that

$$L_{b,c,t} = \frac{(r_{b,c,t} - r_t^f) - \mu_{b,t} - \eta_{b,t}\omega_{b,c}^R}{\varphi_c}. \tag{21}$$

A negative funding shock reduces the resources available to the bank and raises the shadow value of funding or capital whenever the relevant constraints bind. Loan supply then falls across the markets served by the bank. If lost deposits can instead be replaced at the same marginal cost, or if the bank has sufficient slack in its balance-sheet and capital constraints, the shadow values need not rise and the effect on lending can be small. The model therefore predicts heterogeneous lending responses depending on banks' ability to absorb the funding shock. Appendix Section A.2 derives the corresponding cross-market comparative statics in a multi-market bank with an internal capital market. Section 8 tests these implications using deposit reliance, capitalization, bank size, and the ability to move loans off balance sheet.

The bank-county out-of-state exposure provides an empirical measure of the component of this funding shock that is plausibly exogenous to economic conditions in the destination county. Log-linearizing the lending response gives the bank-county empirical first stage

$$\Delta \ln L_{b,c,t} = \lambda_{b,c} s_{b,c,t}^{\setminus s(c)} + \nu_{b,c,t}, \qquad \lambda_{b,c} < 0, \tag{22}$$

where $\lambda_{b,c}$ allows the sensitivity of lending to funding conditions to differ across banks and lending relationships.

Equation (22) is the microeconomic counterpart of the regional first stage. Aggregating bank-county lending growth across the banks serving county c using lagged lending shares gives

$$\ell_{c,t} \approx \sum_b \omega_{b,c,t-1}^L \Delta \ln L_{b,c,t}. \tag{23}$$

If the weighted sensitivity of county lending to the bank-county exposure is summarized by λ_c, then

$$\ell_{c,t} = \lambda_c z_{c,t} + \nu_{c,t}, \tag{24}$$

where $z_{c,t}$ is defined in equation (17). Thus, the county-level first stage used in the regional 2SLS is the aggregation of the bank-county credit-supply responses generated by funding shocks at the banks serving that county.

2.5 Identifying the Regional Elasticity χ

The regional 2SLS specification is

$$g_{c,t} = \theta_c + \theta_t + \beta_{\text{reg}} \ell_{c,t} + u_{c,t}, \tag{25}$$

where county loan growth $\ell_{c,t}$ is instrumented by $z_{c,t}$ and θ_c and θ_t denote county and time fixed effects. From equation (11), the residual after removing these fixed effects contains

$$u_{c,t} = -\kappa \Delta \ln W_{c,t} + \tau d^0_{c,t} + \tau \rho \int_0^1 m_{cc'} g_{c't}\, dc' + q_{c,t}. \tag{26}$$

The 2SLS coefficient identifies χ under the following exclusion restriction:

Assumption 1 (No residual real-economy channel)**.**

$$\mathbb{E}\left[z_{c,t} u_{c,t} \mid \theta_c, \theta_t\right] = 0. \tag{27}$$

Assumption 1 does not require disasters outside a county's state to have no effect on that county. Equation (11) explicitly allows shocks to propagate across locations through real-economy networks. The restriction is narrower: conditional on county and time fixed effects, the county's exposure to funding-shocked banks must not proxy for its exposure to disaster-affected locations through those same real-economy networks.

The exclusion restriction is central to the regional design. Its validity does not require disasters occurring outside county c's state to have no effect on county c. Such a condition would be implausibly strong. Counties are connected across state borders through trade, production networks, migration, commuting, and social ties, so a disaster elsewhere can affect local economic activity even when it has no connection to the banks serving county c. Excluding same-state disasters therefore removes the most immediate geographic channels of direct exposure, but it does not by itself establish the exclusion restriction.

The relevance condition is more specific. The instrument $z_{c,t}$ varies because counties borrow from different banks and those banks obtain different shares of their deposits from disaster-affected locations outside the county's state. Identification requires this *banking-network exposure* to be orthogonal, conditional on the fixed effects and controls, to county c's exposure to the same disasters through the real economy. The restriction can therefore hold even if an out-of-state disaster affects county c through trade, migration, commuting, or other linkages. It fails if counties that borrow more heavily from banks

exposed to a particular set of disaster-hit locations are also systematically connected to those locations through non-banking channels that independently affect local output.

A simple example illustrates the concern. Suppose county c relies heavily on a bank whose deposits are concentrated in county c'. A disaster in county c' reduces that bank's funding and, through its internal capital market, may reduce lending in county c. This is the variation the instrument is designed to capture. But if county c also trades disproportionately with county c', receives migrants from county c', shares commuting flows with it, or is otherwise economically connected to it, the same disaster may affect economic activity in county c directly. In that case, the banking exposure embedded in $z_{c,t}$ would be correlated with the network component of local demand in equation (11), and the 2SLS coefficient could combine the effect of credit supply with the direct propagation of the underlying disaster.

The empirical analysis addresses this threat at both the bank-county and county levels. The bank-county evidence provides the cleanest way to absorb the alternative local-demand channels represented by $u_{c,t}$ in equation (11). County-by-year fixed effects absorb all conditions affecting a given county in a given year that are common across the banks lending there, including local demand arising from the county's real-economic connections to disaster-affected locations. Identification therefore comes from comparing banks lending in the same county and year but experiencing different funding shocks because their deposit bases are exposed differently to disasters elsewhere. Appendix Table G.1 shows that banks with greater out-of-state funding exposure reduce lending within the same county-year. This response is therefore identified after absorbing the common local-demand component that poses the principal threat to the credit-supply interpretation.

The county-level 2SLS necessarily relies on variation at the county-year level, so the same conditions cannot be absorbed with county-by-year fixed effects. Section 5.3 therefore addresses them directly. We construct measures of county c's exposure to out-of-state disasters through real-economic connections and economic importance, including trade, migration, social connectedness, geographic proximity, employment, GDP, population, and establishments, rather than through bank funding relationships. We then include these exposures directly in the regional specification. These tests ask whether $z_{c,t}$ continues to predict local credit and output after accounting for observable non-banking channels through which the same underlying disasters could affect county-level demand.

The two exercises are complementary. The bank-county specification of equation (22) absorbs county-year demand conditions nonparametrically and asks whether banks with different funding exposure adjust lending differently within the same local economy. The county-level specification then asks whether the funding exposure of the banks serving a county predicts local credit and output after controlling directly for the county's observable non-banking exposure to the underlying disasters. The identifying variation therefore comes from the banking network, specifically the interaction between

disaster locations and the predetermined geography of the deposit funding of banks serving county c, rather than from the county's real-economic exposure to those locations.

2.6 Aggregation and the Missing-Intercept Identity

Applying the first-order aggregation in equation (2) to the county structural relationship in equation (7) gives

$$g_t \approx \chi \int_0^1 \omega_c \ell_{c,t}\, dc + \zeta_t, \tag{28}$$

where

$$\zeta_t \equiv -\kappa \int_0^1 \omega_c \Delta \ln W_{c,t}\, dc + \tau \int_0^1 \omega_c \Delta \ln D_{c,t}\, dc + \int_0^1 \omega_c q_{c,t}\, dc. \tag{29}$$

Define aggregate loan growth as

$$\ell_t \equiv \Delta \ln \left(\int_0^1 \omega_c B_{c,t}\, dc \right).$$

To a first-order approximation,

$$\int_0^1 \omega_c \ell_{c,t}\, dc \approx \ell_t,$$

so the aggregate counterpart of the regional structural equation is

$$g_t = \chi \ell_t + \zeta_t. \tag{30}$$

Two approximations are required to take the pooled regional estimate of χ into this aggregate relationship. First, the true credit elasticity may vary across counties. Second, the first-order aggregation in equation (2) omits higher-order terms associated with cross-county dispersion.

Assumption 2 (Aggregability of χ)**.** *The pooled regional estimate χ provides a suitable approximation to the loan-weighted average of county-specific elasticities relevant for aggregate output. In particular, heterogeneity in county-specific elasticities is not systematically aligned with the aggregation weights in a way that materially changes the aggregate loan-quantity response.*

Appendix Section A.5 evaluates this assumption by allowing the regional credit-supply elasticity to vary with county characteristics related to bank size, access to unshocked lenders, borrower composition, lending concentration, and deposit-market importance. The estimated elasticities remain close to the

pooled estimate, with little evidence of systematic heterogeneity across these dimensions, although some specifications are weakly identified.

Assumption 3 (First-order aggregation)**.** *The higher-order cross-county dispersion term omitted by the first-order approximation in equation* (2) *does not respond materially to the granular funding shock* Γ_t^*.

Appendix Section A.4 evaluates this condition by introducing measures of cross-county dispersion into the aggregate specification and examining whether the estimated aggregate output response changes.

Under Assumptions 2 and 3, write the aggregate lending response and the remaining aggregate component as

$$\ell_t = \psi + \phi\Gamma_{t-1}^* + \nu_t, \qquad \zeta_t = \delta\Gamma_{t-1}^* + \eta_t, \tag{31}$$

where the residuals are mean zero and orthogonal to the granular funding shock. Substituting equation (31) into equation (30) and comparing the result with the aggregate reduced-form regression

$$g_t = \mu + \theta\Gamma_{t-1}^* + \varepsilon_t \tag{32}$$

gives

$$\theta = \chi\phi + \delta. \tag{33}$$

Each term has a distinct interpretation. The coefficient ϕ is the aggregate response of bank lending to the granular funding shock, estimated directly from aggregate data. The product $\chi\phi$ is the loan-quantity channel: the aggregate output response predicted by applying the regional credit-supply elasticity to the observed aggregate contraction in bank lending. The remaining term,

$$\delta = \theta - \chi\phi,$$

is the missing intercept, the component of the aggregate output response that the regional loan-quantity channel does not recover.

The identity does not require δ to correspond to a single mechanism. It contains all aggregate adjustment left outside the regional loan-quantity channel, including wage and price adjustment, reallocation across regions and sectors, propagation through production and trade networks, endogenous adjustment of bank and borrower balance sheets, substitution toward non-bank finance, and, absent the funding-specificity condition, any direct aggregate effect of disasters that remains correlated with the

constructed granular shock but does not operate through bank loan quantities. Equation (33) therefore defines δ as a scalar residual rather than a structural decomposition of these mechanisms.

Scope of the decomposition. The regional 2SLS identifies χ under Assumption 1, but by itself says nothing about the total aggregate response to the funding shock. Even granting the regional exclusion restriction and the aggregation assumptions, combining χ with the observed aggregate lending response recovers only $\chi\phi$, one component of the aggregate output response. A difference between $\chi\phi$ and θ is therefore not evidence that the regional design has failed. It is the object the decomposition is designed to measure.

Nor does the decomposition identify the mechanisms contained in that difference. Section 8 provides evidence on financial frictions that govern whether funding shocks are absorbed or propagated. Lending responds more strongly where banks have limited capacity to replace funding or relax capital constraints, and real effects are larger among borrowers with limited financing alternatives. These findings provide a microeconomic basis for broad transmission without assigning a particular share of δ to any individual mechanism.

2.7 Interpreting the Aggregate Funding Shock

The interpretation of θ as the aggregate response to a bank funding shock requires the explanatory power of Γ_t^* to arise from innovations to the funding capacity of economically important banks, rather than from direct aggregate disaster effects, the geographic distribution of bank lending activity, or other aggregate disturbances that independently affect output. This requirement is closely related to the identification logic for external instruments in macroeconomics. An external instrument must be relevant for the structural shock of interest and orthogonal to other contemporaneous structural shocks; here, the granular construction must load on bank-funding disturbances rather than on other disaster-linked aggregate innovations. This condition is an application-specific analogue of the relevance and contemporaneous-exogeneity conditions for an external instrument (Stock and Watson, 2018). We refer to this application-specific requirement as *funding specificity*.

Assumption 4 (Funding specificity)**.** *The innovations in Γ_t^* are correlated with changes in the funding capacity of economically important banks and are orthogonal to other contemporaneous aggregate disturbances that independently affect aggregate lending or output. Equivalently, the predictive content of Γ_t^* for aggregate outcomes arises from the deposit-funding channel embedded in its construction, rather than from direct disaster effects, the geographic concentration of real activity or bank lending, or other aggregate shocks.*

Section 6.2 evaluates this implication directly. Granular lending shocks constructed from HMDA

mortgage lending and CRA small-business lending are economically small and statistically insignificant, while the deposit-based Γ_t^* retains its predictive content for aggregate GDP. The aggregate results therefore depend on where banks obtain their funding rather than simply where they extend credit.

2.8 What the Aggregate Elasticities Measure

The regional and aggregate exercises answer different causal questions and therefore require different identifying conditions. The aggregate condition concerns the identity of the underlying shock, whereas the regional exclusion restriction concerns whether cross-sectional exposure to that shock affects local output through a non-banking channel that contaminates the local loan-supply comparison. This distinction is particularly important because the local disasters used to construct Γ_t^* can affect economic activity through channels other than bank funding.

The coefficient ϕ measures the reduced-form response of aggregate lending to the granular shock, while θ measures the total-equilibrium response of aggregate output to that same shock:

$$\ell_t = \psi + \phi\Gamma_{t-1}^* + \nu_t,$$
$$g_t = \mu + \theta\Gamma_{t-1}^* + \varepsilon_t.$$

These regressions do not instrument aggregate lending in order to estimate the structural effect of lending on output. Accordingly, the aggregate analysis does not require disasters to affect GDP only through bank lending. Wage and price adjustment, reallocation across banks, firms, sectors, and regions, propagation through production and demand networks, substitution between bank and non-bank finance, and policy responses are all part of the aggregate equilibrium response to a disruption in bank funding capacity. Those forces are excluded from the regional estimand because they can contaminate a local credit-supply comparison; they are included in the aggregate estimand because they are part of the economy-wide response to the underlying shock.

The relevant aggregate requirement is instead that the predictive content of Γ_t^* for aggregate lending and output arise from shocks to the funding capacity of economically important banks, rather than from the direct real effects of disasters or from the geographic concentration of economic activity more generally. To state this condition, write the aggregate outcome equation as

$$g_t = \theta^{\text{fund}}\Gamma_{t-1}^* + d_t^{\text{direct}} + r_t^{\text{other}},$$

where d_t^{direct} denotes the component of aggregate activity directly affected by disasters, independently of bank funding, and r_t^{other} denotes other aggregate disturbances. The funding interpretation of θ requires

that, conditional on the controls used in the aggregate specification,

$$\mathbb{E}\left[\Gamma^*_{t-1}\left(d_t^{\text{direct}} + r_t^{\text{other}}\right)\right] = 0. \tag{34}$$

This condition does not require local disasters to have no direct real effects. Such a requirement would be implausible. Rather, it requires that the component of Γ^*_t generated by the interaction of disasters with predetermined deposit shares and bank asset shares not simply proxy for aggregate disaster severity, for disaster exposure in economically important places, for the geographic footprint of bank lending, or for other aggregate shocks that independently move output.

This distinction also clarifies the interpretation of the missing intercept. The identity $\theta = \chi\phi + \delta$ holds by construction under the aggregation assumptions. The product $\chi\phi$ is the aggregate output response predicted by the regional loan-quantity channel, while δ is the residual aggregate response not recovered by that channel. Under the funding-specificity condition in equation (34), δ summarizes general-equilibrium adjustment outside the regional loan-quantity channel. If instead Γ^*_t retained a direct disaster component unrelated to bank funding, that component would enter θ and therefore be absorbed by δ. The decomposition would remain algebraically valid, but its stronger interpretation as a decomposition of the aggregate effect of a bank funding shock would no longer follow.

The empirical analysis evaluates this funding-specificity interpretation using several complementary tests in Section 6.2. First, the shock predicts lower aggregate deposit growth, linking it directly to the funding margin from which it is constructed. Second, granular placebo shocks based on the geography of mortgage and small-business lending have little explanatory power for GDP, while the deposit-based shock remains predictive. Third, granular shocks based on the geographic distribution of employment, GDP, personal income, population, and establishments do not absorb the estimated response to Γ^*_t. Fourth, aggregate disaster intensity and direct measures of home and business losses have little explanatory power for GDP growth at the same horizon, and their inclusion leaves the coefficient on Γ^*_t largely unchanged. Fifth, the relationship survives controls for oil supply shocks, monetary-policy surprises, economic-policy uncertainty, the term spread, government expenditure shocks, and the firm-level granular residual of Gabaix (2011). Finally, the aggregate relationship weakens systematically when the largest banks are removed from the construction of the shock, as implied by the granular funding mechanism.

Taken together, these exercises assess whether the aggregate predictive content of Γ^*_t is specific to disruptions in bank funding capacity. The evidence distinguishes the funding interpretation from the principal alternatives: that Γ^*_t proxies for aggregate disaster damage, granular real activity, the geographic distribution of bank lending, or conventional aggregate shocks. While no single test is decisive, the combined evidence supports interpreting ϕ and θ as the aggregate lending and total-equilibrium output

responses, respectively, to granular disruptions in bank funding capacity.

3 Data

Our empirical analysis combines detailed data on the geographic distribution of bank deposits, natural disasters, bank balance sheets, lending, and economic activity. The core data used to construct the bank funding shocks come from three sources: 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. We supplement these data with information on small business and mortgage lending, aggregate economic outcomes, local economic conditions, migration, and firm outcomes. This section describes the main data sources. Full variable definitions and additional details are provided in Appendix Section C.

Bank Deposits. The Summary of Deposits (SOD), compiled annually by the Federal Deposit Insurance Corporation (FDIC), reports branch-level deposits for all FDIC-insured depository institutions operating in the United States as of June 30 of each year. The data contain information on branch location at the ZIP-code level, branch characteristics, total deposits, and parent-bank identifiers. The branch-level geographic information allows us to measure the distribution of each bank's deposits across counties and is therefore central to the construction of our bank funding shocks. We use the SOD data from 1994 to 2019 and restrict the sample to banks operating in at least two counties. The latter restriction reflects the focus of our analysis on multi-market banks and the transmission of funding shocks across geographic markets.

Natural Disasters. We obtain county-level natural-disaster data from SHELDUS. SHELDUS provides detailed information on natural disasters and their associated losses, including property and crop damages, injuries, and fatalities. It covers a wide range of natural disasters, including thunderstorms, hurricanes, floods, wildfires, tornadoes, and earthquakes, based on the Storm Data and Unusual Weather Phenomena reports published by the National Climatic Data Center. Our primary measure of disaster exposure is property damage per capita at the county level. We combine these local disaster shocks with the geographic distribution of each bank's deposits to construct bank-specific funding shocks in Section 4. Table 1 reports summary statistics for disaster damages, while Appendix Table E.1 reports damages by hazard type, and Appendix Figure E.1 presents the geographic distribution of property damages per capita.

Bank Balance Sheets. We obtain bank-level financial information from the Call Reports, quarterly regulatory filings submitted by insured U.S. commercial banks to the Federal Financial Institutions Examination Council (FFIEC). The Call Reports provide detailed balance-sheet information, including

total assets, liabilities, loans, deposits, equity, and the other bank characteristics used throughout the analysis. We use total assets to measure bank size and, in constructing the aggregate funding shock, to capture each bank's relative importance in the economy. We use the standardized and cleaned version of the Call Report data compiled by Drechsler et al. (2017), which facilitates consistent measurement of bank characteristics over time.

Bank Lending. We use two sources of geographically disaggregated bank lending data. First, small business lending comes from the Community Reinvestment Act (CRA) data, which we use from 1997 to 2019. The CRA data provide broad coverage of small business lending in the United States and report the geographic distribution of loans originated by covered depository institutions. Small business loans are defined as loans of $1 million or less reported under the CRA, comprising commercial and industrial loans and loans secured by nonfarm nonresidential real estate. These loans provide a particularly useful setting for studying the transmission of bank funding shocks because they are relatively difficult to securitize and therefore remain closely tied to bank balance sheets (Wilcox, 2011; Drechsler et al., 2017).

Second, we use mortgage origination data from the Home Mortgage Disclosure Act (HMDA) from 1994 to 2019. HMDA provides information on mortgage originations at the bank and local-market level. In parts of the analysis, we distinguish between conforming and jumbo mortgages. Jumbo mortgages exceed the government-sponsored enterprise conforming-loan limits and therefore cannot generally be purchased by Fannie Mae or Freddie Mac. This distinction allows us to examine whether funding shocks have larger effects on loans that are more dependent on bank balance-sheet funding.

Aggregate Outcomes. We obtain quarterly U.S. GDP growth, aggregate deposit growth, and commercial and industrial (C&I) lending growth from the Federal Reserve Economic Data (FRED). These series are the principal aggregate outcomes used to estimate the response of bank deposits, lending, and economic activity to the aggregate funding shock. We also use a range of other aggregate shocks in robustness exercises, including the term spread from FRED, oil supply shocks from Känzig (2021), the economic policy uncertainty index from Baker et al. (2016), monetary policy shocks from Vats (2020), government expenditure shocks, and granular firm shocks constructed following Gabaix (2011).

Local Economic Activity and Migration. We use several additional datasets to understand why natural disasters affect bank deposits and to distinguish the bank funding channel from direct effects of disasters on local economic activity. County-level information on establishments and employment comes from the County Business Patterns (CBP), and migration flows come from the Internal Revenue Service (IRS). We use these data to examine whether disasters reduce local business activity, employment, and household presence and to assess the extent to which changes in deposit balances following disasters reflect declines in local economic activity rather than the geographic reallocation of deposits associated with migration.

We also use county-level measures of GDP, population, personal income, and establishments to construct alternative disaster exposures used in our identification and robustness exercises.

Firm Outcomes. Finally, we use firm-level data to examine the real effects of bank funding shocks on borrowers. Firm financial information for U.S. non-financial and non-utility firms comes from Compustat. We combine these data with bank–borrower relationships from Dealscan to measure firms' exposure to shocks affecting their lenders. The resulting data allow us to study whether firms exposed to funding shocks through their banking relationships experience changes in debt, assets, employment, and capital expenditures.

Summary Statistics. Table 1 reports summary statistics for the main variables used in the analysis. Panel A reports county-year variables, including deposit growth, natural-disaster damages, establishments, employment, and migration. Panel B reports bank-year variables, including the bank-level funding shock, $\Gamma_{b,t}$, and bank deposits by account type. Panel C reports bank-county-year lending outcomes from the CRA and HMDA data. Panel D reports firm-year outcomes from Compustat. Panel E reports the quarterly aggregate variables, including GDP growth, deposit growth, C&I lending growth, and the aggregate funding shock, Γ_t^*.

The summary statistics illustrate the substantial variation underlying our empirical design. Disaster damages are highly uneven across counties and over time: the median county experiences little property damage in a typical year, while a relatively small number of county-year observations experience very large losses. Deposit growth likewise varies substantially across counties. We exploit this local variation in disaster exposure together with heterogeneity in the geographic distribution of banks' deposit bases to construct the bank-level and aggregate funding shocks described in the next section.

4 Constructing the Bank Funding Shock

Our empirical strategy requires a source of bank funding variation that can be traced to idiosyncratic local shocks but is sufficiently important to affect the balance sheets of large, multi-market banks. We construct such shocks by combining two features of the data. First, bank deposits are geographically concentrated: individual counties account for large shares of the deposit funding of many banks. Second, natural disasters generate large, plausibly exogenous local shocks that reduce deposits in the affected areas. When a disaster strikes a county that is an important source of deposits for a bank, the resulting local deposit decline can therefore become a bank-level funding shock. Because multi-market banks allocate funds across locations through their internal capital markets, these funding shocks can in turn affect credit supply in geographically distant markets.

This section proceeds in three steps. Section 4.1 documents the geographic concentration of bank

deposits and establishes that the pattern reflects the underlying geography of bank funding. Section 4.2 shows that natural disasters generate persistent bank-level funding declines. Section 4.3 combines these two facts to construct the bank-level funding shock, the aggregate granular funding shock, and the county-level instrument used in the regional analysis.

4.1 Geographic Concentration of Bank Deposits

Deposits are highly concentrated across locations within a bank. This concentration is economically important for our design. If a bank raised roughly equal amounts of deposits from many independent geographic markets, a shock to any one county would have little effect on the bank's overall funding position, and idiosyncratic local shocks would largely diversify away. Geographic concentration instead makes particular counties disproportionately important sources of funding, allowing a sufficiently large local shock to generate a meaningful bank-level funding shock.

Figure 1 documents this concentration. Figure 1a ranks counties within each bank according to their share of the bank's deposits and plots the average deposit share by county rank. Deposits are concentrated in a small number of counties: on average, the largest deposit county alone accounts for approximately 30% of a bank's deposits, with deposit shares declining sharply for lower-ranked counties. Figure 1b traces this concentration over time. The figure plots the deposit share of each bank's largest deposit county from 1994 to 2019 using the simple average, the asset-weighted average, and the first and tenth percentiles of the cross-sectional distribution. Geographic concentration is present throughout the sample, although it declines over time as banks become more geographically diversified.

Does Geographic Concentration Vary with Bank Characteristics? We next examine whether geographic concentration is concentrated among small banks with limited geographic footprints. Figure 2 reports the distribution of deposit concentration across banks. Panel 2a relates the deposit share of a bank's largest deposit county to its percentile in the distribution of total assets. Concentration declines with bank size but remains substantial even among the largest banks. Appendix Figure D.1 shows that the same pattern holds when bank size is measured using deposits, total liabilities, book equity, or total loans.

Panel 2b examines the four largest U.S. banks directly. Despite their nationwide operations, their deposits remain concentrated in a relatively small number of counties. The largest deposit county accounts for approximately 59% of Citibank's deposits, 49% of JPMorgan Chase's, 17% of Wells Fargo's, and 12% of Bank of America's deposits. Geographic deposit concentration therefore remains economically meaningful even among institutions with broad national footprints.

The locations underlying this concentration are themselves geographically dispersed. Appendix Figure D.2 maps the counties that serve as banks' largest deposit sources and shows that they are spread

throughout the United States rather than concentrated in a single financial center. At the same time, some counties are important funding sources for multiple banks: more than 50% of largest-deposit counties are the largest source of deposits for at least five banks. Thus, geographic concentration within banks does not arise from all institutions relying on the same small set of locations.

Appendix Figure D.3 shows that concentration among the Big 4 banks also persists throughout the baseline sample, although it declines as these institutions expand geographically. Appendix Figure D.4 then extends the analysis back to 1981 and shows that geographic deposit concentration predates our baseline sample and was, if anything, stronger before the modern interstate banking era.[7]

Does Geographic Mismeasurement of Deposits Drive Concentration? The geographic interpretation of the SOD data depends on how banks assign deposits to individual offices. Appendix Section D.1 describes these reporting conventions in detail, including the assignment of accounts to branch locations and the treatment of deposits without a clear local geographic footprint. These conventions identify several potential sources of geographic mismeasurement, including headquarters and main-office reporting, mergers and acquisitions, tax-driven deposit placement, online and brokered deposits, and the concentration of operational or lending activity in particular locations.

We address these sources of potential mismeasurement directly. Appendix Figure D.5 exploits banks that relocate their headquarters and shows that concentration remains substantial when the increase in deposits reported in the new headquarters county is reassigned under alternative assumptions. Appendix Figure D.6 reaches the same conclusion after removing deposits reported at headquarters branches altogether.

We next consider tax-driven deposit placement, mergers and acquisitions, potentially non-local deposits, major lending centers, main offices, and large operational branches. Appendix Figure D.7 summarizes the effect of these adjustments for the full sample. Appendix Figure D.8 repeats the exercise for the Big 4 and Top 20 banks and shows that geographic concentration remains substantial among the largest institutions. Appendix Figure D.9 reports the corresponding concentration patterns for the full sample in greater detail. Appendix Figures D.10 and D.11 report the analogous results for the Big 4 and Top 20 banks.

We provide two additional checks on whether the SOD measure captures meaningful geographic variation. Appendix Figure D.12 examines the distribution of deposits across branches within banks' largest deposit counties and shows that deposits are distributed across multiple branches rather than

[7] The historical SOD data before 1994 are reported separately from the modern series, and Appendix Figure D.4b shows a discrete change in measured concentration around 1994, coinciding with the transition associated with the Riegle–Neal Interstate Banking and Branching Efficiency Act. We therefore begin the baseline sample in 1994 rather than treating the pre- and post-1994 observations as a single continuous series. The 1994–2019 period provides a coherent sample in which banks can operate across geographic markets, while the historical evidence establishes that geographic deposit concentration predates the modern interstate banking era.

concentrated in a single reporting office. Appendix Figure D.13 constructs an independent measure of geographic concentration using physical branch locations instead of reported deposit balances and finds a similar pattern. Appendix Figure D.14 shows that the branch- and deposit-based measures are strongly related, with a correlation of approximately 86%. Finally, Appendix Figure D.15 shows that the geographic concentration of branches remains substantial across the bank size distribution when size is measured using deposits, liabilities, book equity, or loans. Taken together, these exercises indicate that geographic deposit concentration reflects an economically meaningful feature of banks' funding geography.

These facts provide the first ingredient for the granular mechanism in the sense of Gabaix (2011). Deposit funding is sufficiently uneven across locations that shocks to particular counties need not diversify away within a bank. When the affected banks are themselves economically important, the resulting bank-level funding shocks can also survive aggregation across banks. The construction below exploits both layers of concentration.

4.2 Natural Disasters and Bank Deposits

The second ingredient is a source of idiosyncratic local variation that affects bank deposits. We use property damage from natural disasters. For this variation to represent a bank funding shock, disasters must reduce deposits in affected locations, and those local declines must translate into reductions in the total funding of exposed banks. We begin by estimating

$$\Delta \ln(Deposits)_{c,t} = \beta \times \text{Disaster Shock}_{c,t-1} + \theta_c + \theta_{s(c\in s),t} + \varepsilon_{c,t}, \tag{35}$$

where $\Delta \ln(Deposits)_{c,t}$ is year-over-year county deposit growth, $\text{Disaster Shock}_{c,t-1}$ is lagged property damage per capita, θ_c absorbs persistent county-level differences in disaster exposure and resilience, and $\theta_{s(c\in s),t}$ absorbs time-varying state-level conditions.

Table 2 shows that disaster exposure predicts a decline in subsequent deposit growth. The coefficient is negative, significant at the 1% level, and stable across an increasingly demanding sequence of fixed effects. A one-standard-deviation disaster shock, approximately $2,500 in per-capita property damage, is associated with a 0.09 to 0.11 percentage-point decline in deposit growth, comparable to the 25th percentile of the deposit-growth distribution. Appendix Table E.2 shows that the relationship remains negative and significant after controlling for lagged disaster exposure. Appendix Figure E.2 provides a randomization placebo in which the coefficient estimated from actual disaster exposure lies well outside the distribution generated by randomly assigned shocks. Figure 3 shows that the deposit response is also persistent: Jordà local projections remain negative ten years after the initial disaster.

The local economic response provides a natural explanation for this persistence. Appendix Table E.3 shows that disasters reduce local establishments and employment, while Appendix Table E.4 documents a corresponding decline in household income. Appendix Table E.5 shows that disasters also increase net out-migration by approximately 0.03 percentage points for a one-standard-deviation disaster shock.

The distinction between migration and a genuine loss of bank funding can be tested directly at the bank level. If households relocate after a disaster but retain their accounts at another branch of the same multi-market bank, deposits in the affected county may decline while the bank's total deposits remain unchanged. Table 3 shows instead that banks with greater disaster exposure in their important deposit-supplying counties experience a significant decline in total deposits, concentrated in savings deposits. Table 4 shows that the same relationship survives aggregation: the granular funding shock predicts lower aggregate deposit growth. The county-, bank-, and aggregate-level evidence therefore traces the funding mechanism from disaster-induced local economic losses to a decline in the total deposit funding available to exposed banks.

The appendix provides several visual illustrations of the persistence and bank-level transmission underlying these estimates. Appendix Figure E.3 documents the persistent disruption of a major local establishment following Hurricane Katrina, while Appendix Figure E.4 illustrates the slow recovery of residential capacity in the Lower Ninth Ward. The Hibernia/Capital One case study provides a direct illustration of the funding mechanism. Appendix Figures E.5, E.6, and E.7 trace the bank's exposure to Hurricane Katrina and the resulting adjustment in its funding.

4.3 Constructing the Bank-Level, Aggregate, and County-Level Shocks

We now combine the two facts above, geographic concentration in bank deposits and persistent disaster-induced declines in local funding, into the three shock objects used in the rest of the paper.

Bank-level shock. Let $\varepsilon_{c,t}$ denote property damage per capita in county c at time t, and let $D_{b,c,t-1}$ denote bank b's deposits in county c as of the prior June 30, so that the geographic weights are predetermined with respect to the contemporaneous disaster. Define the deposit-share weight

$$\omega^{D}_{b,c,t-1} \equiv \frac{D_{b,c,t-1}}{\sum_{c'} D_{b,c',t-1}}, \tag{36}$$

so that the bank-level funding shock is

$$\Gamma_{b,t} = \sum_{c} \omega^{D}_{b,c,t-1} \varepsilon_{c,t}. \tag{37}$$

This is the empirical counterpart of the object sketched in Section 2.3. Appendix Section A.3 provides the corresponding microfoundation: if expected deposit withdrawals following a local disaster are proportional to a bank's lagged deposits in that county, aggregating expected county-level withdrawals across the bank produces equations (36)–(37).

Aggregate granular shock. The aggregate construction additionally weights bank-level funding shocks by the economic importance of the affected institution. We use lagged bank asset shares,

$$\omega^{A}_{b,t-1} \equiv \frac{A_{b,t-1}}{\sum_{b'} A_{b',t-1}}, \tag{38}$$

giving the raw aggregate shock

$$\Gamma_t = \sum_{b} \omega^{A}_{b,t-1} \Gamma_{b,t}. \tag{39}$$

The aggregate shock therefore combines concentration within banks through deposit shares with differences in economic importance across banks through asset shares. It is large when disasters strike locations that are important deposit sources for banks that themselves account for substantial shares of the banking system. Figure 4a plots the resulting series over time and shows that its largest movements coincide with major disaster episodes. Appendix Table H.2 identifies these episodes and their associated insurance payouts. Figure 4b shows the close relationship between the aggregate funding shock and disaster-related insurance payouts.

Following the granular instrumental-variables logic of Gabaix and Koijen (2024), we isolate the idiosyncratic component of Γ_t by subtracting its equal-weighted counterpart:

$$\Gamma^{*}_{t} = \Gamma_t - \frac{1}{N_{b,t-1}} \sum_{b} \left[\frac{1}{N_{b,c,t-1}} \sum_{c} \mathbf{1}_{b,c,t-1} \varepsilon_{c,t} \right], \tag{40}$$

where $N_{b,t}$ is the number of banks, $N_{b,c,t}$ is the number of counties in which bank b operates,

and $\mathbf{1}_{b,c,t}$ indicates that bank b operates in county c at time t. The equal-weighted term removes the common component of disaster exposure following the GIV construction, leaving variation generated by the interaction of idiosyncratic disasters with uneven economic weights. This is the sense in which Γ_t^* is *granular*.

County-level instrument. The regional design in Section 5 requires variation in the funding of banks serving county c that originates outside the local economy. For county c in state $s(c)$, define the out-of-state deposit share, renormalized over counties outside county c's state,

$$\omega_{b,c,t-1}^{D,\setminus s(c)} \equiv \frac{D_{b,c,t-1}\,\mathbf{1}_{\{c\notin s(c)\}}}{\sum_{c'\notin s(c)} D_{b,c',t-1}}, \qquad c \notin s(c).$$

The resulting bank shock and its equal-weighted counterpart are

$$\Gamma_{b,t}^{\setminus s(c)} = \sum_{c\notin s(c)} \omega_{b,c,t-1}^{D,\setminus s(c)} \varepsilon_{c,t},$$
$$\bar{\Gamma}_{b,t}^{\setminus s(c)} = \frac{1}{N_{b,c,t-1}^{\setminus s(c)}} \sum_{c\notin s(c)} \mathbf{1}_{b,c,t-1}\varepsilon_{c,t},$$

where $N_{b,c,t}^{\setminus s(c)}$ is the number of out-of-state counties in which bank b operates.

We exclude the entire state containing county c so that the identifying disasters are geographically separated from regional labor markets, commuting patterns, and common state-level conditions that could directly affect county c. Let $\omega_{b,c,t-1}^{L} \equiv \frac{L_{b,c,t-1}}{\sum_{b'} L_{b'c,t-1}}$ denote bank b's lagged share of lending in county c. The county-level instrument is then

$$z_{c,t} = \sum_b \omega_{b,c,t-1}^{L} \left[\Gamma_{b,t}^{\setminus s(c)} - \bar{\Gamma}_{b,t}^{\setminus s(c)}\right]. \tag{41}$$

The construction links the geography of bank funding to the geography of bank lending. For each county c, we first measure each bank's exposure to disasters occurring outside c's state, weighting each disaster by the affected county's importance to the bank's deposit base. We then aggregate these funding shocks using each bank's lagged share of lending in county c. This is the same logic as Guren et al. (2021b), applied to bank deposit geography rather than to the specific intermediary network in that paper. Section 5 examines the exclusion restriction directly using a battery of controls for the transmission of out-of-state disasters through real economic linkages.

We reserve the term *granular funding shock* for the aggregate object Γ_t^*. The bank-level object $\Gamma_{b,t}$ measures an individual bank's exposure and is used in the bank-level lending and mechanism analyses. The aggregate shock Γ_t^* is used in the aggregate regressions of Section 6, while $z_{c,t}$ measures county c's exposure to funding shocks originating outside its state and provides the instrument for the regional analysis.

4.4 Is the Bank-Level Shock Idiosyncratic?

The downstream analyses rely on $\Gamma_{b,t}$ behaving as an idiosyncratic funding shock rather than a persistent bank characteristic or a common economic factor. We examine three properties of the shock: its predictability from observable bank characteristics, its persistence over time, and its correlation across banks.

Appendix Table F.1 shows that lagged bank characteristics, including size, loans, equity, cash, hedging, dividends, and operating income, explain little of the variation in $\Gamma_{b,t}$ even when entered jointly with bank and year fixed effects.[8] Appendix Figure F.1 shows that bank-specific AR(1) coefficients average approximately -0.03 and are concentrated near zero, while pairwise R^2 values across banks' shock series average only 0.08. The shock therefore exhibits little persistence and little common cross-bank variation. These properties follow naturally from its construction: banks differ in the geography of their deposit bases, while the timing and location of major disasters vary substantially over the sample, generating different funding shocks across banks and over time.

5 Estimating the Regional Elasticity (χ)

This section estimates the regional credit-supply elasticity, χ, which measures the response of county output to an instrument-induced change in county bank credit. This estimate is one of the three inputs into the decomposition $\theta = \chi\phi + \delta$. The term $\chi\phi$ captures the component of the aggregate output response that operates through aggregate lending, while δ captures the remaining aggregate effect, or missing intercept. Sections 6 and 7 estimate the remaining components, ϕ and θ, and then recover δ from the decomposition. Estimating χ is therefore the first step in quantifying how much of the aggregate response is explained by the regional credit-supply elasticity.

The regional design identifies χ by comparing counties whose lenders experience different funding shocks. This comparison identifies the effect of relative changes in county credit supply on county output, but it does not identify aggregate effects that move all counties together, such as changes in wages, prices, or aggregate demand. The design therefore treats χ as a local structural moment rather than an aggregate elasticity.

[8] Panel A of Appendix Table F.2 provides additional summary statistics for the bank-level variables.

The instrument $z_{c,t}$, constructed in Section 4.3, addresses the endogeneity of county loan growth. The instrument measures the exposure of banks lending in county c to disasters occurring outside county c's state, with weights that reflect both the importance of the affected locations in each bank's deposit base and the importance of each bank as a lender in county c. The instrument consequently shifts county credit supply through bank funding conditions rather than through contemporaneous changes in local credit demand. The exclusion of same-state disasters removes the most direct disaster channel, while the robustness analysis assesses remaining concerns about cross-state real-economy spillovers. Therefore, the estimate of χ reveals how county output responds to a funding-induced change in county lending.

5.1 Empirical Design

The challenge in estimating χ is that county loan growth reflects local credit demand as well as local credit supply. A county experiencing stronger economic growth may generate greater borrowing demand while also attracting greater loan supply. An ordinary regression of output growth on loan growth therefore does not identify the causal effect of credit supply. Identification instead requires changes in county loan growth that are unrelated to contemporaneous conditions in the county's own economy. We obtain such variation by exploiting changes in the funding capacity of the banks that lend in county c when those changes originate outside county c. Because these funding shocks arise elsewhere, they shift the supply of bank credit in county c without directly reflecting contemporaneous economic conditions in the county itself.

Section 4.3 constructs the instrument $z_{c,t}$ to isolate these funding shocks. For each bank, the instrument measures exposure to natural disasters occurring in counties outside the state containing county c. Each disaster is weighted by the affected county's lagged share of the bank's deposits, so shocks receive greater weight when they occur in locations that are an important source of the bank's funding. These bank-level funding shocks are then aggregated using each bank's lagged share of lending in county c, so banks receive greater weight in the instrument when they play a larger role in supplying credit to that county.

The instrument therefore varies with the exposure of county c's lenders to deposit-funded shocks that originate outside county c's state. Banks receive greater weight in $z_{c,t}$ when they account for a larger share of lending in county c, while disasters receive greater weight when they strike counties that account for a larger share of a bank's deposits. A disaster hitting an important deposit-supplying county therefore generates a larger funding shock for the affected bank. The bank's internal capital market then transmits the resulting funding contraction to the counties in which it lends, including county c. The instrument consequently shifts county loan supply through the balance-sheet constraints of the banks serving the county, rather than through contemporaneous changes in credit demand within the county.

Excluding disasters occurring within county c's state removes the most direct channel through which a disaster can affect county c's economic activity. The state exclusion separates the source of the funding shock from local disaster damage, reconstruction activity, and other state-level shocks that simultaneously affect lending and output. It does not, however, imply that counties are economically isolated from the rest of the country. Trade, migration, geographic proximity, and social connections can transmit real shocks across state borders, and such spillovers would threaten identification if a county's network of lenders systematically overlapped with its exposure to disaster-affected trading partners or other economically connected locations. Assumption 1 formalizes this requirement. Section 5.3 examines this concern directly, and Appendix Section G reports the corresponding reduced-form robustness tests using controls for real-activity-weighted disaster exposure, trade, migration, geographic proximity, and social connectedness. The empirical specifications follow equations (24) and (25):

$$\ell_{c,t} = \alpha_0 + \alpha_1 z_{c,t-1} + \theta_c + \theta_t + \varepsilon_{c,t}, \tag{42}$$

$$g_{c,t} = \beta_0 + \chi^{\text{reg}} \ell_{c,t} + \theta_c + \theta_t + u_{c,t}, \tag{43}$$

where $g_{c,t}$ is county nominal GDP growth, $\ell_{c,t}$ is county loan growth, θ_c denotes county fixed effects, and θ_t denotes year fixed effects. The first-stage equation measures the effect of out-of-state funding shocks at a county's lenders on the county's loan growth. The second-stage equation measures the effect of the resulting credit-supply-induced change in loan growth on county output growth.

County fixed effects absorb persistent differences across counties, including differences in industrial composition, banking-market structure, and average exposure to banks with geographically concentrated deposit bases. Year fixed effects account for national changes in credit conditions and aggregate economic activity. Identification in the preferred specification therefore comes from within-county changes over time in exposure to funding shocks at the banks serving that county. Standard errors are clustered by county throughout.

5.2 Results: Estimating χ

Table 5 reports the first-stage and 2SLS estimates. Columns 1 and 2 provide the benchmark without fixed effects, while columns 3 and 4 report the preferred specification with county and year fixed effects.

Columns 3 and 4 provide our preferred specification because they include county and year fixed effects. County fixed effects absorb persistent differences across counties that may be correlated with both local economic activity and the composition of banks serving the county. Year fixed effects absorb common national movements in credit conditions and economic activity. Identification therefore comes from within-county changes over time in exposure to funding shocks at local lenders. The fixed

effects make Assumption 1 less demanding: the instrument must be orthogonal only to time-varying county-level shocks that remain after persistent county characteristics and common national shocks have been removed.

Before aggregating the funding shocks of individual lenders into $z_{c,t}$, we can examine directly whether the underlying bank-county shocks affect loan supply. Appendix Section G.1 performs this test using the same out-of-state construction at the bank-county level. For each bank lending in a given county, the shock is constructed from the bank's exposure to disaster-induced funding losses outside that county's state. The bank-county setting is particularly useful because multiple banks lend in the same county and year. County-by-year fixed effects, therefore, absorb local credit demand, local economic conditions, and direct disaster effects, while bank-by-county fixed effects absorb persistent differences across lending relationships. The remaining variation compares differently exposed banks serving the same local economy.

Appendix Table G.1 shows that these out-of-state funding shocks reduce bank-county lending. The coefficient is negative and statistically significant across specifications, including the specification with county-by-year and bank-by-county fixed effects.[9] The lending response also remains negative in counties that did not themselves experience a disaster, where a direct local-disaster explanation is particularly difficult to sustain. This exercise therefore establishes the credit-supply response before the bank-county shocks are aggregated into $z_{c,t}$ and provides a direct microeconomic validation of the county-level first stage.

The first stage in Table 5 shows that this bank-county transmission survives aggregation to the county level. The coefficient on $z_{c,t}$ is negative and statistically significant in every specification: when banks serving a county experience larger funding shocks outside the state, loan growth in that county falls. In the preferred specification the coefficient is -1.4250, so a one-standard-deviation increase in $z_{c,t}$ lowers county loan growth by approximately 1.43 percentage points. In the preferred specification, the Kleibergen–Paap F-statistic is 27.6, comfortably above conventional weak-instrument thresholds. The instrument therefore generates meaningful variation in county credit supply in the direction predicted by the bank-optimization model in Section 2.4.

The second-stage estimates show that these funding-induced changes in credit supply translate into economically meaningful changes in local activity. The coefficient on instrumented loan growth is positive and statistically significant, indicating that counties receiving an exogenous expansion in bank credit experience faster output growth. Equivalently, a funding-induced contraction in loan supply reduces county output growth. Our preferred estimate of the regional elasticity is 0.0876, implying that a

[9] The bank-county lending response is also robust to excluding specialized credit-card banks under alternative classifications; see Appendix Table G.2.

one-percentage-point increase in county loan growth induced by bank funding conditions raises county nominal GDP growth by approximately 0.09 percentage points.

The estimate identifies the local loan-quantity channel that enters the aggregate decomposition. The remainder of the paper combines this regional elasticity with the aggregate lending response to measure the share of the aggregate output response that operates through changes in bank credit.

5.3 Discussion on the Exclusion Restriction

The exclusion restriction requires that the instrument $z_{c,t}$ affect county c's output through the funding conditions of the banks that lend there, rather than through other consequences of disasters outside the state. The exclusion of disasters from county c's own state removes the most direct channel from local disaster damage to local output. The state exclusion does not eliminate all real-economy spillovers. Banks that lend in county c may raise deposits in locations that are economically connected to county c through trade, migration, or other networks. A disaster in one of these locations may reduce the funding of banks serving county c while also affecting economic activity in county c directly. The instrument would then reflect real spillovers in addition to credit-supply variation.

Assumption 1 formalizes the required restriction. The assumption requires that, conditional on county and year fixed effects, a county's exposure to funding-shocked banks does not proxy for its exposure to disaster-shocked economic partners through the real-economy network M in equation (10). Table 7 evaluates this restriction by progressively introducing controls that capture alternative channels through which disasters outside county c's state may affect local economic activity.

Columns 1 through 4 introduce measures of out-of-state disaster exposure weighted by the affected county's national share of employment, GDP, population, and establishments. The employment and establishment measures capture exposure to disasters in locations that account for a large share of national production and business activity. The GDP measure captures exposure to disasters in locations that contribute substantially to aggregate output. The population measure captures exposure to disasters in locations that may affect household demand, migration, and other population-based connections. These controls absorb the possibility that $z_{c,t}$ proxies for exposure to disasters in economically important locations rather than variation in bank funding.

Columns 5 through 8 introduce measures of out-of-state disaster exposure through specific economic links between locations. The trade control captures spillovers through supply-chain and goods-market relationships. The migration control captures spillovers through household relocation and labor-market connections. The distance control captures spillovers from geographically proximate disasters that affect regional economic conditions. The social-connectedness control captures spillovers through social

networks that may transmit information, transfers, migration, or other forms of economic adjustment. Column 9 includes all of these control families jointly.

The estimated elasticity remains stable across this sequence of specifications. Each individual control produces an estimate between 0.072 and 0.089. The fully controlled specification yields an estimate of 0.075 that remains positive and statistically significant. The first stage also remains strong. The Kleibergen-Paap F-statistic ranges from 22.7 to 26.7 across the individual specifications and rises to 34.2 when all controls enter jointly.

The evidence supports the interpretation of $z_{c,t}$ as a credit-supply instrument. The alternative controls capture economically meaningful channels through which disasters may affect county output independently of bank funding. The inclusion of these controls does not materially alter the estimated effect of instrumented loan growth on county output. The stability of the estimated elasticity therefore indicates that the identifying variation in $z_{c,t}$ is unlikely to primarily reflect a county's broader exposure to disaster-affected parts of the country. For completeness, Appendix G.3 reports the corresponding reduced-form results in Appendix Tables G.3 and G.4, which show that the reduced-form relationship between $z_{c,t}$ and county outcomes is similarly stable across the alternative specifications.

A related concern is that the first stage may capture not a bank funding shock, but rather the within-bank reallocation of credit toward disaster-affected markets with elevated reconstruction demand, as documented by Cortés and Strahan (2017). Under this alternative mechanism, a bank exposed to disasters outside county c could reduce lending in c, not because its deposit base has contracted, but because it shifts lending capacity toward affected markets. Table 6 addresses this possibility directly by conducting a horse race between the baseline deposit-geography instrument, $z_{c,t-1}$, and a lending-geography instrument, $z^{L}_{c,t-1}$. The latter is constructed from the same set of disasters but weights each bank's out-of-state disaster exposure by the geographic distribution of its lending, rather than its deposits. If our first stage primarily reflected the reallocation of lending across banks' credit markets, then $z^{L}_{c,t-1}$ should predict county-level loan growth. It does not.[10] The deposit-geography instrument remains strong and highly significant, with a Kleibergen–Paap F-statistic of 27.6, whereas the lending-geography instrument is weak, with a Kleibergen–Paap F-statistic of 3.9. Moreover, conditional on the deposit-geography instrument, the marginal effect of the lending-geography instrument is statistically indistinguishable from zero. These results indicate that the regional first stage operates through the geography of banks' funding relationships rather than through the geography of their lending markets.

[10] This evidence is consistent with the findings of Cortés and Strahan (2017), while highlighting a distinct channel of disaster transmission. Their analysis emphasizes how smaller banks respond to disaster-induced increases in local loan demand by reallocating credit away from connected markets. By contrast, our results are driven primarily by large banks and are most closely linked to the geographic incidence of their deposit funding. The two mechanisms can therefore operate simultaneously: disasters may induce credit reallocation through changes in local loan demand while also generating funding shocks that affect lending through banks' deposit networks.

6 Estimating Aggregate Responses

Having estimated the regional elasticity, χ, we next examine the aggregate consequences of granular funding shocks. Specifically, we ask: how do aggregate bank lending and aggregate output respond when the banking system is exposed to a granular funding shock? Our key equation $\theta = \chi\phi + \delta$, implies that answering this question requires two additional aggregate objects beyond the regional elasticity estimated in Section 5. The first is the aggregate lending elasticity, $\phi \equiv \frac{\partial \ell}{\partial \Gamma^*}$; the second is the aggregate output elasticity, $\theta \equiv \frac{\partial g}{\partial \Gamma^*}$. Both elasticities are defined with respect to the same aggregate granular funding shock, Γ_t^*, constructed in Section 4.3.

Unlike the regional elasticity, the aggregate elasticities are identified from time-series variation in the granular funding shock, Γ_t^*. This difference follows from the distinct objects estimated in the two exercises.

The regional design uses a county's exposure to funding-shocked lenders as an instrument for county loan growth. Its purpose is to isolate the causal effect of a change in local credit supply on local output. The exclusion restriction is therefore essential: conditional on county and time fixed effects, the instrument must affect county output only through the lending of the banks that serve the county. If the same out-of-state disasters that tighten a county's lenders also affect the county through trade, migration, labor-market, or other real-economy links, the regional 2SLS coefficient would combine the effect of credit supply with these direct spillovers and would no longer identify χ.

The aggregate exercise addresses a different question. We do not use Γ_t^* as an instrument for aggregate lending in order to recover a structural effect of lending on output. Instead, we estimate the reduced-form responses of aggregate lending and aggregate output to the funding shock itself:

$$\ell_t = \psi + \phi\,\Gamma_{t-1}^* + \nu_t, \tag{44}$$

$$g_t = \mu + \theta\,\Gamma_{t-1}^* + \varepsilon_t, \tag{45}$$

Here, ϕ and θ summarize how aggregate lending and output respond to the constructed granular shock. We interpret these reduced-form coefficients as responses to an idiosyncratic disruption in the funding capacity of sufficiently large banks under the funding-specificity condition developed in Section 2.8. The relevant causal object is therefore the total equilibrium response to Γ_t^*, not the effect of lending holding fixed every other margin of adjustment.

This distinction matters because the channels that would threaten the exclusion restriction in the regional design are part of the aggregate estimand. A granular funding shock can affect aggregate output not only by reducing the quantity of bank credit, but also through equilibrium changes in wages

and prices, the reallocation of activity across banks, firms, and regions, propagation through trade and production networks, substitution toward non-bank finance, and endogenous policy responses. At the county level, a direct effect of the instrument through any of these channels would contaminate an attempt to isolate the partial effect of local lending. At the aggregate level, however, these same responses are not confounds. They are part of the mechanism through which a banking-sector funding disruption affects national output.

Accordingly, the aggregate regressions require a different identifying condition. We require that innovations in Γ_t^* represent variation in the funding capacity of granular banks, rather than other aggregate shocks that are correlated with aggregate output. The construction of Γ_t^* is designed to isolate precisely this variation: it combines plausibly exogenous local disasters with predetermined deposit shares and bank asset weights, and removes the equal-weighted component of disaster exposure. Under this funding-specificity condition, the coefficients ϕ and θ identify the reduced-form aggregate responses to granular bank funding shocks. No exclusion restriction analogous to that in Section 5 is required, because the aggregate analysis does not seek to net out the general-equilibrium forces that the regional design must exclude.

6.1 Results: Aggregate Responses to Granular Funding Shocks

Table 8 reports the estimated aggregate responses to the granular funding shock, Γ_t^*. The table implements the time-series regressions in equations (44) and (45) using quarterly data from 1994 to 2019. The dependent variables are aggregate commercial and industrial lending growth and aggregate GDP growth. We estimate the regressions with Newey–West standard errors, allowing for heteroskedasticity and serial correlation through eight lags. The table also reports the response of aggregate deposit growth, which provides an independent validation of the interpretation of Γ_t^* as a funding shock.

The estimated aggregate lending elasticity is $\phi = -0.2605$. The estimate indicates that a positive realization of Γ_t^*. That is, a realization in which disasters disproportionately affect the deposit markets of large banks predicts a statistically significant decline in aggregate commercial and industrial lending growth in the following quarter. The negative sign is the one implied by the funding mechanism: a deterioration in the deposit base of economically important banks tightens their balance-sheet capacity and reduces the credit they extend. This result establishes that the granular shock has aggregate consequences for the supply of bank credit, rather than merely redistributing lending across banks or locations.

The corresponding aggregate output elasticity is $\theta \equiv \frac{\partial g}{\partial \Gamma^*} = -0.2577$. The estimate is negative and statistically significant. Economically, it implies that disruptions to the deposit funding of granular banks are followed not only by lower aggregate lending, but also by lower aggregate output growth. The coefficient is a reduced-form aggregate elasticity: it measures the total equilibrium response of GDP

growth to the funding shock. It therefore incorporates the direct consequences of reduced bank lending together with the adjustment margins induced by the shock, including changes in firms' borrowing and investment, employment, wages, prices, the allocation of credit across banks and borrowers, and propagation through production and demand linkages.

The economic magnitude is substantial. Because Γ_t^* is standardized, the coefficient in equation (45) is itself the response to a one-standard-deviation funding shock: such a shock reduces quarterly GDP growth by approximately 0.26 percentage points. This decline is roughly 23 percent of mean quarterly GDP growth in the sample and approximately 10 percent of its standard deviation. The estimated response of aggregate lending is of a similar magnitude relative to the distribution of lending growth.

The aggregate deposit response provides an independent check on the economic interpretation of the shock. Aggregate deposit growth declines by 0.17 percentage points following a positive one-standard-deviation realization of Γ_t^*. This response is consistent with the balance-sheet channel underlying the construction of the shock: disasters affecting important deposit markets reduce aggregate bank funding alongside the contractions in lending and output documented above. The deposit regression does not enter the decomposition, but it links the aggregate estimates directly to the funding margin from which Γ_t^* is constructed.

Table 9 examines whether the estimate of θ is sensitive to the dynamic specification. Columns 1 through 6 enter the contemporaneous shock and each of its first five lags separately, while column 7 includes the contemporaneous shock and all five lags jointly. The negative response of aggregate output is robust to allowing for these richer dynamics. The coefficient on Γ_{t-1}^* is -0.2577 in the single-lag specification, corresponding to the estimate of θ in Table 8, and becomes -0.2918 when the full lag structure is included jointly. The contemporaneous response is also negative and statistically significant in the joint specification. The second lag is an exception to this pattern: its coefficient is positive and statistically significant in column 7. This positive response, however, is not robust to the inclusion of year fixed effects in column 8, whereas the contemporaneous and first-lag coefficients remain negative and increase in magnitude to -0.4585 and -0.4947, respectively. Thus, the benchmark estimate of θ does not arise from imposing a particular one-quarter response: allowing GDP to respond dynamically to the funding shock preserves, and if anything strengthens, the negative aggregate relationship.

The richer dynamics also contain substantial explanatory information beyond the benchmark specification. In column 7, the R^2 rises to 6.1 percent, compared with 0.9 percent in the first-lag specification. The information criteria reported at the bottom of Table 9 account for the additional parameters when comparing these specifications and likewise favor the richer dynamic model. Because the number of usable observations falls as additional lags are added, the information criteria across columns are computed on different samples and are not directly comparable; we therefore read them

as descriptive rather than as a formal model-selection ranking. We nevertheless retain the one-lag specification in Table 8 as our benchmark because it places θ, ϕ, and the deposit response on a common dynamic specification. Table 9 therefore shows that the benchmark estimate is not an artifact of imposing a one-lag specification and, if anything, provides a conservative summary of the richer dynamic response.

Figure 4 provides additional intuition for the source of the aggregate variation. The largest realizations of Γ_t^* occur around major disaster episodes, including Hurricanes Katrina, Sandy, Harvey, Ike, Ivan, Wilma, and Floyd, as well as major floods, wildfires, and the Nisqually earthquake. Appendix Table H.2 identifies these events and their associated insurance payouts. These disasters generate large values of Γ_t^* when they affect counties that are important deposit sources for banks with large asset shares, rather than simply when nationwide disaster intensity is high.

Together, the estimates provide the two aggregate objects needed for the decomposition. The estimate $\phi = -0.2605$ describes the contraction in aggregate bank lending induced by the granular funding shock and the estimate $\theta = -0.2577$ measures the total aggregate output effect of that same shock.

6.2 Robustness

The aggregate estimates in Table 8 are interpreted as the responses of lending and output to the granular funding shock, Γ_t^*. We examine four potential challenges to this interpretation. First, Γ_t^* may proxy for other aggregate shocks that coincide with the underlying disaster episodes. Second, its predictive content may not depend on the granularity of the bank-size distribution, contrary to the mechanism motivating its construction. Third, the shock may capture the geographic footprint of bank activity more generally rather than disruptions to bank funding specifically. Finally, Γ_t^* may proxy for the direct effects of disasters in economically important locations rather than for their effects on bank funding. We address each possibility in turn.

These exercises provide complementary evidence on the maintained funding-specificity condition. In the spirit of the relevance and contemporaneous-exogeneity conditions for external instruments, the aggregate interpretation requires that innovations in Γ_t^* load on disruptions to the funding capacity of economically important banks rather than proxy for other contemporaneous disturbances that independently affect aggregate activity (**?**). This condition cannot be established by a single regression. We therefore evaluate whether the predictive content of Γ_t^* is absorbed by other aggregate shocks, depends on the large banks whose size makes the banking system granular, is specific to deposit funding rather than lending or real-activity geography, and survives controls for the direct aggregate effects of disasters.

These exercises do not attempt to remove all direct real or general-equilibrium effects induced by a genuine disruption in bank funding from the aggregate outcome. Such effects are part of the aggregate

estimand. The concern is instead that Γ_t^* may proxy for disaster-driven aggregate activity independently of bank funding.

Other aggregate shocks. To assess the first concern, we run a horse race between Γ_t^* and other prominent sources of aggregate fluctuations including oil-supply shocks, monetary-policy surprises, economic-policy uncertainty, the term spread, government-expenditure shocks, and the firm-level granular residual of Gabaix (2011).[11] Appendix Table H.1 introduces these shocks separately and then jointly into the aggregate GDP specification. The coefficient on Γ_t^* is stable throughout, moving from -0.2952 in the baseline specification to -0.2906 when all six controls are included jointly. None of the additional shocks is individually statistically significant, and the explanatory power associated with Γ_t^* is comparable to, and in several cases exceeds, that of these conventional aggregate shocks. The relationship between the granular funding shock and GDP growth therefore is not absorbed by these alternative sources of aggregate fluctuations.

Granularity and bank size. The second concern goes directly to the granularity underlying the aggregate construction. If idiosyncratic funding shocks survive aggregation because a small number of banks account for a disproportionate share of the banking system, then shocks to large banks should matter disproportionately for aggregate outcomes. Conversely, if the relationship between Γ_t^* and GDP growth reflects a common aggregate component rather than granularity, removing the largest banks from the construction should leave its predictive content largely intact.

We test this implication by reconstructing Γ_t^* after excluding banks with asset shares above the kth percentile, with k ranging from the 95th to the 20th percentile in five-point increments, and re-estimating the aggregate GDP regression using each placebo shock. Figure 5 reports the resulting point estimates, with *All* denoting the baseline shock constructed from the full set of banks. The estimated coefficient of the regression coverages to a null effect once the largest banks are excluded, with the intermediate estimates small and statistically indistinguishable from zero. The aggregate relationship therefore depends precisely on the banks whose size allows idiosyncratic funding shocks to survive aggregation, consistent with the granular mechanism underlying Γ_t^*.

The bank-county evidence provides a complementary test of this interpretation. The granular argument itself does not require large banks to respond more strongly to a given funding shock; their disproportionate aggregate weight is sufficient for shocks to those institutions to survive aggregation. In the data, however, the two margins reinforce one another. Appendix Table H.3 estimates the small-business lending response to the out-of-state bank-county funding shock separately across bank-size groups, holding fixed county-by-year conditions and persistent bank-county relationships. Small banks

[11] Panel B of Appendix Table F.2 provides additional summary statistics for the aggregate shock measures.

exhibit no statistically significant response, whereas the contraction is largest and statistically significant among systemically important banks.[12] Thus, the institutions responsible for the granularity of Γ_t^* are also those for which the underlying funding shocks generate the strongest lending response. Appendix Section H.3 reports the full exercise.

Funding versus lending geography. The third concern is that deposit geography may simply proxy for the geographic distribution of bank activity more generally, particularly the geography of lending, rather than isolate funding conditions. We therefore construct placebo granular shocks using each bank's geographic distribution of lending rather than deposits. The lending weights are constructed from mortgage lending reported in HMDA ($\Gamma_{t-1}^{L,HMDA}$), small-business lending reported under the CRA ($\Gamma_{t-1}^{L,CRA}$), and the average of the two ($\Gamma_{t-1}^{L,Total}$). Table 10 reports the lending-based shocks separately and alongside the deposit-based Γ_t^*. The lending-based shocks are statistically insignificant throughout, though their point estimates are larger in the joint specifications, and explain approximately 0.02 percent of the variation in aggregate GDP growth, compared with 0.94 percent for the deposit-based shock. At the same time, the coefficient on Γ_t^* remains negative and statistically significant when the lending-based shocks are included. The aggregate relationship therefore depends on the geography of bank funding rather than on the geographic distribution of bank credit more generally.

Direct disaster exposure. The fourth concern is that disasters in economically important locations may affect aggregate GDP directly, independently of bank funding. If so, Γ_t^* could inherit predictive power from the fat-tailed distribution of local economic activity rather than from the geographic concentration of bank deposits. Table 11 addresses this possibility by constructing granular real-activity shocks from the same underlying disasters, with weights based on each county's national share of employment, GDP, personal income, population, and establishments rather than bank deposits. The coefficient on Γ_t^* remains negative and statistically significant across every specification, while the real-activity shocks add little independent explanatory power. The aggregate relationship therefore does not appear to arise from the concentration of economic activity in the locations underlying the funding shock.

Appendix Section H.4 provides two complementary tests of the same interpretation. Appendix Figures H.1 and H.2 compare the dynamic response of GDP growth to the granular funding shock with its response to aggregate disaster intensity. GDP responds materially to Γ_t^*, whereas the response to aggregate disaster damage is economically small and statistically indistinguishable from zero over the reported horizon. Appendix Table H.4 instead controls directly for aggregate home and business losses verified by the Small Business Administration. The coefficient on Γ_t^* remains negative, statistically

[12] Cortés and Strahan (2017) study the response to natural disasters primarily through small banks and document an increase in lending associated with short-run local credit demand. Our evidence instead emphasizes persistent funding shocks and their transmission through large, multi-market banks. Appendix Section B discusses the differences between the two settings and shows how the findings can coexist.

significant, and close to its baseline magnitude. Together, these exercises distinguish the funding consequences of disasters from their direct effects on aggregate economic activity.

Measurement of deposit geography. We next examine whether the aggregate relationship is sensitive to the measurement of deposit geography itself. Appendix Section H.5 reports two complementary exercises. Appendix Table H.5 reconstructs Γ_t^* after adjusting the underlying deposit measure for the potential sources of mismeasurement examined in Section 4.1, including tax-driven deposits, banks involved in mergers and acquisitions, non-local deposits, and banks' largest lending counties. The estimated relationship remains negative and statistically significant across the alternative constructions, including when the adjustments are imposed jointly. Appendix Table H.6 then replaces deposit geography altogether with the geographic distribution of bank branches. The branch-based shock produces a similar negative response of GDP growth and, in the joint lag specification, explains 6.5 percent of its variation, compared with 6.1 percent for the baseline deposit-based shock. The aggregate results therefore do not depend on a particular treatment of geographically reported deposits.

Historical evidence. Finally, we examine whether the aggregate relationship is specific to the modern SOD sample. Our baseline analysis begins in 1994 to maintain a consistent series around the transition to the modern SOD reporting regime and the interstate-banking liberalization associated with the Riegle–Neal Interstate Banking and Branching Efficiency Act. Historical SOD data allow us to extend the analysis back to 1981.[13] Appendix Figure D.4 shows that geographic deposit concentration predates the baseline sample and was substantially higher during the 1980s, when geographic restrictions on banking remained more binding. Appendix Table H.7 reconstructs the granular funding shock over the longer sample and reports the aggregate GDP relationship for the full period and separately before and after 1994. The relationship remains present in both subperiods. Its explanatory power is larger in the pre-1994 sample, with an R^2 of 16.3 percent compared with 5.8 percent after 1994. We interpret this difference cautiously because the pre- and post-1994 SOD series are not directly comparable and the two periods differ along many dimensions. The historical evidence nevertheless establishes that the aggregate relationship is not unique to the modern SOD sample and is consistent with a larger role for geographically concentrated funding when restrictions on banks' geographic expansion were more binding.

Taken together, these exercises provide complementary evidence in support of the funding-specificity interpretation of the aggregate shock. The relationship between Γ_t^* and GDP growth is not absorbed by other prominent aggregate shocks, depends on the large banks whose size makes the banking system granular, is specific to the geography of bank funding rather than lending, and survives controls

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

for the direct economic consequences of disasters. It is also robust to alternative treatments of deposit geography, an independent branch-based construction, and extension to the historical sample. We next examine whether the estimated aggregate output response is sensitive to the dynamic specification.

7 Recovering the Missing Intercept

This section combines three objects estimated from the same underlying class of granular funding shocks: the regional credit-supply elasticity χ, the aggregate lending response, ϕ, and the aggregate output response, θ. The relationship, $\theta = \chi\phi + \delta$, provides a direct comparison between the aggregate output response predicted by the regional loan-quantity channel and the aggregate response observed in the data. The residual, δ, is the missing intercept: the component of the aggregate response that the regional design does not recover.

Table 12 combines the regional and aggregate estimates to implement equation (33). The regional credit-supply elasticity is $\chi = 0.0876$, reported in Table 5. The aggregate lending elasticity is $\phi = -0.2605$, and the aggregate output elasticity is $\theta = -0.2577$, both reported in Table 8. Together, these estimates determine the component of the aggregate response predicted by the regional loan-quantity channel, $\chi\phi = -0.0228$, and, by subtraction, the remaining aggregate response, $\delta = \theta - \chi\phi = -0.2349$.

Expressing these two components as shares of the observed aggregate response establishes the central quantitative result of the paper. The regional loan-quantity channel accounts for approximately 9 percent of the aggregate output response, leaving 91 percent to the missing intercept. Thus, although the regional design recovers a precisely estimated and economically meaningful effect of bank credit on local output, that channel accounts for only a small fraction of the economy-wide response to the same funding shock.

The economic interpretation follows directly from the decomposition. The product $\chi\phi$ is the aggregate decline in output predicted by applying the regional elasticity of output with respect to bank credit to the observed aggregate contraction in bank lending. It is therefore the aggregate response implied by the loan-quantity channel alone, holding fixed the common adjustment that a comparison across regions differences out. The gap between this prediction and the observed aggregate response is δ, the component of aggregate adjustment that regional identification does not recover. Thus, this gap indicates that the local causal elasticity recovered from cross-regional variation and the total aggregate response to the same shock are different objects.

The arithmetic underlying the 9 percent share is informative about why the missing intercept is large. The fraction of the aggregate output response accounted for by the loan-quantity channel is $\chi\frac{\phi}{\theta}$. The estimated aggregate lending and output responses, ϕ and θ, are approximately equal, so the

loan-quantity channel's share of the aggregate response is approximately χ, the regional elasticity. This near equality is not imposed by the model but is an empirical feature of the data.

The near equality of ϕ and θ therefore connects the local and aggregate interpretations of χ. As a local elasticity, $\chi = 0.0876$ implies that a one-percentage-point increase in county loan growth induced by bank funding conditions raises county nominal GDP growth by approximately 0.09 percentage points. At the aggregate level, because lending and output respond to the funding shock in nearly equal proportion, χ also approximately measures the share of the aggregate output response accounted for by the loan-quantity channel. The same estimate can therefore represent an economically meaningful local effect while implying that most of the aggregate response operates outside the channel identified by regional variation.

This relationship also clarifies the benchmark under which the missing intercept would disappear. The loan-quantity channel accounts for the full aggregate response when $\chi\phi = \theta$. With ϕ/θ close to one, this condition requires χ to be approximately one. The model illustrates why such a regional elasticity would require unusually strong transmission from bank credit to local economic activity. Equation (8) expresses χ as a weighted combination of the response of the productive input to bank credit, e_B, and the response of employment to bank credit, ψ_B, with weights α and $1 - \alpha$ given by the corresponding output elasticities in equation (4). For χ to approach one, both margins would have to respond strongly to bank credit. In particular, bank lending would have to account for nearly all of the financing supporting local production, while employment would have to adjust nearly one for one with bank credit. Neither condition is natural in an economy in which firms can substitute toward retained earnings, equity, trade credit, and non-bank finance and in which employment adjusts only partially to financing conditions. Existing regional evidence is consistent with this reasoning. Huber (2018), for example, reports that firms fully dependent on Commerzbank held 20.5 percent less bank debt and had 5.3 percent lower employment following the lending cut, implying an employment-to-credit elasticity of approximately 0.26. Similarly, Berton et al. (2018) estimate an employment-to-credit-supply elasticity of approximately 0.36, while Greenstone et al. (2020) finds economically modest employment responses to county-level small-business lending shocks. Our estimate of $\chi = 0.0876$ is therefore consistent with a broader empirical literature in which local economic activity responds meaningfully, but considerably less than one for one, to changes in bank credit.

Although the near equality of ϕ and θ gives χ this particularly simple interpretation in our setting, the decomposition applies more generally. The regional elasticity alone does not determine the share of the aggregate response attributable to the regional channel. That share is $\chi\frac{\phi}{\theta}$ and therefore also depends on the relative aggregate responses of credit and output to the same underlying shock. In our setting, ϕ/θ happens to be close to one, making χ itself a close approximation to the loan-quantity share. This near

equality is an empirical feature of our sample, not a structural restriction, and need not hold in other settings. Translating a regional elasticity into an aggregate prediction therefore requires both the regional elasticity and the aggregate responses of credit and output to the same underlying shock.

This aggregation exercise is related to, but distinct from, Herreño (2023). That paper embeds cross-sectional bank credit-supply estimates in a calibrated general-equilibrium model and finds that general-equilibrium adjustment moderately dampens the cross-sectional effect, with the aggregate output response equal to roughly 70 percent of the partial-equilibrium response. The two exercises compare different objects. That analysis holds the credit-transmission channel fixed and asks how general-equilibrium adjustment changes the response operating through that channel. Our residual is defined relative to the total aggregate output response and therefore also contains adjustment that does not operate through loan quantities. The general-equilibrium wedge studied by Herreño (2023) is therefore conceptually nested within the broader set of forces that can contribute to δ, rather than providing an alternative estimate of the same residual.

Having established what the residual measures, its interpretation requires two additional considerations. The first concerns the interpretation of the aggregate shock itself. Because δ is recovered residually from θ, its interpretation depends critically on what Γ_t^* measures. The validation exercises in Section 6.2 therefore matter directly for the decomposition. They establish four features of the shock: its predictive content is not absorbed by other prominent aggregate shocks; it depends on the large banks whose size allows idiosyncratic shocks to survive aggregation; it is tied to the geography of bank funding rather than bank lending; and it is not explained by the direct macroeconomic consequences of disasters in economically important locations. These exercises do not identify the mechanisms contained in δ, but they substantially narrow the set of alternative explanations for the residual.

The second consideration concerns the comparability of the regional and aggregate credit measures entering $\chi\phi$. The regional elasticity is estimated at annual frequency from county nominal GDP growth and CRA small-business lending, instrumented by $z_{c,t}$ with county and year fixed effects. The aggregate responses are estimated at quarterly frequency from aggregate nominal GDP growth and commercial and industrial lending growth. The two objects are closely related but not identical. Both output measures are nominal, and CRA small-business loans are commercial and industrial loans of one million dollars or less, so the regional credit measure is a subset of the aggregate credit measure rather than a different asset class. The designs nonetheless differ in frequency and in the breadth of the credit aggregate. We therefore interpret $\chi\phi$ as a first-order approximation to the loan-quantity component of the aggregate response, under the maintained assumption that the elasticity estimated from county small-business lending at annual frequency is informative about the corresponding elasticity for aggregate commercial and industrial lending.

These considerations discipline the interpretation of the missing intercept but do not turn it into a decomposition of mechanisms. δ is a scalar residual. As discussed in Section 2.6, equation (33) does not distinguish among the channels operating outside the regional loan-quantity channel. Wage and price adjustment, reallocation across regions, sectors, banks, and borrowers, propagation through production and trade networks, endogenous adjustment of bank and borrower balance sheets, substitution toward non-bank finance, and other general-equilibrium responses are all contained in the same term. The decomposition establishes their combined quantitative importance but assigns no separate share to any one mechanism. Identifying the individual channels underlying the missing intercept is beyond the scope of this paper.

8 Financial Frictions and the Transmission of Funding Shocks

The preceding sections establish that funding shocks originating outside a county's state reduce the credit supplied by banks serving that county, that these changes in credit affect local output, and that granular funding shocks generate substantially larger aggregate responses. This section asks what determines the strength of that transmission. The central hypothesis is that funding shocks have larger effects when substitution is limited on either side of the credit relationship: when banks cannot readily replace lost funding or balance-sheet capacity, and when borrowers cannot readily replace the credit those banks withdraw.

The bank model in Section 2.4 provides the organizing logic. A loss of deposits need not reduce lending if a bank can replace the lost funding at similar cost, draw on excess capital, or otherwise expand its balance sheet without friction. A funding shock affects loan supply when these margins are limited. In that case, the shock raises the shadow value of funding or capital, making balance-sheet capacity scarce and inducing the bank to reduce or reallocate lending.

Borrowers face an analogous substitution problem. A reduction in bank credit need not affect real activity if firms can replace the lost financing with internal funds, credit from another bank, equity, trade credit, or non-bank finance at similar cost. The real effects of a lending contraction are larger when these alternatives are costly or unavailable and the borrower's external-finance constraint becomes more binding. Transmission therefore depends on two related margins: the bank's ability to absorb the initial funding shock and the borrower's ability to absorb the resulting contraction in bank credit.

We examine these margins directly. We first ask whether funding shocks produce larger lending contractions at banks with fewer opportunities to substitute across funding and balance-sheet margins, and whether constrained banks reallocate scarce lending capacity across markets. We then ask whether the effects of withdrawn credit are concentrated among borrowers with fewer financing alternatives. The evidence does not decompose the missing intercept, δ, into particular mechanisms. Rather, it identifies

the financial frictions that determine whether a funding shock is absorbed or propagates through credit markets and into real activity.

8.1 Bank Constraints and Credit Allocation

The bank-side mechanism implies that the lending response to a funding shock should be stronger when replacing lost funding or expanding balance-sheet capacity is more costly. Table 13 examines this prediction along three margins: reliance on deposit funding, capitalization, and the allocation of lending across core and non-core markets.

Column 1 examines reliance on deposit funding. Banks whose balance sheets depend more heavily on deposits have less scope to replace a deposit outflow with alternative sources of funds. A given funding shock should therefore raise the shadow value of balance-sheet capacity by more at these banks. Consistent with this prediction, lending contracts more sharply among deposit-reliant banks: a one-standard-deviation funding shock is associated with an additional 1.2 percentage-point decline in lending growth for banks with high deposit reliance. Appendix Table I.1 shows that this relationship is stable across alternative fixed-effect specifications.

Column 2 examines capitalization. Banks with less capital have less capacity to accommodate a funding shock while remaining within their regulatory constraints. The same funding shock should therefore raise the shadow value of capital by more when capital buffers are limited. Consistent with this prediction, lending contracts substantially more at capital-constrained banks. A one-standard-deviation funding shock is associated with an additional 13 percentage-point decline in lending growth relative to other banks, and the interaction ranges from 9 to 14 percentage points across the alternative fixed-effect specifications. Appendix Table I.2 reports similar results across alternative specifications.

Column 3 examines how banks allocate scarce balance-sheet capacity across markets. When a funding shock tightens a bank's constraint, the bank need not reduce lending uniformly. It may preserve credit in markets where its relationships or informational advantages are more valuable and contract lending more heavily elsewhere. We use the absence of a physical branch as a proxy for a non-core market. Lending falls more in these markets following a funding shock. Appendix Tables I.3 and I.4 show that the same pattern holds under an alternative definition based on the bank's local lending share. Funding constraints therefore affect not only the amount of credit supplied but also its allocation across markets.

Appendix Table I.5 provides a complementary test based on banks' ability to free balance-sheet capacity after origination. Conforming mortgages can be sold to Fannie Mae and Freddie Mac, whereas jumbo mortgages generally cannot (Loutskina and Strahan, 2009). Jumbo lending therefore remains more dependent on the originating bank's own balance sheet. Following the same funding shock to the

same bank in the same county and year, jumbo mortgage originations contract more than conforming originations. The response is therefore stronger where banks have less ability to accommodate a funding shock by moving loans off balance sheet.

Taken together, the bank-side evidence points to a common mechanism. Funding shocks have larger effects on lending when alternative funding, capital, or balance-sheet capacity is more difficult to obtain. Banks also respond to scarce capacity by reallocating credit away from relationships in which their informational or strategic advantage is weaker. The strength and allocation of the credit-supply response therefore depend on the constraints banks face when attempting to absorb the initial funding shock.

8.2 Borrower Constraints and Real Effects

The contraction in bank loan supply need not translate one for one into a contraction in borrower financing. Its real consequences depend on whether affected borrowers can replace withdrawn credit with other sources of funds. The borrower-side evidence in Appendix Tables I.6 and I.7 is consistent with this substitution channel. Within the same bank, county, and year, lending contracts more to smaller firms following a funding shock. Using Dealscan to link firms to their banks, we also find larger effects of bank funding shocks on debt, assets, employment, and capital expenditure among younger firms, which tend to have fewer financing alternatives (Hadlock and Pierce, 2010; Petersen and Rajan, 1994). Thus, funding shocks have stronger financing and real effects among borrowers for whom replacing bank credit is more difficult.

Together, the bank- and borrower-side evidence points to substitution frictions as an important determinant of transmission. Funding shocks reduce credit more sharply when banks have less capacity to replace funding or release balance-sheet capacity, while the resulting credit contraction has larger effects when borrowers have fewer alternative sources of finance. These findings do not assign particular components of the missing intercept to individual mechanisms; the missing intercept remains the residual defined in Section 7. Instead, the mechanism evidence points to a more specific microeconomic result: funding shocks propagate more strongly when the relevant substitution margins on either side of the credit relationship are limited.

9 Conclusion

Regional designs provide credible estimates of the causal effects of bank credit supply, but translating these estimates into aggregate effects requires accounting for adjustments that are common across regions. This paper develops a framework for making this connection and implements it using a common source of bank funding variation. By interacting local natural disasters with the geographic concentration of

bank deposits, we construct funding shocks that generate both differential exposure across local credit markets and aggregate variation when economically important banks are affected.

Using the same underlying funding variation, we estimate the regional credit-supply response and the aggregate responses of bank lending and output. The regional elasticity is precisely estimated and economically meaningful, and the aggregate funding shock predicts contractions in deposits, lending, and output. Combining these responses yields the paper's central result: the regional loan-quantity channel accounts for approximately 9 percent of the aggregate output response to the funding shock. The remaining 91 percent is the missing intercept, the component of aggregate adjustment not recovered by the regional loan-quantity channel.

The magnitude of the missing intercept does not diminish the importance of the regional estimate. Rather, it illustrates that causal identification and quantitative importance for aggregate fluctuations are distinct questions. The mechanism evidence points to substitution frictions on both sides of the credit relationship: transmission is stronger when banks have less capacity to replace funding and when borrowers have fewer alternative sources of credit. These forces help characterize how funding shocks propagate, although the decomposition does not assign the missing intercept to individual mechanisms. Identifying the mechanisms that account for the missing intercept, and measuring their relative importance, is an important direction for future research.

The 9 percent share is specific to the bank funding shocks studied here, but the broader implication extends beyond this setting. When the same underlying shock can support both cross-sectional identification and an aggregate response, the framework provides a way to determine how much of the economy-wide effect is accounted for by the causal channel identified locally. For bank funding shocks, that share is small. More generally, connecting well-identified cross-sectional estimates to aggregate outcomes requires measuring not only whether a channel matters, but how much of the aggregate response it explains.

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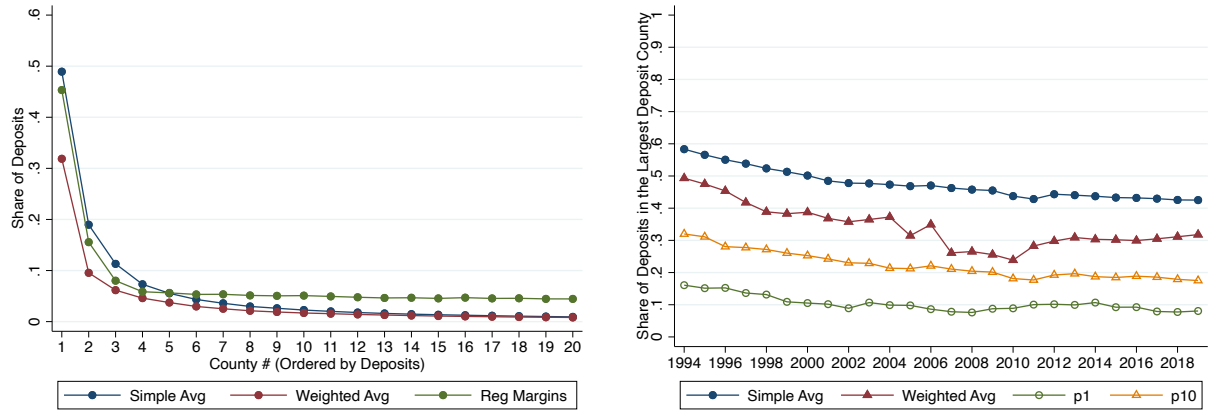
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Figure 1: Geographic Concentration of Deposits

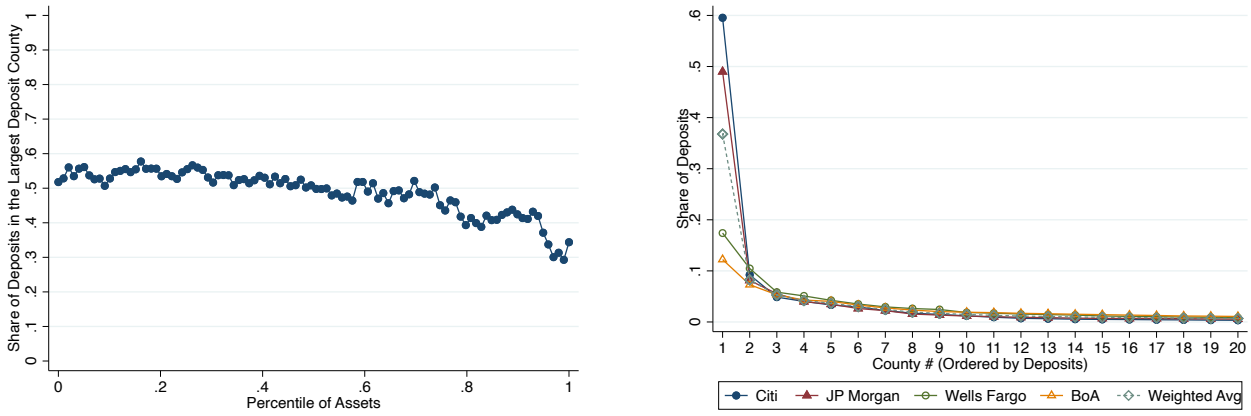


(a) Cross Section

(b) Time Series

Notes: 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

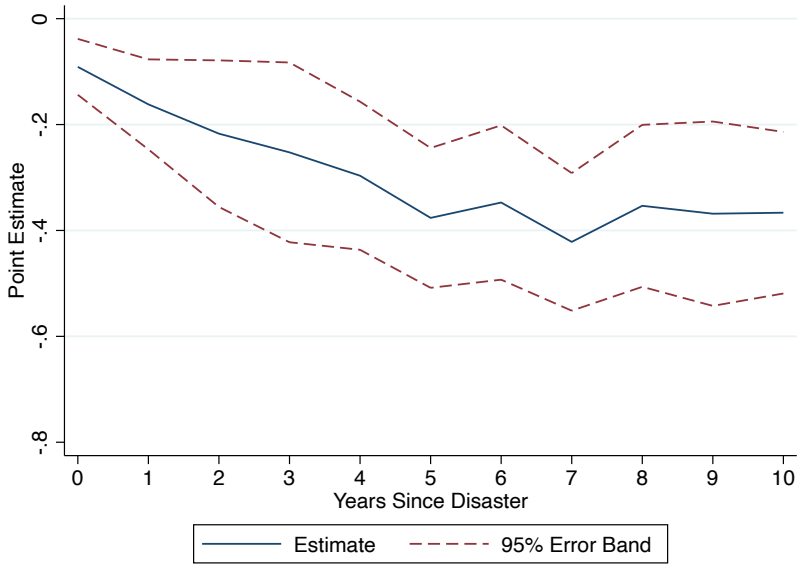


(a) Banks by Size

(b) Four Largest Banks

Notes: This figure uses Summary of Deposits (SOD) data from 1994 to 2019 and examines the relation between geographic deposit concentration and bank size. Panel (a) sorts banks by total assets and reports the average share of deposits in the largest deposit county by percentile of bank assets. Panel (b) reports the average deposit shares of the top 20 deposit counties for the four largest U.S. banks: Citibank, JPMorgan Chase, Wells Fargo, and Bank of America. Counties are ranked separately within each bank by their deposit shares, so county rank 1 denotes the bank's largest deposit county.

Figure 3: Long-Run Response of Deposit to Disaster Shocks

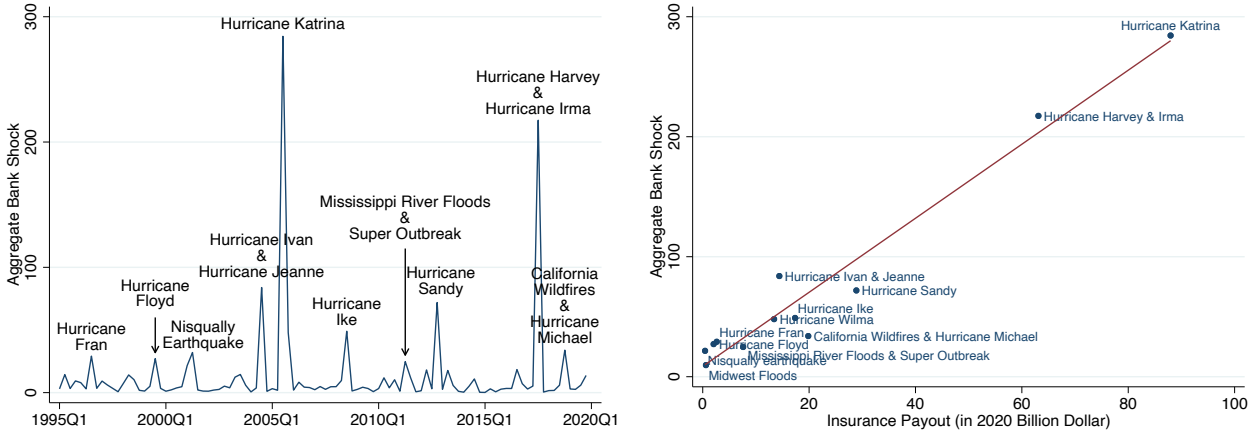


Notes: This figure uses the Summary of Deposits (SOD) data matched with the Spatial Hazard Events and Losses Database for the United States (SHELDUS) and plots the estimated coefficient β_h's from the following specification:

$$\{ln(Deposit)_{c,t+h} - ln(Deposit)_{c,t-1}\} \times 100 = \beta_h \times \text{Disaster Shock}_{c,t-1} + \theta_c + \theta_{s(c\in s),t} + \varepsilon_{c,t}.$$

The data span from 1994 to 2019. The dependent variable is deposit growth in percent defined as $\{\ln(Deposits)_{c,t+h} - \ln(Deposits)_{c,t-1}\} \times 100$, where $\ln(Deposits)_{c,t}$ is the natural logarithm of total deposits in county c and year t, and h denotes the forecast horizon. 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 4: Aggregate Bank Deposit Shock

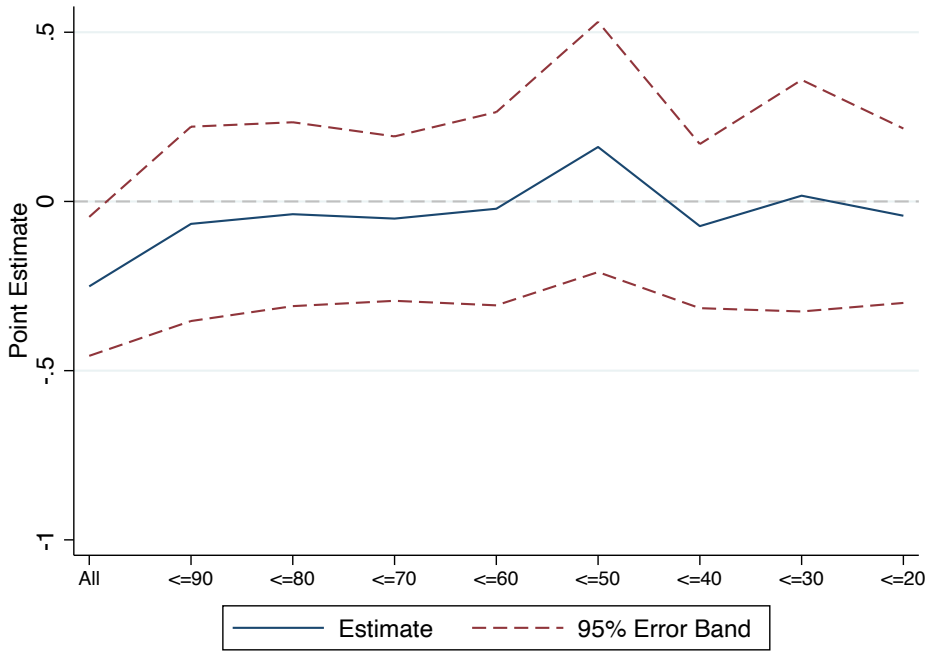


(a) Aggregate Shock over Time

(b) Aggregate Shock and Insurance Payout

Notes: Figure 4a plots the aggregate bank deposit shock (Γ_t) from Q1-1995 until Q4-2019 and indicates major disasters at its notable peaks. Figure 4b 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 5: Large-Bank Placebo: Point Estimate



Notes: Notes: This figure reports the placebo test that excludes large banks, described in Section 6.2. Γ_t^* is reconstructed after excluding banks with asset shares above the kth percentile, where k falls from 90 to 20 in decrements of ten percentile points. Each reconstructed shock is used to re-estimate

$$\Delta \ln(GDP)_t \times 100 = \alpha + \beta \times \Gamma_{t-1}^* + \varepsilon_t,$$

where the dependent variable is aggregate GDP growth in percent. Figure 5 plots the resulting estimate of β against k , which falls sharply once the largest banks are excluded.

Table 1: Summary Statistics

	# Obs	Mean	SD	P25	P50	P75
Panel A. County×Year						
Deposit Growth (%)	79,866	3.21	6.31	0.03	2.97	6.12
Total Property Damage (in 2021 USD)	79,866	7,916,310	221,444,206	139	52,746	421,015
Total Property Damage per Capita (in 2021 USD)	79,866	126.76	2,509.18	0.00	1.58	13.36
GDP Growth (%)	54,275	3.45	8.75	0.05	3.59	6.96
Small Buiness Lending Growth (%)	54,275	6.00	66.53	-20.62	1.57	25.22
$z_{c,t}$	54,275	-71.24	228.78	-74.46	-34.67	-20.09
Ln(Number of Establishments)	81,596	6.44	1.45	5.43	6.30	7.28
Ln(Number of Employees)	81,098	8.87	1.68	7.69	8.77	9.88
Migration: Outflow per 100 residents	78,321	4.91	1.55	3.89	4.64	5.59
Migration: Inflow per 100 residents	78,321	5.04	1.86	3.77	4.70	5.91
Migration: Net Outflow per 100 residents	78,321	-0.13	1.06	-0.63	-0.03	0.45
Panel B. Bank×Year or Firm×Year						
$\Gamma_{b,t}$	12,481	63.87	476.42	1.03	5.36	23.01
Total Deposit Growth (%)	11,258	7.64	12.66	0.93	5.21	10.81
Demand Deposit Growth (%)	11,180	6.31	31.11	-2.66	7.03	17.81
Transaction Deposit Growth (%)	11,204	4.97	30.36	-2.05	6.53	15.67
Saving Deposit Growth (%)	11,256	11.67	20.63	0.80	7.50	16.85
ln(Debt)	11,537	6.08	2.56	4.59	6.28	7.80
ln(Asset)	12,156	7.42	2.25	5.86	7.40	8.97
ln(Number of Employees)	11,530	1.82	1.44	0.60	1.55	2.78
ln(CapEx)	10,794	4.04	2.37	2.41	4.17	5.73
Panel C. Bank×County×Year						
Small Business Lending Growth (%)	575,000	5.14	108.78	-42.88	0.00	49.77
$\Gamma_{b,c,t}$	575,000	68.93	688.48	2.88	10.66	31.31
Panel D. Year						
GDP Growth (%)	102	1.11	2.58	-0.48	1.75	3.34
C&I Lending Growth (%)	102	1.32	2.33	0.16	1.82	2.88
Deposit Growth (%)	102	1.64	1.13	0.88	1.58	2.25
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
$\Gamma_t^{L,CRA}$	87	20.58	43.14	2.73	7.75	20.65
$\Gamma_t^{L,HMDA}$	87	19.71	41.65	2.65	7.43	20.37
$\Gamma_t^{L,Total}$	87	20.15	42.39	2.72	7.59	20.51
Γ_t^{Emp}	101	17.49	41.91	3.38	5.91	13.00
Γ_t^{GDP}	101	15.30	52.12	0.00	3.78	8.50
Γ_t^{Inc}	101	30.17	56.18	7.10	16.22	30.12
Γ_t^{Pop}	101	20.13	50.20	3.56	6.53	16.65
Γ_t^{Est}	101	18.57	42.21	3.69	6.43	15.22

Notes: This table reports summary statistics for the main variables used in the analysis. Panel A reports county-year variables. Deposit growth is constructed from Summary of Deposits (SOD) data. GDP growth is constructed from BEA county GDP data. Total Property Damage and Total Property Damage per Capita are from the Spatial Hazard Events and Losses Database for the United States (SHELDUS), measured in thousands of 2021 dollars. Small Business Lending Growth is constructed from Community Reinvestment Act (CRA) data. $z_{c,t}$ is the county's out-of-state funding shock, constructed from bank call report and SOD data. Ln(Number of Establishments) and Ln(Number of Employees) are from County Business Patterns (CBP). Migration variables are from IRS Statistics of Income (SOI) data, measured per 100 residents. Deposit Growth, GDP Growth, and Small Business Lending Growth are in percent, defined as log differences multiplied by 100. Panel B reports bank-year or firm-year variables. $\Gamma_{b,t}$ is the bank-level funding shock, constructed from bank call report and SOD data. Deposit growth variables (Total, Demand, Transaction, and Saving) are constructed from bank call report data. Ln(Debt), Ln(Asset), Ln(Number of Employees), and Ln(CapEx) are from Compustat. All growth variables are in percent, defined as log differences multiplied by 100. Panel C reports bank-county-year variables. Small Business Lending Growth is in percent, defined as the log difference of small business lending originated by the bank in the county multiplied by 100. $\Gamma_{b,c,t}$ is the bank's out-of-state funding shock reaching county c, constructed from bank call report and SOD data. Panel D reports aggregate, year-level variables. GDP Growth and Deposit Growth are constructed as in Panels A and B, respectively. C&I Lending Growth is constructed from bank call report data. Γ_t^* is the aggregate funding shock, and $\Gamma_t^{*Branch}$ is the aggregate funding shock constructed using branch-level deposit weights. $\Gamma_t^{L,CRA}$, $\Gamma_t^{L,HMDA}$, and $\Gamma_t^{L,Total}$ are the aggregate granular bank lending shocks constructed from CRA small business lending data, HMDA mortgage lending data, and their average, respectively, each divided by 1,000. Γ_t^{Emp}, Γ_t^{GDP}, Γ_t^{Inc}, Γ_t^{Pop}, and Γ_t^{Est} are the aggregate granular real shocks, constructed as the weighted average of county-level property damage per capita, with weights given by each county's national share of employment, GDP, personal income, population, and number of establishments, respectively.

Table 2: Disaster Shock and Deposit Growth

Dep Var: Deposit Growth (%)	(1)	(2)	(3)	(4)	(5)	(6)
Disaster Shock$_{c,t-1}$	-0.1034***	-0.1133***	-0.0932***	-0.1036***	-0.1072***	-0.0910***
	(0.0278)	(0.0284)	(0.0285)	(0.0291)	(0.0270)	(0.0269)
Year FE		✓		✓		
County FE			✓	✓		✓
State × Year FE					✓	✓
# Obs	79,866	79,866	79,866	79,866	79,866	79,866
R^2	0.0003	0.0306	0.0688	0.0991	0.1435	0.2033

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:

$$\Delta ln(Deposit)_{c,t} \times 100 = \beta \times \text{Disaster Shock}_{c,t-1} + \theta_c + \theta_{s(c\in s),t} + \varepsilon_{c,t}$$

where c and t indicate county and year, respectively. The data span from 1994 to 2019. The dependent variable is deposit growth in percent, defined as $\Delta \ln(Deposits)_{c,t} \times 100$, where $\Delta \ln(Deposits)_{c,t}$ is the first difference of the natural logarithm of total deposits held by all banks 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. 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: Deposits and Bank Funding Shocks (by Account Type)

Dep Var: Deposit Growth (%)	(1) Total	(2) Demand	(3) Transaction	(4) Savings
$\Gamma_{b,t-1}$	-0.2011***	-0.3833	-0.1699	-0.3263***
	(0.0757)	(0.2579)	(0.1841)	(0.1143)
Bank FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
# Obs	11,258	11,180	11,204	11,256
R^2	0.2073	0.0945	0.0856	0.1568

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

$$\Delta ln(Deposits)_{b,t} \times 100 = \beta \times \Gamma_{b,t-1} + \theta_b + \theta_t + \varepsilon_{b,t}$$

where b and t indicate bank and year, respectively. The data span from 1996 to 2019.The dependent variable is deposit growth in percent, defined as $\Delta \ln(Deposits)_{b,t} \times 100$, where $\Delta \ln(Deposits)_{b,t}$ is the first difference of the natural logarithm of various deposit accounts: total deposits in column (1); demand deposits in column (2); transaction savings deposits in column (3); and saving deposits in column (4). θ_b and θ_t are bank and year fixed effects, respectively. $\Gamma_{b,t-1}$ refers to a standardized bank-specific funding shock, measured as the deposit-weighted average of disaster damage per capita in year $t-1$. Standard errors clustered at the bank level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 4: Granular Shock and Deposit Growth

Dep Var: Deposit Growth (%)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Γ^*_t	0.0798						0.0719	0.0856
	(0.1091)						(0.1079)	(0.1350)
Γ^*_{t-1}		-0.1726*					-0.2026**	-0.1688*
		(0.0999)					(0.0867)	(0.0955)
Γ^*_{t-2}			-0.0544				-0.0607	0.2079
			(0.0661)				(0.0583)	(0.2662)
Γ^*_{t-3}				0.0601			0.0182	0.3395
				(0.0690)			(0.0512)	(0.3255)
Γ^*_{t-4}					0.0524		0.0299	0.3507
					(0.0528)		(0.0510)	(0.3507)
Γ^*_{t-5}						-0.2836***	-0.3015***	0.0006
						(0.0800)	(0.0803)	(0.3043)
Year FE								✓
# Obs	102	101	100	99	98	97	97	96
R^2	0.0047	0.0222	0.0022	0.0028	0.0021	0.0622	0.1026	0.1217

Notes: This table reports estimates of β_h from

$$\Delta \ln(Deposits)_t \times 100 = \alpha + \sum_h \beta_h \times \Gamma^*_{t-h} + \theta_t + \varepsilon_t$$

where the dependent variable is deposit growth in percent, defined as the log difference of aggregate deposits multiplied by 100, and Γ^*_{t-h} is the granular funding shock at lag h. Columns (1)–(6) include the shock and each lag individually; columns (7)–(8) include them jointly, and column (8) further includes year fixed effects θ_t. Newey-West heteroskedasticity- and autocorrelation-robust standard errors (8 lags) are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 5: Regional Evidence: The Credit-Supply Elasticity of Output χ (County-Level 2SLS)

Dep Var: Growth (%)	(1) 2nd Stage	(2) 1st Stage	(3) 2nd Stage	(4) 1st Stage
	GDP	Loan	GDP	Loan
Loan Growth (%)	0.0560***		0.0876***	
	(0.0216)		(0.0340)	
$z_{c,t-1}$		-1.7801***		-1.4250***
		(0.2428)		(0.2710)
Constant	3.1126***	5.9840***		
	(0.1335)	(0.1803)		
KP LM-Statistics	47.1		26.2	
KP F-Statistics	53.7		27.6	
County FE			✓	✓
Year FE			✓	✓
# Obs	54,275	54,275	54,275	54,275

Notes: This table reports two-stage least squares (2SLS) granular-IV estimates of the regional system (24)–(25), using county exposure to out-of-state funding shocks $z_{c,t-1}$ as the instrument. Odd columns report the second stage (county GDP growth on instrumented loan growth); even columns report the first stage (loan growth on the funding-shock instrument $z_{c,t-1}$). The dependent variables are growth rates in percent, defined as log differences multiplied by 100. The instrument is the county's exposure to out-of-state funding shocks hitting the banks that lend there, weighted by banks' lagged county lending shares and net of the equal-weighted component (Section 4). $z_{c,t-1}$ is standardized. Columns (1)–(2) include no fixed effects; columns (3)–(4) include county and year fixed effects, and the constant is omitted in these columns as it is absorbed by the fixed effects. Standard errors clustered by county are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 6: Regional Horse-Race: Funding versus Lending Geography (County Loan-Growth First Stage)

Dep. Var.: County Loan Growth (%)	(1) Deposit	(2) Lending	(3) Both
Deposit-Geography Shock $z_{c,t-1}$	-1.4250^{***}		-1.4555^{***}
	(0.2710)		(0.3047)
Lending-Geography Shock $z^{L}_{c,t-1}$		-0.6301^{**}	0.0929
		(0.3173)	(0.3612)
KP LM-Statistics	26.3	3.9	26.3
KP F-Statistics	27.6	3.9	13.9
County FE	✓	✓	✓
Year FE	✓	✓	✓
# Obs	54,275	54,275	54,275

Notes: This table reports the county-level first stage of the regional 2SLS, regressing county small-business loan growth (SBL+SFL) on the leave-state-out granular funding shock, 1997–2019. Column (1) uses the baseline *deposit-geography* instrument $z_{c,t-1}$, which weights each bank's out-of-state disaster exposure by the geographic distribution of its *deposits*. Column (2) replaces it with a *lending-geography* instrument $z^{L}_{c,t-1}$, constructed identically except that each bank's out-of-state disaster exposure is weighted by the geographic distribution of its *lending*. Column (3) includes both. Both instruments are aggregated to the county using banks' lending shares in the destination county and are standardized to unit variance. All columns include county and year fixed effects, and standard errors are clustered by county. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 7: Regional 2SLS Robustness: Alternative Out-of-State Controls

Dep Var: GDP Growth (%)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Loan Growth (%)	0.0838**	0.0841**	0.0856**	0.0837**	0.0880**	0.0876**	0.0892**	0.0723**	0.0751***
	(0.0354)	(0.0351)	(0.0358)	(0.0356)	(0.0358)	(0.0341)	(0.0361)	(0.0334)	(0.0281)
Employment-Weighted Damage$_{t-1}$	-0.4474**								-14.4002***
	(0.1814)								(5.4903)
GDP-Weighted Damage$_{t-1}$		-0.4357*							10.8312***
		(0.2351)							(2.4413)
Population-Weighted Damage$_{t-1}$			-0.3466**						9.4339***
			(0.1443)						(2.4858)
Establishment-Weighted Damage$_{t-1}$				-0.5076***					-6.5803**
				(0.1884)					(2.8557)
Trade-Weighted Damage$_{t-1}$					0.0440				0.0118
					(0.0484)				(0.0477)
Migration-Weighted Damage$_{t-1}$						0.0368			-0.0538
						(0.0307)			(0.0533)
Distance-Weighted Damage$_{t-1}$							-0.3696		-0.2631
							(0.2411)		(0.3428)
Social-Connectedness-Weighted Damage$_{t-1}$								0.0932**	0.1127
								(0.0410)	(0.0694)
KP LM-Statistics	21.2	21.3	21.2	21.0	22.7	24.3	21.5	24.1	30.3
KP F-Statistics	22.9	23.1	22.8	22.7	24.8	26.7	23.3	26.0	34.2
County FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
# Obs	48,280	48,280	48,280	48,280	48,280	48,280	48,280	48,280	48,280

Notes: This table reports two-stage least squares (2SLS) granular-IV estimates of the regional system (24)–(25), using out-of-state funding shocks $z_{c,t-1}$ as the instrument for loan growth, with county GDP growth as the dependent variable. Both growth measures are defined as log differences multiplied by 100. Columns (1)–(4) each add a real-activity-weighted out-of-state disaster-damage variable as a control. Employment-Weighted Damage, GDP-Weighted Damage, Population-Weighted Damage, and Establishment-Weighted Damage are county property damage per capita occurring *outside the county's state* weighted by the county's national share of employment, GDP, population, or establishments, respectively. Columns (5)–(8) each add a network-weighted out-of-state disaster-exposure variable as a control. Trade-Weighted Damage, Migration-Weighted Damage, Distance-Weighted Damage, and Social-Connectedness-Weighted Damage are constructed analogously, replacing the real-activity weights with trade, migration, distance, and social-connectedness weights. Column (9) includes all controls jointly. All control variables are lagged one year and standardized. All specifications include county and year fixed effects. Standard errors clustered by county are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 8: Macroeconomic Effects of Granular Shocks

Dep Var: Growth (%)	(1) GDP	(2) Loan	(3) Deposits
Γ^*_{t-1}	-0.2577**	-0.2605**	-0.1726*
	(0.1075)	(0.1084)	(0.0999)
Constant	1.1111***	1.3223***	1.6544***
	(0.1035)	(0.4751)	(0.1050)
# Obs	101	101	101
R^2	0.0094	0.0118	0.0222

Notes: This table reports estimates of β from

$$\Delta \ln(Y_t) \times 100 = \alpha + \beta \times \Gamma^*_{t-1} + \varepsilon_t,$$

where Y_t is GDP in column (1), lending in column (2), and deposits in column (3). The dependent variable is the quarterly growth rate in percent, defined as the log difference multiplied by 100. Γ^*_{t-1} is the granular funding shock. The sample is quarterly, spanning 1994Q4 to 2019Q4. Newey-West heteroskedasticity- and autocorrelation-robust standard errors (8 lags) are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 9: Granular Shock and Aggregate Fluctuations

Dep Var: GDP Growth (%)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Γ^*_t	-0.2983**						-0.2873**	-0.4585*
	(0.1444)						(0.1151)	(0.2645)
Γ^*_{t-1}		-0.2577**					-0.2918***	-0.4947**
		(0.1075)					(0.1016)	(0.2256)
Γ^*_{t-2}			0.3865***				0.3307***	0.0525
			(0.0878)				(0.0841)	(0.5011)
Γ^*_{t-3}				0.0246			0.0084	-0.2763
				(0.2751)			(0.2427)	(0.7483)
Γ^*_{t-4}					-0.0669		-0.1086	-0.3908
					(0.1674)		(0.1471)	(0.6207)
Γ^*_{t-5}						-0.3233***	-0.3702***	-0.6483
						(0.1071)	(0.1203)	(0.6020)
Constant	1.1181***	1.1111***	1.0751***	1.1293***	1.1081***	1.1119***	1.1228***	
	(0.1003)	(0.1035)	(0.1162)	(0.1134)	(0.1077)	(0.1128)	(0.1165)	
Year FE								✓
# Obs	102	101	100	99	98	97	97	96
R^2	0.0126	0.0094	0.0213	0.0001	0.0007	0.0155	0.0605	0.0746
AIC	484.7	481.3	475.5	470.5	465.9	460.8	466.2	455.9
AICC	484.9	481.5	475.6	470.6	466.1	460.9	467.5	456.8
CAIC	492.0	488.6	482.7	477.6	473.1	467.9	491.2	477.3
BIC	490.0	486.6	480.7	475.6	471.1	465.9	484.2	471.3

Notes: This table reports estimates of β_h from

$$\Delta \ln(GDP)_t \times 100 = \alpha + \sum_h \beta_h \times \Gamma^*_{t-h} + \theta_t + \varepsilon_t,$$

where Γ^*_{t-h} is the granular funding shock at lag h. The dependent variable is GDP growth in percent, defined as the log difference of GDP multiplied by 100. Columns (1)–(6) include the shock and each lag individually; columns (7)–(8) include them jointly, and column (8) further includes year fixed effects θ_t, in which case the constant is omitted as it is absorbed by the fixed effects. AIC, AICC, CAIC, and BIC are the corresponding information criteria for each specification. The sample is quarterly, spanning 1994Q4 to 2019Q4. Newey-West heteroskedasticity- and autocorrelation-robust standard errors (8 lags) 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}	-0.2390**		-0.3457**		-0.3384**		-0.3421**
	(0.0951)		(0.1700)		(0.1665)		(0.1683)
$\Gamma^{L,CRA}_{t-1}$		-0.0353	-0.2187				
		(0.2294)	(0.2936)				
$\Gamma^{L,HMDA}_{t-1}$				-0.0303	-0.2069		
				(0.2243)	(0.2892)		
$\Gamma^{L,Total}_{t-1}$						-0.0328	-0.2129
						(0.2269)	(0.2916)
Constant	1.0423***	1.0872***	1.0963***	1.0872***	1.0961***	1.0872***	1.0962***
	(0.1232)	(0.1342)	(0.1339)	(0.1341)	(0.1335)	(0.1341)	(0.1337)
# Obs	87	87	87	87	87	87	87
R^2	0.0094	0.0002	0.0148	0.0001	0.0143	0.0002	0.0146

Notes: This table reports estimates of β_1 and β_2 from

$$\Delta \ln(GDP)_t \times 100 = \alpha + \beta_1 \times \Gamma^*_{t-1} + \beta_2 \times \Gamma^L_{t-1} + \varepsilon_t,$$

where Γ^*_{t-1} is the granular funding shock and Γ^L_{t-1} is the granular bank lending shock. The dependent variable is GDP growth in percent, defined as the log difference of GDP multiplied by 100. The bank lending shock is constructed as a weighted average of county-level disaster shocks, with weights based on the share of each bank's mortgage and small business lending in each county. We construct the lending shocks using the geographic distribution of lending: from HMDA mortgage data ($\Gamma^{L,HMDA}_{t-1}$), from CRA small business lending data ($\Gamma^{L,CRA}_{t-1}$), and as the average of the two ($\Gamma^{L,Total}_{t-1}$). The county-level CRA data begin in 1997 and the county-level HMDA data begin in 1994. The sample is quarterly, spanning 1998Q2 to 2019Q4. Newey-West heteroskedasticity- and autocorrelation-robust standard errors (8 lags) are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 11: Granular Funding Shocks versus Granular Real Shocks

Dep Var: GDP Growth (%)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Γ^{*}_{t-1}	-0.2577**	-0.2720**	-0.2088**	-0.3008**	-0.2758**	-0.2724**	-0.2340**	-0.1352**	-0.2245**
	(0.1075)	(0.1194)	(0.0871)	(0.1391)	(0.1193)	(0.1163)	(0.1024)	(0.0675)	(0.0932)
Γ^{Emp}_{t-1}		-0.1165					2.2366	2.4348	2.2826
		(0.2085)					(1.4349)	(2.8756)	(1.3885)
Γ^{GDP}_{t-1}			-0.1163					0.8236	
			(0.2533)					(2.4642)	
Γ^{Inc}_{t-1}				-0.1384					0.0327
				(0.2658)					(0.1830)
Γ^{Pop}_{t-1}					-0.1656		-1.9867	-2.8876*	-2.0293
					(0.2262)		(1.7229)	(1.4886)	(1.7084)
Γ^{Est}_{t-1}						-0.1651	-0.3900	-0.3544	-0.4088
						(0.2204)	(1.2813)	(1.1787)	(1.2700)
Constant	1.1111***	1.1119***	1.0730***	1.1126***	1.1122***	1.1121***	1.1114***	1.1203***	1.1111***
	(0.1035)	(0.1038)	(0.1361)	(0.1041)	(0.1052)	(0.1052)	(0.1200)	(0.1858)	(0.1206)
# Obs	101	101	71	101	101	101	101	71	101
R^2	0.0094	0.0114	0.0107	0.0120	0.0134	0.0134	0.0292	0.0546	0.0293

Notes: This table reports estimates of β and γ from

$$\Delta \ln(GDP)_t \times 100 = \alpha + \beta \times \Gamma^{*}_{t-1} + \gamma \times \Gamma^{R}_{t-1} + \varepsilon_t,$$

where Γ^{*}_{t-1} is the granular funding shock and Γ^{R}_{t-1} denotes a granular real shock. The dependent variable is GDP growth in percent, defined as the log difference of GDP multiplied by 100. Γ^{Emp}_{t-1}, Γ^{GDP}_{t-1}, Γ^{Inc}_{t-1}, Γ^{Pop}_{t-1}, and Γ^{Est}_{t-1} are granular real shocks, constructed as county-level property damage per capita weighted by the county's national share of employment, GDP, personal income, population, and number of establishments, respectively. All columns include the funding shock Γ^{*}_{t-1}: column (1) includes it alone; columns (2)–(6) each add the employment, GDP, personal-income, population, or establishment shock; column (7) adds the employment, population, and establishment shocks jointly; column (8) adds the employment, GDP, population, and establishment shocks jointly; and column (9) adds the employment, personal-income, population, and establishment shocks jointly. County GDP data begin in 2001, so columns that include Γ^{GDP}_{t-1} (columns (3) and (8)) use 71 quarters; all other columns use the full sample, spanning 1994Q4 to 2019Q4. Newey-West heteroskedasticity- and autocorrelation-robust standard errors (8 lags) are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 12: The Missing-Intercept Decomposition $\theta = \chi\phi + \delta$

Object	Estimate	Share of θ
Regional elasticity χ, as reported in Table 5	0.0876^{**} (0.0340)	
Aggregate loan response ϕ, as reported in Table 8	-0.2605^{**} (0.1084)	
Aggregate output response θ, as reported in Table 8	-0.2577^{**} (0.1075)	100%
Loan-quantity channel $\chi\phi$	-0.0228^{*} (0.0130)	9%
Missing intercept $\delta = \theta - \chi\phi$	-0.2349^{**} (0.1083)	91%

Notes: χ is from the regional 2SLS, reported in Table 5, column 4, county and year fixed effects, with Kleibergen-Paap $F = 27.6$ and $N = 54{,}275$. θ and ϕ are the aggregate GDP and loan responses to the granular funding shock, reported in Table 8. $\delta = \theta - \chi\phi$ follows by subtraction. The standard errors for all the estimates are reported in parentheses. The standard errors for the loan-quantity channel and the missing intercept, reported in rows 4 and 5, respectively, are calculated using the delta-method. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 13: Small Business Lending and Funding Shocks by Bank Characteristics

Dep Var: Lending Growth (%)	(1)	(2)	(3)
High Core-Dep Share$_{b,t-1} \times \Gamma_{b,c,t-1}$	-1.1922***		
	(0.3521)		
High Core-Dep Share$_{b,t-1}$	5.4328***		
	(0.4269)		
Low Tier 1 Ratio$_{b,t-1} \times \Gamma_{b,c,t-1}$		-13.0968***	
		(0.8198)	
Low Tier 1 Ratio$_{b,t-1}$		-2.0652***	
		(0.4663)	
NC$_{b,c,t-1} \times \Gamma_{b,c,t-1}$			-1.4470***
			(0.3043)
NC$_{b,c,t-1}$			38.1818***
			(0.9142)
$\Gamma_{b,c,t-1}$	-0.6779**	-0.7118***	-0.1374
	(0.2695)	(0.1801)	(0.2067)
County × Year FE	✓	✓	✓
County × Bank FE	✓	✓	✓
# Obs	575,000	575,000	575,000
R^2	0.1924	0.1927	0.1952

Notes: This table reports estimates of β and δ from

$$\Delta \ln(Loans)_{b,c,t} \times 100 = \alpha + \beta \times D_{b,t-1} \times \Gamma_{b,c,t-1} + \delta \times D_{b,t-1} + \gamma \times \Gamma_{b,c,t-1} + \theta_{c,t} + \theta_{b,c} + \varepsilon_{b,c,t},$$

where $\Gamma_{b,c,t-1}$ is the out-of-state bank-county funding shock and $D_{b,t-1}$ is a bank characteristic. High Core-Dep Share$_{b,t-1}$, used in column (1), is an indicator equal to one if bank b's share of core deposits (demand and time deposits over total deposits) in year $t-1$ is above the year-$t-1$ cross-sectional median. Low Tier 1 Ratio$_{b,t-1}$, used in column (2), is an indicator equal to one if bank b's Tier 1 capital ratio in year $t-1$ is below the year-$t-1$ cross-sectional median. NC$_{b,c,t-1}$, used in column (3), is an indicator equal to one if bank b does not operate a branch in county c in year $t-1$. The dependent variable is small-business lending growth in percent, defined as the log difference of lending multiplied by 100. The funding shock $\Gamma_{b,c,t-1}$ measures bank b's exposure to disaster-induced funding losses originating outside county c's state: it is the standardized lagged deposit-share-weighted average of disaster damage per capita across the counties in which bank b raises deposits, excluding all counties in the state containing county c. County-by-year fixed effects $\theta_{c,t}$ absorb local credit demand, local economic conditions, and direct disaster effects common to lenders operating in the same county and year; bank-by-county fixed effects $\theta_{b,c}$ absorb persistent differences across lending relationships. Standard errors clustered at the bank-county level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Online Appendix for:

The Regional and the Aggregate Effects of Bank Funding Shocks

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Appendix A Model: Microfoundations, Derivations, and Aggregation

This appendix provides additional notation, derivations, and validation for the framework in Section 2. Section A.1 collects the notation used throughout the model. Section A.2 supplements the bank-optimization model in Section 2.4 by making explicit the comparative statics underlying the heterogeneity tests in Section 8. Section A.3 provides a microfoundation for the bank-level funding shock, while Section A.4 relaxes the first-order aggregation used to derive the missing-intercept decomposition and examines whether changes in cross-county dispersion can account for the aggregate response.

To avoid overloading Section 2 notation, this appendix writes p_c for branch-level informational/productivity rents (α is the capital share) and μ—not λ, the first-stage slope in equation (24)—for the Lagrange multiplier, the single-constraint counterpart of μ_b in the two-constraint bank problem (19).

A.1 Notation

Table A.1 collects the notation used throughout the model in Section 2 and in this appendix.

A.2 Multi-Market Banks and Internal Capital Markets

Consider a single bank operating in n regions, one branch each ($c \in \{1, \ldots, n\}$). Branch c takes deposits d_c and makes loans l_c, producing end-of-period revenue $p_c f(l_c)$ with $f' > 0$, $f'' < 0$, $f(0) = 0$, and Inada conditions; p_c is the branch's informational/productivity rent, analogous to (but distinct from) the marginal-lending-cost parameter φ_c in Section 2.4: here it scales revenue, there it scales cost. Deposits must be repaid at $(1 + r_c)d_c$. With an internal capital market, the budget constraint binds at the bank level, $\sum_c d_c \geq \sum_c l_c$, and the bank solves

$$\max_{\{l_c, \mu\}} \left[\sum_c p_c f(l_c) - \sum_c (1 + r_c) d_c \right] + \mu \left[\sum_c (d_c - l_c) \right], \tag{A.1}$$

where $\mu \geq 0$ is the multiplier on the bank-wide balance-sheet constraint. The first-order conditions are $p_c f'(l_c) = \mu \; \forall c$ and $\mu[\sum_c d_c - \sum_c l_c] = 0$. Differentiating with respect to a deposit shock in region c',

$$\frac{\partial l_c}{\partial d_{c'}} = \frac{1}{p_c f''(l_c)} \frac{\partial \mu}{\partial d_{c'}} > 0, \qquad \frac{\partial \mu}{\partial d_{c'}} = \left[\sum_c \frac{1}{p_c f''(l_c)} \right]^{-1} < 0. \tag{A.2}$$

A negative deposit shock in region c' raises the shadow value of funds μ and contracts lending in *all* regions, more so for tighter constraints and lower-p_c regions. This is the cross-region loan-supply transmission that underlies the county first stage (24) and the instrument $z_{c,t}$: funding shocks in a bank's

Table A.1: Notation Reference

Symbol	Meaning
Y_t, $Y_{c,t}$, g_t, $g_{c,t}$	Aggregate / county output level and growth
σ, ω_c	Elasticity of substitution; county c's steady-state expenditure share
$A_{c,t}$, $a_{c,t}$	County productivity, level and growth
$N_{c,t}$, $W_{c,t}$	County employment, county wage
$X_{c,t}$, $B_{c,t}$, $H_{c,t}$	Effective productive input; bank loans; other finance
e_B, e_H	Elasticity of $X_{c,t}$ with respect to bank loans, other finance
α	Capital share in production
$\psi_B, \psi_W, \psi_D, \psi_A$	Labor-demand/supply parameters: credit, wage, demand, productivity
χ	Regional credit-supply elasticity of output, $\equiv \alpha e_B + (1-\alpha)\psi_B$
κ, τ	Composite wage-response, demand-response parameters, $\equiv (1-\alpha)\psi_W,\ (1-\alpha)\psi_D$
$q_{c,t}$	Residual productivity and non-bank-financing term
$M = [m_{cc'}]$, ρ	Real-economy network matrix; network propagation strength
$D_{c,t}$, $d^0_{c,t}$	County demand shifter; exogenous local demand component
$\mathrm{Dmg}_{c,t}$	County disaster shock, property damage per capita
$\omega^D_{b,c,t-1}$	Bank b's lagged deposit share from county c
$\omega^{D,\setminus s(c)}_{b,c,t-1}$	Bank b's lagged deposit share from county c, renormalized outside state $s(c)$
$\Gamma^{\setminus s(c)}_{b,t}$, $\bar{\Gamma}^{\setminus s(c)}_{b,t}$	out-of-state bank shock and equal-weighted counterpart
$\Gamma_{b,t}$, $s_{b,t}$	Bank-level disaster exposure; realized bank funding shock
$\omega^A_{b,t-1}$	Bank b's asset weight
Γ_t, Γ^*_t	Aggregate bank funding shock, raw and granular
$\omega^L_{b,c,t-1}$	Bank b's lagged lending share in county c
$z_{c,t}$	County-level out-of-state funding-exposure instrument
$E_{b,t}$, $D_{b,t}$, $F_{b,t}$	Bank equity, deposits, wholesale funding
$r_{b,c,t}$, r^f_t	County loan rate; marginal cost of funds
φ_c	Bank lending marginal-cost curvature in county c
$\omega^R_{b,c}$, κ^{lev}	Regulatory risk weight; leverage constraint parameter
μ_b, η_b	Multipliers on the balance-sheet, capital constraints
λ, $\ell_{c,t}$, ℓ_t	First-stage loan-supply coefficient; county, aggregate loan growth
θ_c, θ_t	County, year fixed effects
β_{reg}	Regional 2SLS coefficient, identifies χ under Assumption 1
ζ_t	Aggregate residual: wage, demand, productivity terms
ϕ	Aggregate elasticity of loan growth with respect to Γ^*_t
θ	Aggregate elasticity of GDP growth with respect to Γ^*_t
δ	Missing intercept, $\equiv \theta - \chi\phi$
$\delta^{(1)}, \delta^{(2)}$	First-order aggregate adjustment; second-order dispersion component
$\mathbf{Disp}_t$	Cross-county dispersion measures

disaster-hit counties reduce its lending elsewhere. Two comparative statics follow directly from (A.2) and motivate the bank-friction tests in Section 8: (i) the pass-through $\partial\mu/\partial d_{c'}$ is larger in magnitude when the bank is closer to its constraint, so more capital-constrained banks should contract lending by more

following the same funding shock; and (ii) the contraction $\partial l_c / \partial d_{c'}$ is smaller in regions with high p_c, so a bank should cut lending less in counties where it holds an informational or relationship advantage.

A.3 Microfoundation of the Bank Funding Shock

Assume withdrawals are proportional to lagged deposit shares, where $\Delta D_{b,c,t}$ denotes the expected deposit withdrawal (a nonnegative outflow) at bank b in county c, so

$$\mathbb{E}_t(\Delta D_{b,c,t} / \sum_b D_{b,c,t-1}) = (D_{b,c,t-1} / \sum_b D_{b,c,t-1}) \mathrm{Dmg}_{c,t}.$$

Then $\mathbb{E}_t(\Delta D_{b,c,t}) = D_{b,c,t-1} \mathrm{Dmg}_{c,t}$; dividing by $\sum_c D_{b,c,t-1}$ and summing over counties gives the bank funding shock (12),

$$\Gamma_{b,t} = \sum_c (D_{b,c,t-1} / \sum_c D_{b,c,t-1}) \mathrm{Dmg}_{c,t},$$

whose asset-weighted, equal-weighted-differenced aggregate is Γ^* in (14). This is the empirical counterpart of $s_{b,t}$ and Γ^*_t in (13)–(40).

A.4 Second-Order Aggregation and Cross-County Dispersion

The decomposition in Section 2.6 maps the regional credit-supply elasticity into the aggregate economy using a first-order approximation to the CES aggregator. Under this approximation, aggregate output growth is the expenditure-share-weighted average of county output growth. This mapping raises an important question for the interpretation of the missing intercept. A granular funding shock may affect not only average economic activity across counties, but also its cross-sectional distribution. Because the CES aggregator is nonlinear, changes in cross-county dispersion can themselves contribute to aggregate output. If this second-order component responds substantially to the funding shock, part of the gap between the observed aggregate response and the response predicted by the regional loan-quantity channel could reflect nonlinear aggregation omitted from the baseline decomposition.

We examine this possibility by relaxing the first-order approximation. A second-order expansion of the CES aggregator in equation (1) around the symmetric steady state gives

$$g_t \approx \int_0^1 \omega_c g_{c,t} \, dc + \frac{\sigma - 1}{2\sigma} \Delta \left\{ \mathrm{Var}_\omega(\hat{y}_{c,t}) \right\}, \tag{A.3}$$

where $\hat{y}_{c,t}$ is log county output relative to its steady-state value and Var_ω denotes the expenditure-share-weighted cross-sectional variance. The first term is the component retained in the baseline decomposition. The second captures the additional contribution of changes in the cross-county distribution of economic activity.

This expansion provides a refinement of the missing-intercept identity. Allowing for second-order aggregation, the aggregate response to the granular funding shock can be written approximately as

$$\theta \approx \chi\phi + \delta^{(1)} + \delta^{(2)}, \tag{A.4}$$

where $\chi\phi$ is the regional loan-quantity component, $\delta^{(1)}$ collects the aggregate adjustment represented by the first-order missing intercept, and

$$\delta^{(2)} \approx \frac{\sigma - 1}{2\sigma} \frac{\partial\Delta\left\{\mathrm{Var}_\omega(\hat{y}_{c,t})\right\}}{\partial\Gamma^*_{t-1}}, \tag{A.5}$$

captures the contribution of funding-induced changes in cross-county dispersion. The first-order decomposition is therefore a useful approximation when this second-order component is quantitatively small.

We evaluate this condition empirically in Table A.2. The theoretical second-order term depends on changes in the cross-county distribution of output. Because the county-level data do not permit us to construct its exact quarterly counterpart, we proxy for this distributional adjustment using changes in the cross-county dispersion of GDP growth, loan growth, and the county-level funding instrument, $z_{c,t}$. These measures capture whether the granular funding shock is accompanied by greater dispersion in real activity, credit, or funding exposure across counties. We estimate

$$g_t = \mu + \theta\Gamma^*_{t-1} + \boldsymbol{\beta}'\Delta\mathbf{Disp}_t + \varepsilon_t, \tag{A.6}$$

where $\Delta\mathbf{Disp}_t$ collects the three dispersion measures. The county-level variables are observed annually, so the dispersion measures are constructed at the annual frequency and merged onto the quarterly aggregate series.

Table A.2 separates the effect of changing the estimation sample from the effect of introducing the dispersion controls. Column 1 reports the baseline aggregate specification over the full sample and recovers the benchmark coefficient of -0.2577. Column 2 re-estimates the same specification on the 68 observations for which all three dispersion measures are available. The coefficient remains negative and statistically significant at -0.2037. Column 3 then introduces the three dispersion measures while holding this estimation sample fixed. This comparison between columns 2 and 3 isolates the effect of accounting for cross-county dispersion.

The results provide little evidence that dispersion accounts for the aggregate response. Once the three dispersion measures are included, the coefficient on Γ^*_{t-1} remains negative and statistically

significant and moves from −0.2037 to −0.2317. Thus, controlling for cross-county dispersion does not attenuate the aggregate response; if anything, the point estimate becomes somewhat larger in magnitude and moves closer to the full-sample benchmark. None of the changes in the cross-county dispersion of GDP growth, loan growth, or the county-level funding instrument is individually statistically significant.

Taken together, these results support the first-order aggregation used in the baseline decomposition. Accounting for observable changes in cross-county dispersion does not explain the aggregate response or materially reduce the gap between that response and the response predicted by the regional loan-quantity channel. The missing intercept can contain many forms of aggregate adjustment, but the evidence in Table A.2 indicates that its estimated magnitude is not driven by the second-order cross-county dispersion term omitted from the baseline aggregation.

Table A.2: Second-Order Aggregation and Cross-County Dispersion

Dep Var: GDP Growth (%)	(1)	(2)	(3)
Γ^*_{t-1}	-0.2577**	-0.2037**	-0.2317***
	(0.1075)	(0.0800)	(0.0843)
ΔVar(GDP growth)			-0.0265
			(0.0222)
ΔVar(Loan growth)			-0.0002
			(0.0003)
ΔVar($z_{c,t-1}$)			-0.0000
			(0.0000)
Constant	1.1111***	1.0146***	0.9782***
	(0.1035)	(0.1332)	(0.1325)
Dispersion controls	No	No	Yes
Sample	Full	Common	Common
# Obs	101	68	68

Notes: This table examines whether changes in cross-county dispersion affect the estimated aggregate response to the granular bank funding shock. Column (3) reports estimates of β, γ_1, γ_2, and γ_3 from

$$\Delta \ln(GDP)_t \times 100 = \alpha + \beta \times \Gamma^*_{t-1}$$
$$+\gamma_1 \times \Delta\text{Var(GDP growth)}_t + \gamma_2 \times \Delta\text{Var(Loan growth)}_t + \gamma_3 \times \Delta\text{Var}(z_{c,t-1})_t + \varepsilon_t$$

columns (1) and (2) omit the three dispersion terms. The dependent variable is GDP growth in percent, defined as the log difference of GDP multiplied by 100. Column (1) reports the baseline specification over the full available sample. Column (2) re-estimates the baseline specification on the common sample for which all three dispersion measures are available. Column (3) adds changes in the expenditure-share-weighted cross-county variance of GDP growth, loan growth, and the county-level funding shock $z_{c,t-1}$ to the same common sample. The county-level variables are observed annually, so the dispersion measures are constructed at the annual frequency and merged onto the quarterly aggregate series. Newey-West heteroskedasticity- and autocorrelation-robust standard errors (8 lags) are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

A.5 Heterogeneity in the Regional Elasticity

The aggregation exercise applies a single pooled estimate of χ to the aggregate contraction in lending. This is appropriate only if the regional elasticity does not vary systematically across the counties that contribute to the aggregate response. Table A.3 therefore re-estimates the regional system allowing the elasticity to differ with five county characteristics measured over 1997–2001: the share of local lending originated by large banks, the ratio of lending by banks without out-of-state deposit shocks to lending by banks with such shocks, the ratio of small to large establishments, the concentration of local lending, and the county's share of national bank deposits. Both loan growth and its interaction with the county characteristic are instrumented.

The estimated elasticity is positive and statistically significant in every column, at the 10 percent level in column 1 and at the 5 percent level or better elsewhere. It ranges from 0.084 to 0.123 and remains close to the pooled estimate of 0.0876 throughout. Four of the five interaction terms are statistically insignificant, so we find no statistically significant heterogeneity in the elasticity with respect to local bank size, borrower composition, lending concentration, or deposit market share. The exception is column 2, where the interaction with the relative importance of unshocked lenders is negative and significant at the 10 percent level, indicating a somewhat weaker response in counties served more heavily by banks without out-of-state deposit exposure.

Two caveats apply. Interacting the endogenous regressor splits the identifying variation across two instrumented terms, and the first stage weakens accordingly: the Kleibergen-Paap F-statistic falls to 1.6 in column 1 and 3.1 in column 4, and is 9.0 in column 2. The estimates in those columns should therefore be read with caution, and the design has limited power to detect moderate heterogeneity. Subject to that qualification, the evidence supports treating the pooled estimate of χ as a reasonable summary for the aggregation exercise in Section 7.

Table A.3: Testing Regional Heterogeneity

Dep Var: GDP Growth (%)	(1)	(2)	(3)	(4)	(5)
H =	Large Banks	Banks w/o Shocks	Small Firms	Lending HHI	Deposit Share
Loan Growth (%)	0.1228*	0.0937**	0.0948**	0.0836**	0.0910***
	(0.0722)	(0.0374)	(0.0377)	(0.0334)	(0.0331)
Loan Growth (%) × H	-0.0661	-0.1360*	-0.0246	-0.0253	0.0367
	(0.0655)	(0.0777)	(0.0188)	(0.0366)	(0.0286)
KP LM-Statistics	3.3	17.7	21.1	7.1	27.0
KP F-Statistics	1.6	9.0	11.1	3.1	14.1
County FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
# Obs	53,128	53,128	53,128	53,128	53,128

Notes: This table reports 2SLS estimates of β_1 and β_2 from

$$\Delta \ln(GDP)_{c,t} \times 100 = \beta_1 \times \Delta \ln(Loans)_{c,t} \times 100 + \beta_2 \times \Delta \ln(Loans)_{c,t} \times 100 \times H_c + \theta_c + \theta_t + \varepsilon_{c,t},$$

instrumenting loan growth and its interaction with H_c using a granular IV (GIV) based on out-of-state deposit shocks and its interaction with H_c. The sample is a county-year panel from 2002 to 2019. The dependent variable is GDP growth in percent, defined as the log difference of GDP multiplied by 100, and loan growth is defined analogously. H_c is measured over 1997–2001 and is standardized. In column (1), H_c is the share of county c's CRA lending originated by large banks, where large banks are banks with out-of-state deposit shocks and average annual CRA loan volume, over 1997–2001, above $2 billion; this threshold falls at a natural discontinuity in the loan volume distribution and corresponds to roughly the 15th-largest bank (the top 2 percent by loan volume) among banks with out-of-state deposit shocks. In column (2), H_c is the ratio of CRA lending by banks without out-of-state deposit shocks to CRA lending by banks with such shocks, averaged over 1997–2001. In column (3), H_c is the ratio of establishments with fewer than 50 employees to larger establishments, based on County Business Patterns data and averaged over 1997–2001. In column (4), H_c is the Herfindahl-Hirschman Index of CRA lending, averaged over 1997–2001. In column (5), H_c is the county's share of national bank deposits, taken as the median over 1997–2001. KP LM-statistics and KP F-statistics denote the Kleibergen-Paap underidentification and weak-instrument test statistics, respectively. Standard errors clustered at the county level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Appendix B Comparison to the Existing Empirical Literature

Our supply-side, large-bank findings complement rather than contradict the demand-side, small-bank findings of Cortés and Strahan (2017). In this section, we argue that our results do not contradict theirs but that the two sets of findings can coexist and are, in fact, 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 and bank funding. 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 funding outflows. When the affected counties serve as key deposit bases – particularly for larger banks – these localized shocks can translate into broader bank-level funding declines and show up in the aggregate.

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-side funding 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 funding shocks.

Can the two results co-exist? At face value, 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 funding 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. Thus, initial credit expansions can coexist with longer-run funding constraints. This is also consistent with 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.** 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 et al. (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 et al. (2017) provide evidence that small banks have comparative advantages in alleviating information frictions, and 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 et al. (2020) and Celil et al. (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 et al. (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 funding 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.

Consistent with this discussion, Table H.3 in the main text shows that large banks – and especially systemically important banks (SIBs) – respond to funding shocks by reducing credit in areas affected by natural disasters, while the estimated response for small banks (defined the same way as in Cortés and Strahan (2017)) is, if anything, positive.

Relative to work on local liquidity windfalls transmitted by small, capital-constrained banks (Gilje et al., 2016; Gilje, 2019; Plosser, 2014), our contribution is to show that funding shocks matter for *large, multi-market* banks because of the within-bank geographic concentration of deposits, and to deliver an elasticity of output usable for aggregation.

Appendix C Definitions of Key Bank-Level Variables

We list the names of the variables from the Drechsler et al. (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)

Appendix D Addressing Concerns about the Geographic Measurement of Deposits

The geographic concentration documented in Section 4.1 relies on the location of deposits reported in the FDIC Summary of Deposits (SOD). Interpreting these locations therefore requires understanding how banks assign deposits to individual offices. We first describe the relevant SOD reporting conventions and their implementation in practice. We then use these institutional details to identify the principal sources of potential geographic mismeasurement and examine each of them empirically.

D.1 Geographic Assignment of Deposits in the SOD

The Summary of Deposits is an annual survey conducted by the Federal Deposit Insurance Corporation (FDIC) that reports deposits assigned to each office of an FDIC-insured institution as of June 30. The SOD therefore provides the branch-level information from which we construct banks' geographic deposit shares. The economic interpretation of those shares depends on how institutions assign customer deposits to individual offices.

Under the SOD reporting instructions, institutions generally assign deposits to an office based on the location associated with the depositor or the account. In practice, the relevant location can be the office where the account was opened, the office closest to the account holder's reported address, or the office with which the account is most closely associated through its activity. Our understanding of these practices is based on the FDIC's SOD reporting instructions and conversations with bankers about how the guidelines are implemented in practice.[14]

For accounts opened in person, deposits are commonly associated with the branch at which the account was established. For accounts opened remotely, banks may instead assign deposits to an office near the customer's reported address. Banks collect and periodically update customer addresses through their Know Your Customer procedures, providing a geographic basis for this assignment. Existing accounts need not be reassigned mechanically when a customer moves, however, and institutions can differ in whether they retain the original branch assignment or associate the account with an office near the customer's new address.

Several circumstances can weaken the connection between the reported office and the economic location of the depositor. When a bank has no branch near the customer, deposits may be assigned to a main office or other designated location. Branch closures can similarly cause deposits previously associated with a closed office to be transferred to another office. Certain deposit categories, including brokered deposits, reciprocal deposits, and deposits obtained through listing services, have no natural

[14] See the FDIC Summary of Deposits Reporting Instructions.

local geographic footprint and may therefore be reported at a main office or headquarters. Deposits collected through foreign branches are excluded from domestic SOD deposits, which are reconciled to the corresponding domestic-deposit totals reported in the Call Reports.

These reporting conventions imply that SOD geography contains economically meaningful information about the location of banks' deposit relationships, but also identify specific cases in which reported deposit location may differ from the underlying depositor's economic location. The empirical exercises that follow are organized around these cases. We examine headquarters and main-office reporting, mergers and acquisitions, tax-related deposit placement, brokered and other potentially non-local deposits, online banking, major lending and operational centers, and the possibility that concentration is generated by individual "special" branches. We then construct an alternative measure based entirely on the geographic distribution of physical branches, which does not depend on the assignment of deposit balances to locations.

D.2 Is Geographic Concentration a Small-Bank Phenomenon?

A natural concern with the geographic concentration documented in Section 4.1 is that it may be driven primarily by small banks. Smaller institutions tend to operate in fewer markets and may therefore mechanically raise a large share of their deposits from a single county. If geographic concentration disappeared among large, multi-market banks, it would be considerably less relevant for our aggregate analysis. We therefore examine how deposit concentration varies across the bank-size distribution and across alternative measures of bank size.

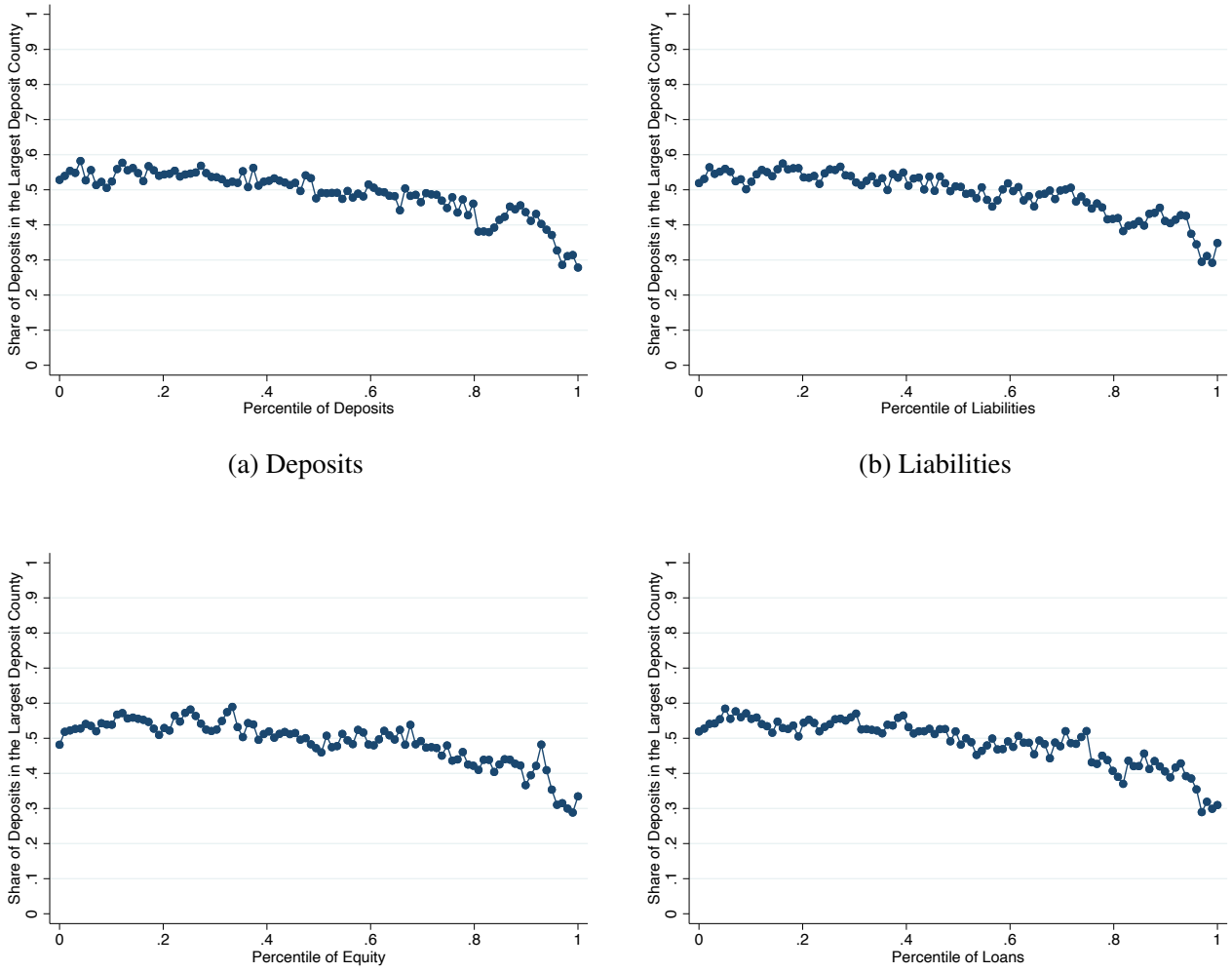
Figure 2a in the main text relates the deposit share of a bank's largest deposit county to its percentile in the distribution of total assets. Larger banks tend to have less geographically concentrated deposit bases than smaller banks, but the decline in concentration is gradual and concentration remains economically substantial throughout the size distribution. Thus, geographic concentration is not confined to small or locally oriented institutions.

The largest U.S. banks provide a particularly informative test. Figure 2b reports the geographic distribution of deposits for the Big 4 banks—Citibank, JPMorgan Chase, Wells Fargo, and Bank of America. Despite their large balance sheets and extensive geographic footprints, each raises a substantial share of its deposits from a relatively small number of counties. The largest deposit county accounts for approximately 59% of Citibank's deposits, 49% of JPMorgan Chase's, 17% of Wells Fargo's, and 12% of Bank of America's deposits. Geographic concentration therefore remains present even among banks with nationwide operations.

The relationship is not specific to total assets as a measure of bank size. Figure D.1 repeats the exercise using four alternative balance-sheet measures: total deposits, total liabilities, book equity, and

total loans. In each panel, banks are sorted into percentiles according to the relevant balance-sheet characteristic, and we plot the average deposit share of the largest deposit county against the corresponding percentile.

Figure D.1: Geographic Concentration Across Bank Characteristics



(a) Deposits

(b) Liabilities

(c) Equity

(d) Loans

Note: This figure uses Summary of Deposits (SOD) data from 1994 to 2019 to illustrate the relationship between the geographic concentration of deposits and bank size, measured by deposits (Figure D.1a), total liabilities (Figure D.1b), book equity (Figure D.1c), and loans (Figure D.1d). In each panel, banks are sorted by the relevant size measure, and we plot the average deposit share in the county where the bank has its largest presence against the corresponding percentile of deposits, liabilities, equity, or loans.

The same pattern emerges across all four measures. Deposit concentration generally declines with bank size, consistent with larger institutions operating across more geographic markets. Importantly, however, it does not disappear among banks in the upper tail of deposits, liabilities, equity, or loans. The result documented using total assets in the main text is therefore not an artifact of a particular definition of bank size.

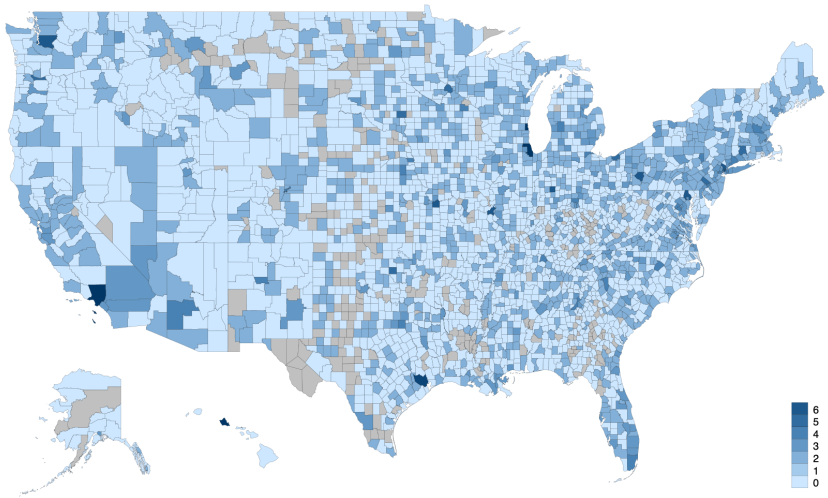
This distinction matters for the aggregate mechanism studied in the paper. Geographic concentration

among small banks alone would generate bank-specific exposure to local shocks, but shocks to those institutions would tend to receive little weight in the aggregate economy. The fact that concentration remains substantial among large banks creates the possibility that a local shock can simultaneously be important for an individual bank's funding and affect a bank that is economically important in the aggregate. The granular aggregate construction in Section 4.3 exploits precisely this interaction between geographic concentration within banks and differences in economic size across banks.

Taken together, the evidence shows that geographic concentration is a pervasive feature of bank deposit funding rather than a small-bank phenomenon. Larger banks are more geographically diversified than smaller banks, but even the largest institutions continue to rely disproportionately on particular counties for their deposit funding. This result is robust to measuring bank size using assets, deposits, liabilities, equity, or loans.

The counties that serve as banks' most important deposit sources are also geographically dispersed. Figure D.2 maps counties that are the largest deposit county for at least one bank and shows that the funding locations underlying our construction are not concentrated in a single financial center or region. At the same time, some counties are important funding sources for multiple banks, which helps explain why a geographically local shock can affect several institutions.

Figure D.2: Geography of Largest Deposit County



Note: 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.

D.3 Temporal Variation in Deposit Concentration

A second question is whether the geographic concentration of bank deposits is a recent phenomenon. The structure of U.S. banking changed substantially over our sample period as restrictions on interstate

banking were relaxed, banks expanded geographically, and consolidation produced larger multi-market institutions. These changes could have reduced banks' dependence on individual local deposit markets. We therefore examine the evolution of geographic concentration over time, first within our baseline 1994–2019 sample and then using historical SOD data extending back to 1981.

D.3.1 Deposit Concentration over the Baseline Sample.

Figure 1b in the main text plots several measures of the deposit share of the largest deposit county from 1994 to 2019. Geographic concentration is present throughout the sample. The figure reports the simple average and asset-weighted average of the largest-county deposit share, together with the first and tenth percentiles of the cross-sectional distribution.

Two features are apparent. First, concentration is not generated solely by a small number of banks with unusually concentrated deposit bases. Even at the lower percentiles of the distribution, individual counties account for meaningful shares of bank deposits. Second, geographic concentration declines over time. This pattern is consistent with the expansion of banks across geographic markets and suggests that banks have become more geographically diversified over the past several decades. Importantly, however, concentration remains substantial even at the end of the sample.

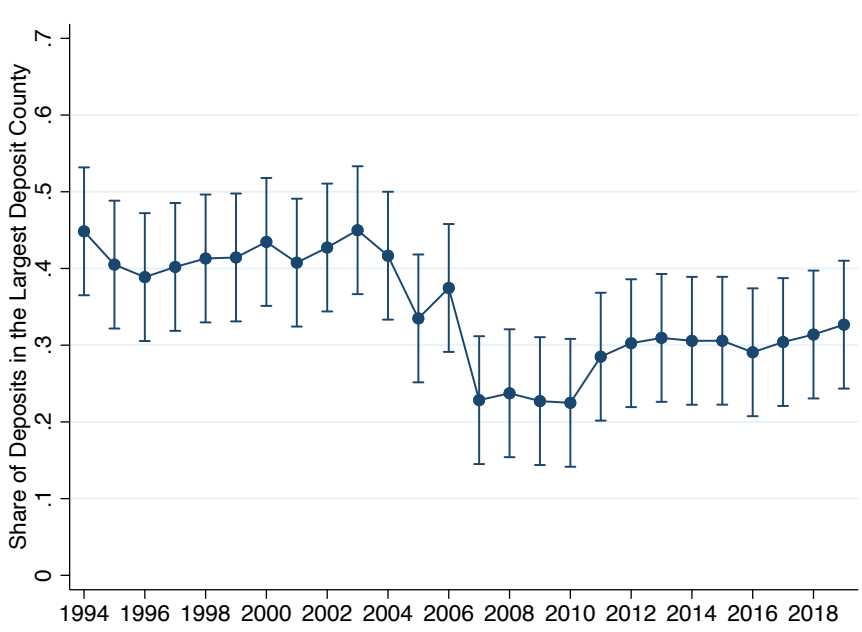
The downward trend also provides useful evidence against the concern that the concentration we measure is mechanically generated by the growth of online banking. If deposits raised through online channels were increasingly assigned to a small number of reporting locations, one would expect measured geographic concentration to rise as online banking became more important. Instead, concentration declines over precisely the period in which online banking expanded rapidly.

D.3.2 Temporal Variation among the Largest Banks.

The decline in concentration is not driven solely by the changing composition of smaller institutions. Figure D.3 plots the deposit share of the largest deposit county over time for the Big 4 banks: Citibank, JPMorgan Chase, Wells Fargo, and Bank of America. These institutions expanded substantially across geographic markets over the sample period and are among the banks most likely to have developed nationwide deposit franchises and online banking platforms. Nevertheless, their deposit bases remain geographically concentrated.

Figure D.3 shows that concentration among these banks generally declines over time, consistent with the broader pattern in Figure 1b. Yet the largest deposit county continues to account for a meaningful share of deposits even for these nationwide institutions. The persistence of concentration among the Big 4 reinforces the conclusion of Appendix Section D.2: geographic concentration is not simply a consequence of small banks operating in a limited number of markets.

Figure D.3: Time Series of Deposit Concentration for Big 4 Banks



Note: This figure uses Summary of Deposits (SOD) data from 1994 to 2019 and illustrates the geographic concentration of deposits among the four largest U.S. banks. The figure reports the equal-weighted average (net of bank fixed effects) share of deposits in each bank's largest deposit county, by year, across Citibank, JPMorgan Chase, Wells Fargo, and Bank of America.

D.3.3 Historical Evidence: 1981–2019.

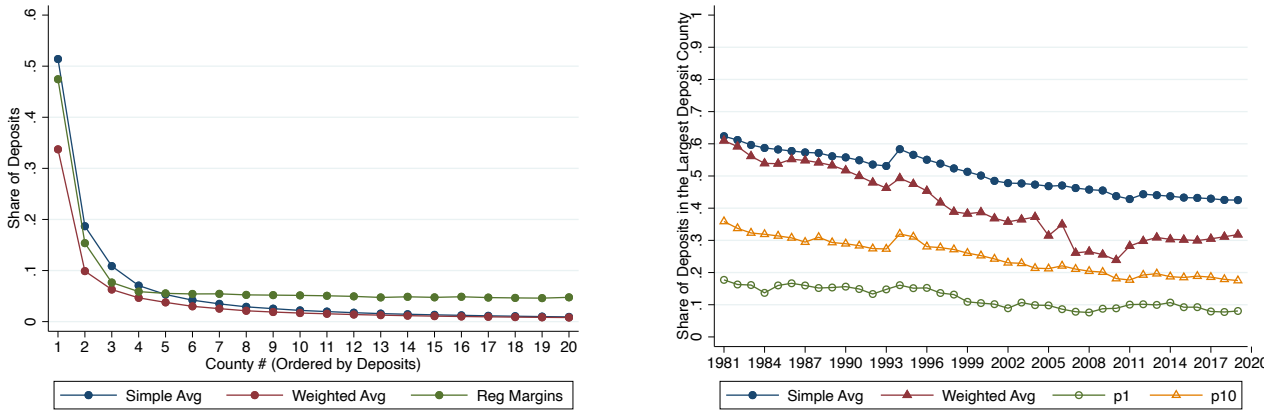
Our baseline sample begins in 1994 because the modern SOD data provide consistent branch-level information beginning in that year. To determine whether the concentration documented in the baseline sample predates this period, we extend the analysis using historical SOD data back to 1981. This extension is particularly informative because the earlier period predates much of the geographic expansion and consolidation of U.S. banking that occurred following the relaxation of interstate banking restrictions.

Figure D.4 repeats the concentration analysis over the extended 1981–2019 sample. Panel D.4a reports the cross-sectional relationship between county rank and deposit share, while Panel D.4b traces the deposit share of the largest deposit county over time.

The historical data reinforce the baseline result. Geographic concentration is not a phenomenon that emerged during the modern banking era. If anything, deposit funding was more geographically concentrated in the earlier part of the sample. Concentration subsequently declines as banks expand across geographic markets, but remains economically meaningful through 2019.

The historical pattern is consistent with the evolution of U.S. banking regulation. Prior to the widespread relaxation of restrictions on interstate banking, banks faced greater constraints on geographic expansion and therefore relied more heavily on deposits raised in a smaller set of local markets. As those restrictions were relaxed and banks expanded across state lines, their deposit bases became

Figure D.4: Geographic Concentration of Deposits: 1981–2019



(a) Cross Section

(b) Time Series

Note: This figure uses historical Summary of Deposits (SOD) data from 1981 to 2019 and illustrates the geographic concentration of bank deposits over the extended sample. Panel (a) orders counties by their deposit shares for each bank and reports the average deposit share by county rank. The blue line reports the simple average, the red line the average weighted by bank total assets, and the green line the regression-adjusted measure controlling for bank-year and county-year fixed effects. Panel (b) reports the deposit share of the largest deposit county over time using the simple average, asset-weighted average, first percentile, and tenth percentile of the cross-sectional distribution.

more geographically diversified. The downward trend in Figure D.4b is therefore consistent with the institutional evolution of the banking system rather than with geographic concentration being a recent artifact of modern deposit reporting.

Taken together, the baseline and historical evidence show that geographic concentration is a persistent feature of U.S. bank funding. Its magnitude has declined as banks have become geographically broader, but the phenomenon predates our baseline sample and remains substantial throughout it. Thus, the concentration exploited in our shock construction does not arise from a short-lived feature of the 1994–2019 period.

D.4 Addressing Concerns about the Geographic Measurement of Deposits

The geographic concentration documented in Section 4.1 relies on the location of deposits reported in the FDIC Summary of Deposits (SOD). A potential concern is that reported deposit locations need not always coincide with the economic location of the underlying depositor. SOD reporting instructions generally assign deposits to the office closest to the account holder's address, the office where the account is most active, or the office where the account was opened. However, certain classes of deposits or customers may be assigned to a single office for operational convenience. As a result, headquarters, main offices, or other operational centers could report deposits raised outside their immediate geographic market.

Several other features of banking could create similar concerns. Mergers and acquisitions may

change where acquired deposits are recorded. Tax considerations could affect the reported location of some depositors. Brokered, uninsured time, and online deposits may have a weaker connection to a physical branch. Banks may also report unusually large deposit balances at major lending centers or operational offices. If these practices systematically concentrate reported deposits in a small number of counties, the concentration documented in the main text could overstate the geographic concentration of banks' true funding sources.

We conduct a series of exercises addressing these concerns. The tests differ in how they identify potentially non-local deposits, but they deliver the same conclusion: the precise magnitude of concentration changes across adjustments, but individual counties continue to account for substantial shares of bank deposits.

We conduct a comprehensive set of exercises addressing potential geographic mismeasurement. Figure D.5 exploits banks that relocate their headquarters and recalculates deposit concentration under alternative assumptions about the deposits that appear in the new headquarters county. Figure D.6 instead removes deposits reported at the headquarters branch altogether, for the full sample as well as the Big 4 and Top 20 banks. Both exercises continue to show substantial geographic concentration.

We next consider tax incentives, mergers and acquisitions, brokered and uninsured deposits, online banking, large lending centers, and main-office reporting. Figure D.7 summarizes the effect of these adjustments for the full sample, while Figure D.8 shows that geographic concentration remains substantial under the same adjustments among the Big 4 and Top 20 banks. Figure D.9 reports the corresponding concentration patterns for the full sample in greater detail. Figures D.10 and D.11 show that the same conclusion holds among the largest banks when the adjustments are considered jointly.

We also test whether the result is generated by particular counties or individual "special" branches. Figures D.8 and D.12 examine the distribution of deposits across branches within banks' most important deposit counties. Deposits are spread across multiple branches rather than being assigned almost entirely to a single reporting office, and this pattern is present in the full sample, the Big 4, and the Top 20 banks.

Finally, we construct an alternative measure based on the geographic distribution of physical branches, which is not subject to the same deposit-location reporting concerns. Figure D.13 shows that branches themselves are geographically concentrated across the cross section, over time, and across bank size. Figure D.14 documents the strong relationship between branch-based and deposit-based concentration, while Figure D.15 shows that the branch-concentration result is robust across alternative bank balance-sheet characteristics. Together, these exercises provide independent evidence that the geographic concentration of deposits reflects the underlying geography of banking activity rather than a particular SOD reporting convention.

D.4.1 Headquarters Reporting

We begin with headquarters because SOD reporting conventions make headquarters branches a natural location at which non-local deposits could be recorded. We use two complementary approaches.

First, we exploit banks that relocate their headquarters during our sample. A headquarters relocation provides a direct setting in which to assess whether a large amount of deposits mechanically moves to the new headquarters location. For banks that change headquarters, we identify the increase in deposits reported in the new headquarters county and recalculate geographic concentration under three alternative assumptions. We redistribute the increase across the bank's counties according to their prior deposit shares; redistribute it equally across all counties in which the bank operates; or remove the increase entirely from the calculation. The resulting concentration measures remain close to the baseline estimates, indicating that headquarters relocations do not account for the concentration documented in the data.

Second, we take a more direct approach and exclude deposits reported at the headquarters branch altogether. Figure D.6 recomputes deposit concentration after removing each bank's headquarters branch. Even under this adjustment, approximately 20% to 30% of bank deposits originate from a single county. The pattern remains visible not only in the full sample but also among the Big 4 and Top 20 banks.

These exercises suggest that headquarters reporting can affect the measured location of some deposits but cannot explain the broader concentration pattern.

D.4.2 Taxes, Mergers and Acquisitions, and Non-Local Deposit Categories

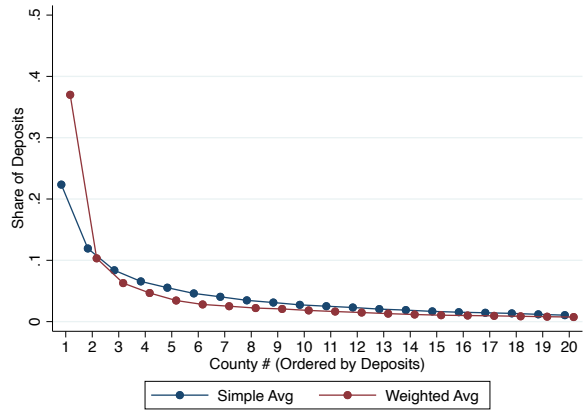
We next examine several additional reasons deposits might be assigned to locations that do not correspond closely to the underlying depositor.

First, tax considerations may cause some depositors to report addresses in states without state income taxes. We therefore exclude Alaska, Florida, Nevada, New Hampshire, South Dakota, Tennessee, Texas, Washington, and Wyoming. Deposit concentration remains largely unchanged after excluding these states.

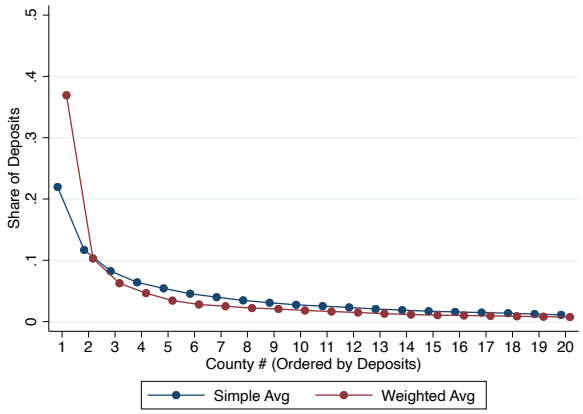
Second, mergers and acquisitions may alter the geographic assignment of deposits. An acquiring institution may consolidate some of an acquired bank's deposits into its own principal reporting locations. We therefore exclude banks involved in mergers and acquisitions beginning in the year of their first acquisition. The resulting concentration measure remains substantial. Because this restriction disproportionately removes larger banks and leaves a sample of smaller institutions with more limited geographic footprints, the estimated concentration can, if anything, increase under this exercise.

Third, brokered deposits and uninsured time deposits may have a particularly weak connection to the location at which they are reported. We identify each bank's main office using the SOD main-office indicator and subtract brokered and uninsured time deposits, obtained from the Call Reports, from

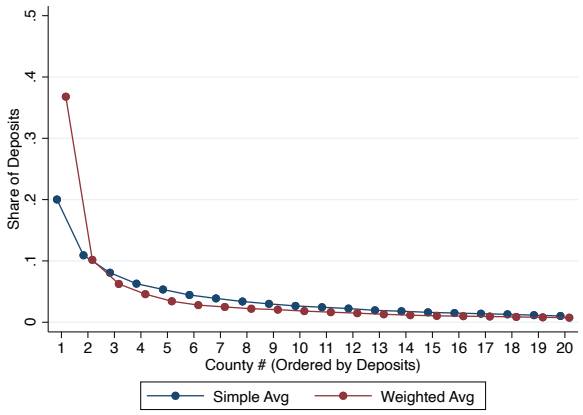
Figure D.5: Deposit Concentration of Banks that Changed Headquarters



(a) Deposit-Weighted Distribution



(b) Equal Distribution



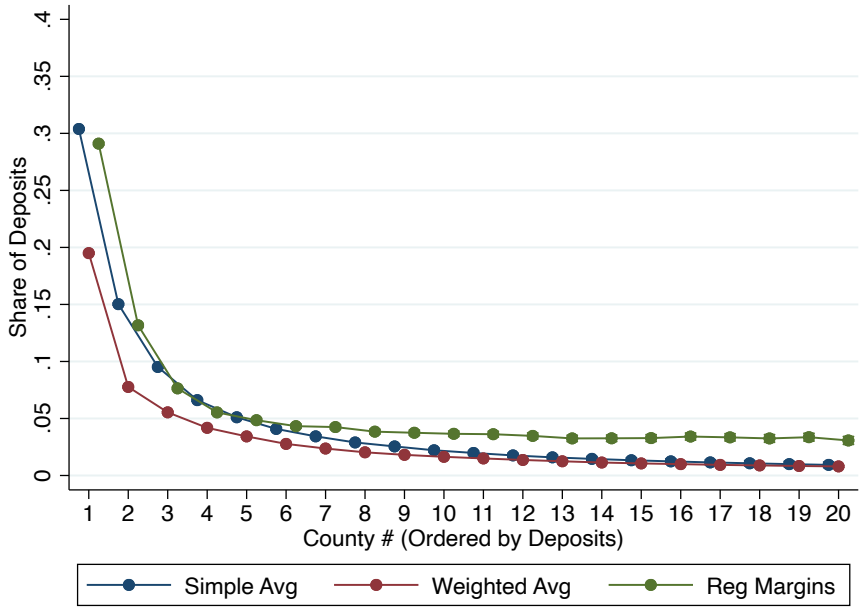
(c) Omission

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 D.5a 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 D.5b plots the deposit concentration after removing the change in deposits at the headquarter county and equally distributing this change across all counties. Figure D.5c plots the deposit concentration after removing the change in deposits at the headquarter county and completely omitting this change in calculating the deposit shares.

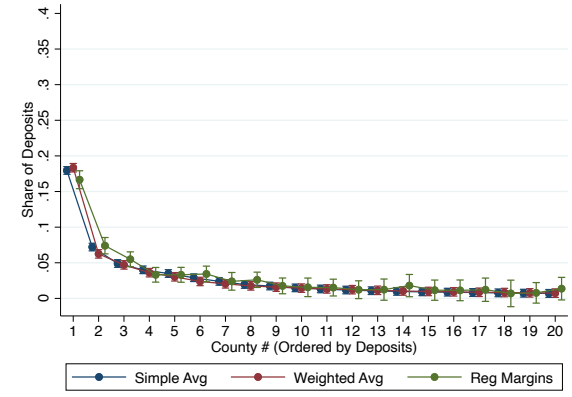
deposits reported at the main office. After this adjustment, approximately 45% of deposits are still attributed to the largest deposit county under the concentration measure used in this robustness exercise.

Online deposits present a related concern. If the expansion of online banking caused geographically dispersed deposits to be increasingly recorded at a small number of branches, measured concentration should rise as online banking becomes more important. The opposite occurs. As shown in Figure 1b, geographic concentration declines over the 1994–2019 sample. Figure D.3 shows the same broad decline

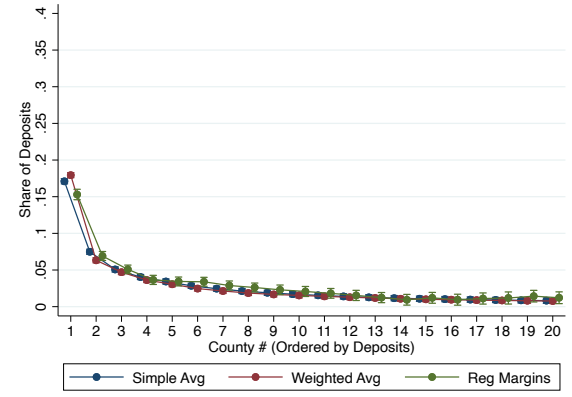
Figure D.6: Geographic Concentration of Deposits after Excluding the Headquarters Branch



(a) All Banks



(b) Big 4



(c) Top 20

Note: This figure uses Summary of Deposits (SOD) data from 1994 to 2019 and illustrates geographic deposit concentration after excluding deposits reported at each bank's headquarters branch. Counties are ordered according to their deposit shares within each bank. The blue line reports the simple average, the red line the average weighted by bank total assets, and the green line the regression-adjusted measure controlling for bank-year and county-year fixed effects. Panel (a) reports the full sample, panel (b) the Big 4 banks, and panel (c) the Top 20 banks ranked by total assets each year.

among the Big 4 banks, which are among the institutions most active in online banking. Our baseline sample also excludes pure single-branch online banks. These patterns make it unlikely that the rise of online banking explains the geographic concentration we document.

D.4.3 Large Lending Centers and Main Offices

Banks may have incentives to report deposits at locations that are particularly important for lending. Loans can themselves create deposits, and banks may concentrate operational activity in major lending centers. Geographic deposit concentration could therefore partly reflect the geographic concentration of bank credit rather than independent variation in funding sources.

We address this concern by excluding each bank's five largest lending counties, measured using mortgage and small-business lending. After removing these major lending centers, the largest remaining deposit county still accounts for approximately 42% of deposits.

We separately consider banks' main offices. Main-office branches often serve as important administrative or operational centers and could therefore report disproportionately large amounts of non-local deposits. After dropping banks' main-office branches and recomputing deposit concentration, the largest deposit county still accounts for approximately 41% of deposits.

As a further check, we remove the largest deposit branch of each bank in each state. These branches are especially likely to correspond to major corporate or operational offices. The largest remaining deposit county still accounts for approximately 40% of bank deposits.

Figure D.7 summarizes these exercises. Figure D.8 reports the analogue of Figure D.7 for the Big 4 and Top 20 banks. Figure D.9 reports the corresponding concentration distributions across all banks in greater detail.

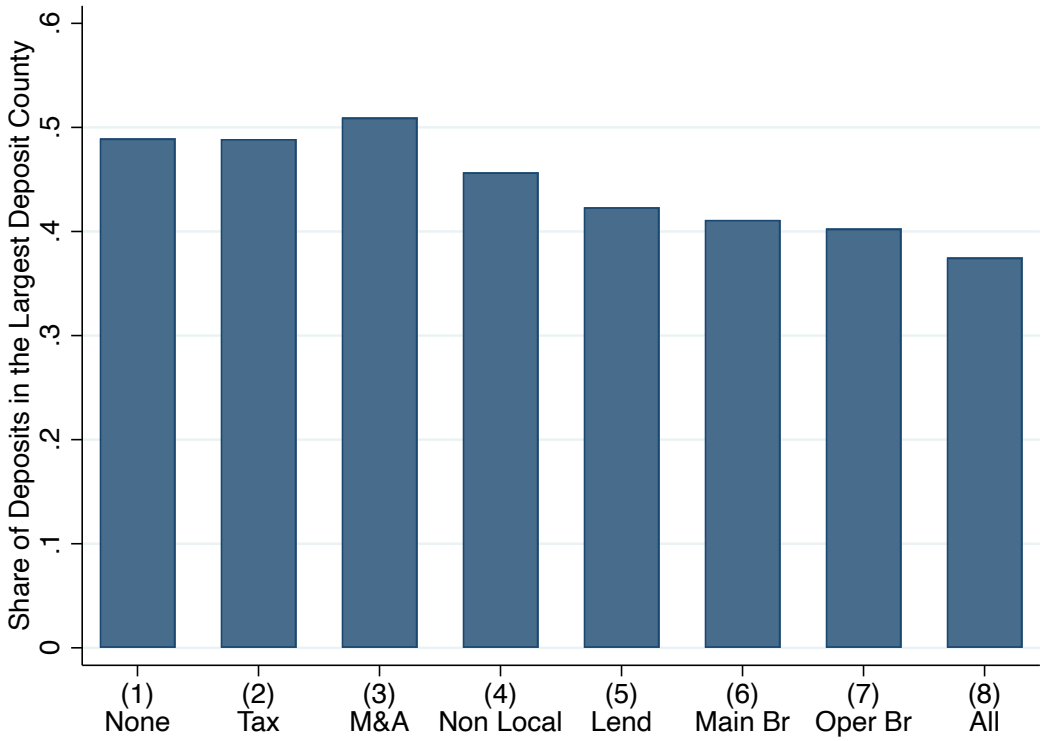
D.4.4 All Measurement Adjustments Jointly

The preceding exercises alter one potential source of geographic mismeasurement at a time. We next apply the adjustments jointly. This is intentionally demanding: we remove or adjust variation associated with tax considerations, mergers and acquisitions, potentially non-local deposit categories, large lending centers, and major operational branches simultaneously.

The baseline concentration measure in this exercise attributes approximately 48% of deposits to the largest deposit county. After applying all adjustments jointly, the corresponding share falls to approximately 37%. Thus, the corrections affect the estimated magnitude of geographic concentration, as one would expect if some reported deposits are geographically misassigned. They do not eliminate the underlying fact. Even after removing several of the most plausible sources of geographic mismeasurement simultaneously, more than one-third of deposits are associated with a single county.

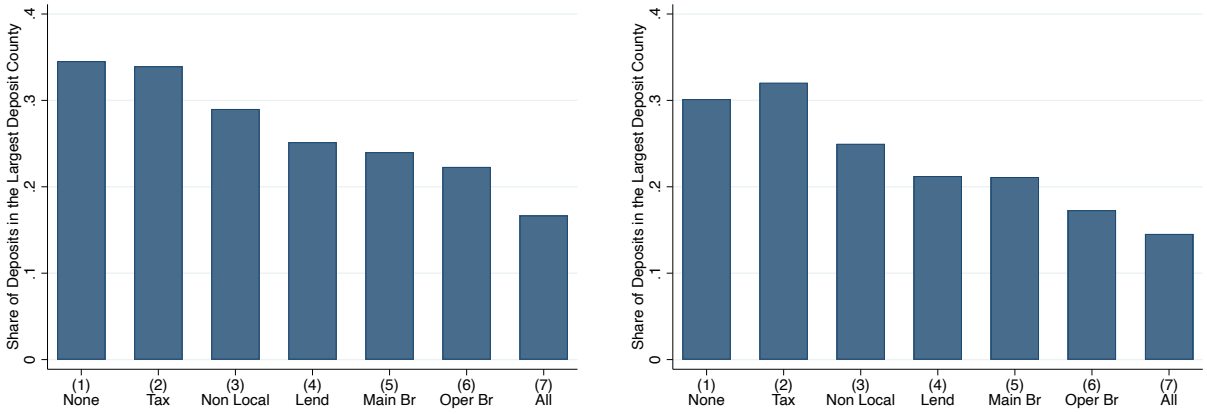
The same conclusion holds among the largest banks. Figures D.10 and D.11 report the corresponding Big 4 and Top 20 exercises and show that concentration remains substantial after these adjustments, reinforcing the conclusion that the result is neither a small-bank phenomenon nor an artifact of a particular class of reporting locations.

Figure D.7: Share of Deposits in Top County After Excluding Certain Counties/Branches



Note: 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 (tax states; M&A banks; non-local/brokered deposits; largest lending counties; main office; largest branch in each state; and all of the above jointly).

Figure D.8: Share of Deposits in Top County After Excluding Certain Counties: Big 4 & Top 20



(a) Big 4 Banks

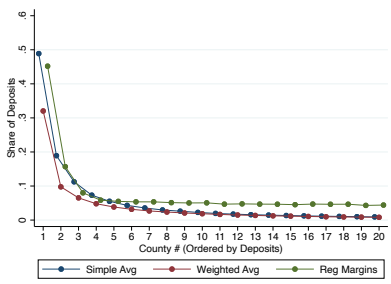
(b) Top 20 banks

Note: This figure reports the Big 4 and Top 20 analogue of Figure D.7.

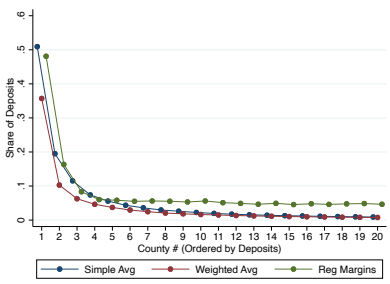
D.4.5 Are Deposits Concentrated in a Single "Special" Branch?

The preceding exercises focus on why a bank might report non-local deposits in a particular county. A related concern is that the apparent importance of the largest deposit county could itself be driven by

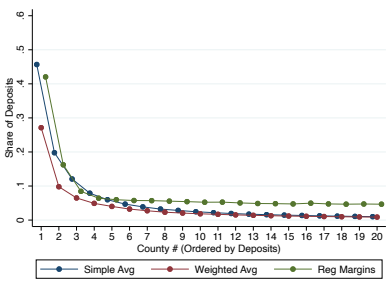
Figure D.9: Deposit Concentration after Addressing Confounding Factors



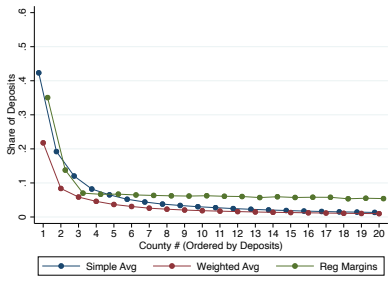
(a) Exclusion of Tax States



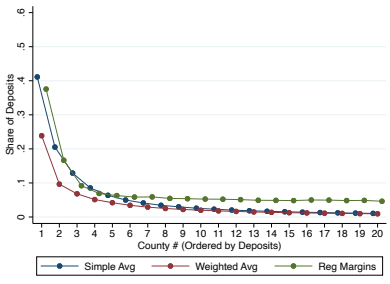
(b) Exclusion of Banks with M&A



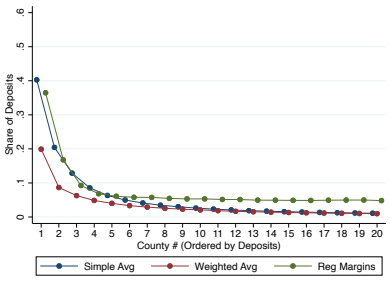
(c) Exclusion of Non-Local Deposits



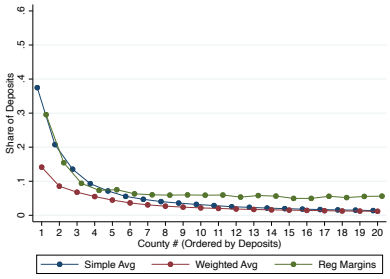
(d) Exclusion of Large Lending Counties



(e) Exclusion of Main Offices



(f) Exclusion of Operational Branches

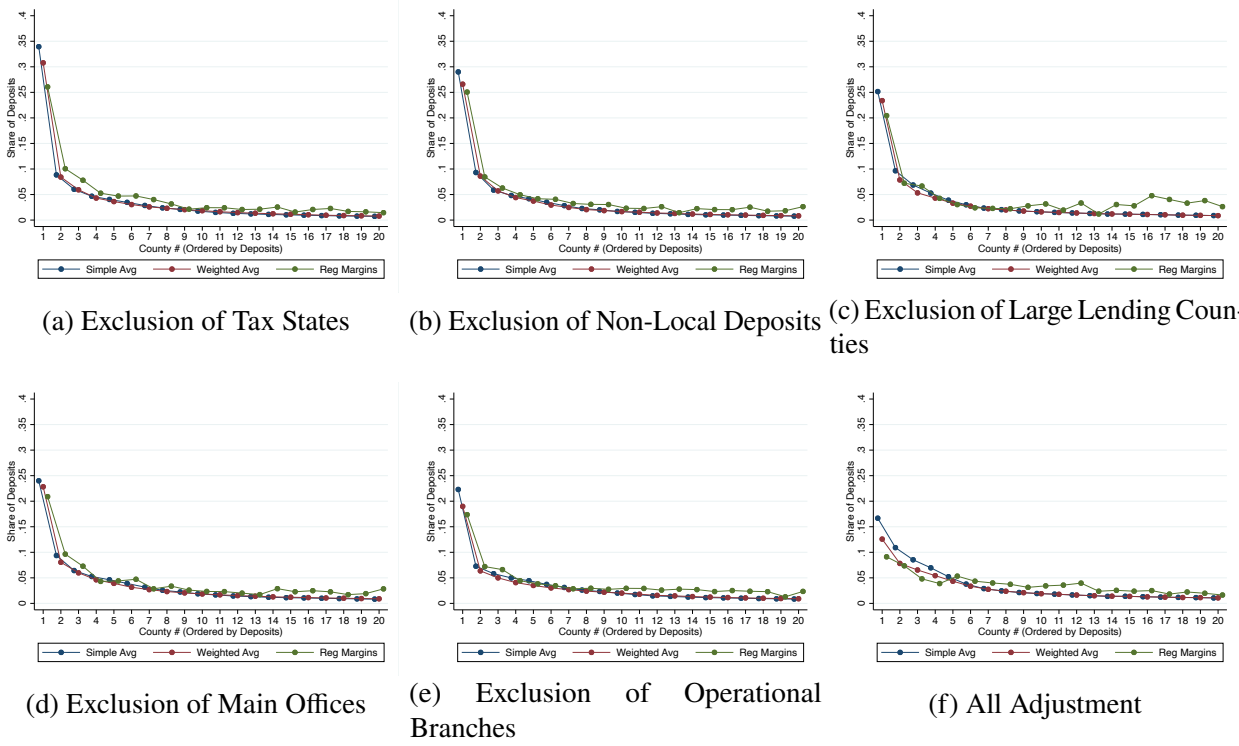


(g) All Adjustment

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 brokered 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.

a single unusual branch. For example, a headquarters, operational center, or specialized branch could report a very large amount of deposits even though the rest of the bank's branches in the county raise relatively little funding.

Figure D.10: 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

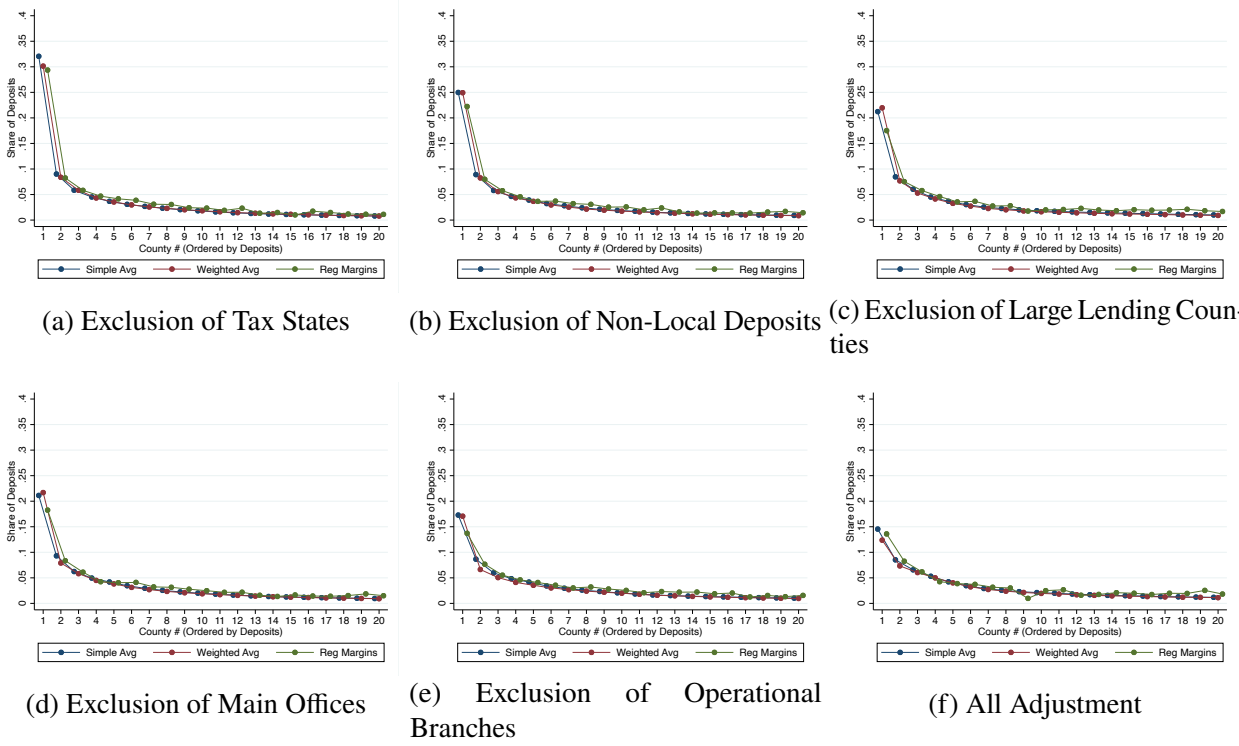
Note: This figure uses the Summary of Deposits (SOD) data from 1994 to 2019 and illustrates the geographic concentration of bank deposits. All figures order counties by their deposit shares for each bank (the county number refers to the rank of a county by the amount of deposits it raises, i.e., county #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 brokered 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.

If the county itself is an important source of deposits, however, deposits should be distributed across multiple branches within that county rather than concentrated entirely in one "special" branch.

Figure D.12 compares deposits held at the largest branch in each of a bank's three largest deposit counties with deposits held at all other branches in the same county. We first rank counties according to their deposit shares within each bank and then rank branches within each county. For ease of comparison, deposits at the largest branch in the bank's largest deposit county are normalized to 100.

The results show that the concentration of deposits in the largest deposit counties is not generated solely by a single branch. In the largest deposit county, the other branches collectively raise at least as many deposits as the largest branch itself. The same broad pattern holds for the full sample, the Big 4 banks, and the Top 20 banks. Thus, when a county appears as an important source of bank deposits, its

Figure D.11: 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 brokered 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

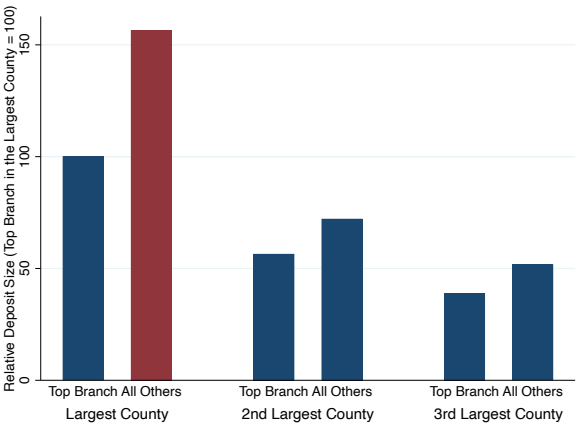
importance is generally reflected across multiple physical branches.

D.4.6 Alternative Measure: Geographic Concentration of Branches

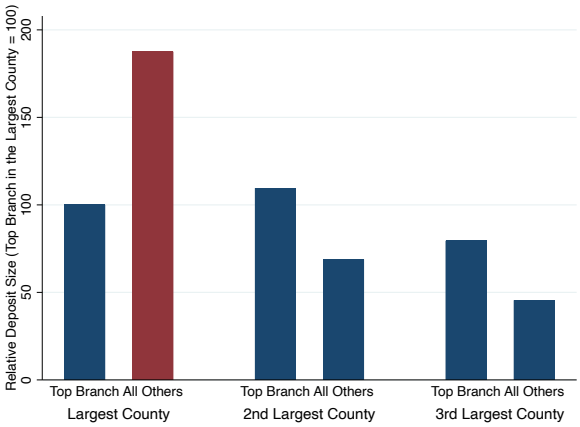
Finally, we construct an alternative measure that does not depend on the geographic assignment of deposits at all. Instead of measuring the share of a bank's deposits located in each county, we measure the share of its physical branches located there. Branch locations are not subject to the same deposit-location reporting concerns and therefore provide an independent way to assess whether banks' geographic footprints are themselves concentrated.

Figure D.13 repeats the main concentration exercises using branch shares. Panel D.13a shows that branches are geographically concentrated within banks: the county containing the largest share

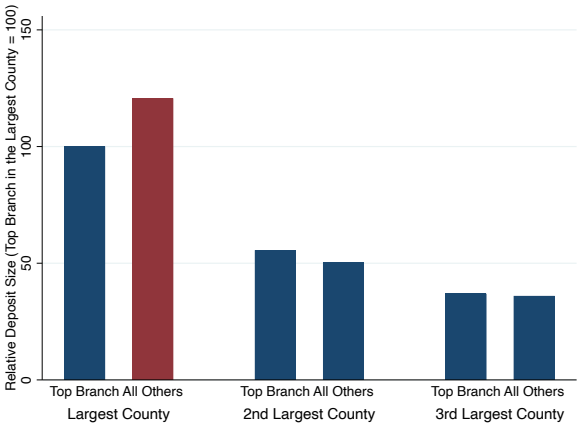
Figure D.12: Dispersion of Deposits within the Largest Deposit Counties



(a) All Banks



(b) Big 4



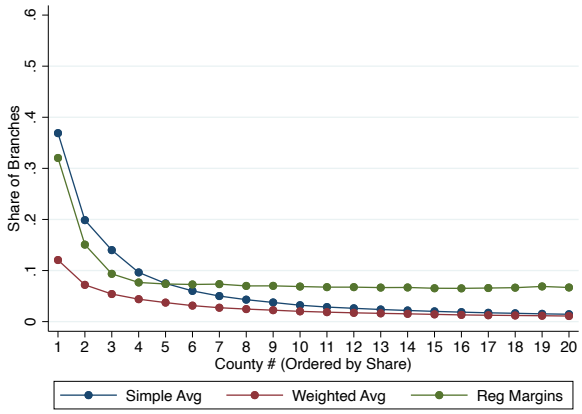
(c) Top 20

Note: This figure uses Summary of Deposits (SOD) data from 1994 to 2019 and compares deposits at the largest branch in a county with deposits held at all other branches in that county. Counties are first ranked by their deposit shares within each bank, and branches are then ranked within counties. Deposits at the largest branch in the largest deposit county are normalized to 100. Panel (a) reports all banks, panel (b) the Big 4 banks, and panel (c) the Top 20 banks ranked by total assets each year.

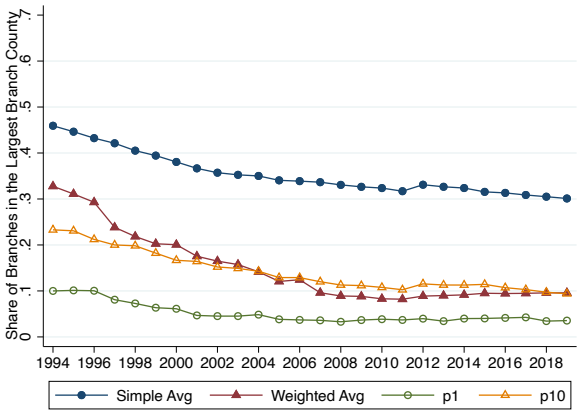
of a bank's branches accounts for approximately 30% of its branches. Panel D.13b shows that branch concentration is present throughout the 1994–2019 period. Panel D.13c shows that branch concentration declines somewhat with bank size but remains present among large institutions, while Panel D.13d documents concentration among the Big 4 banks.

The branch-based and deposit-based concentration measures are strongly related: their correlation is approximately 86%, as reported in Figure D.14. Thus, banks that report geographically concentrated deposits also tend to have geographically concentrated physical branch networks. Because the branch measure does not rely on assigning individual deposits to particular locations, this result is difficult to reconcile with an explanation based entirely on deposit-reporting conventions. Figure D.15 confirms that the branch-concentration result is similarly robust when bank size is measured using deposits, liabilities,

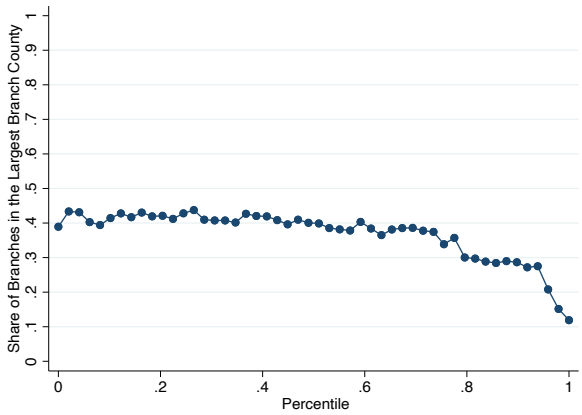
Figure D.13: Geographic Concentration of Bank Branches



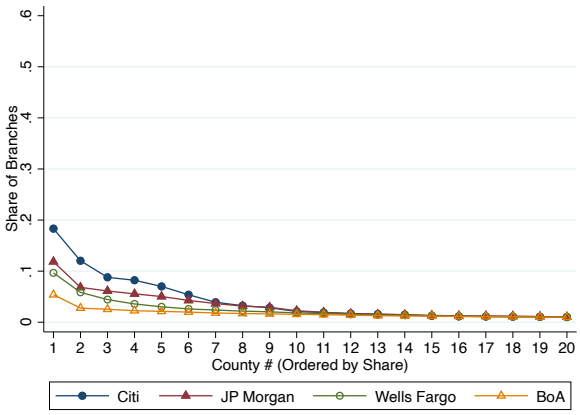
(a) Cross Section



(b) Time Series



(c) Banks by Size



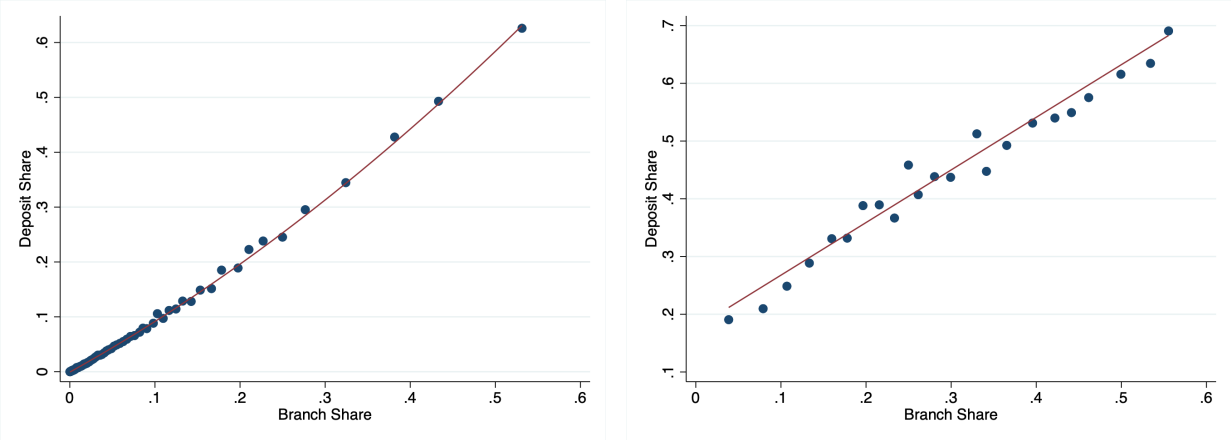
(d) Four Largest Banks

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.

book equity, or loans rather than total assets.

Taken together, the exercises in this subsection indicate that measurement issues can affect the precise magnitude of geographic deposit concentration but do not explain the phenomenon itself. Concentration survives adjustments for headquarters reporting, taxes, mergers and acquisitions, potentially non-local deposit categories, online banking, lending centers, and main-office reporting; survives these adjustments when imposed jointly; is visible across multiple branches within the largest deposit counties;

Figure D.14: Relationship between Deposit Share & Branch Share

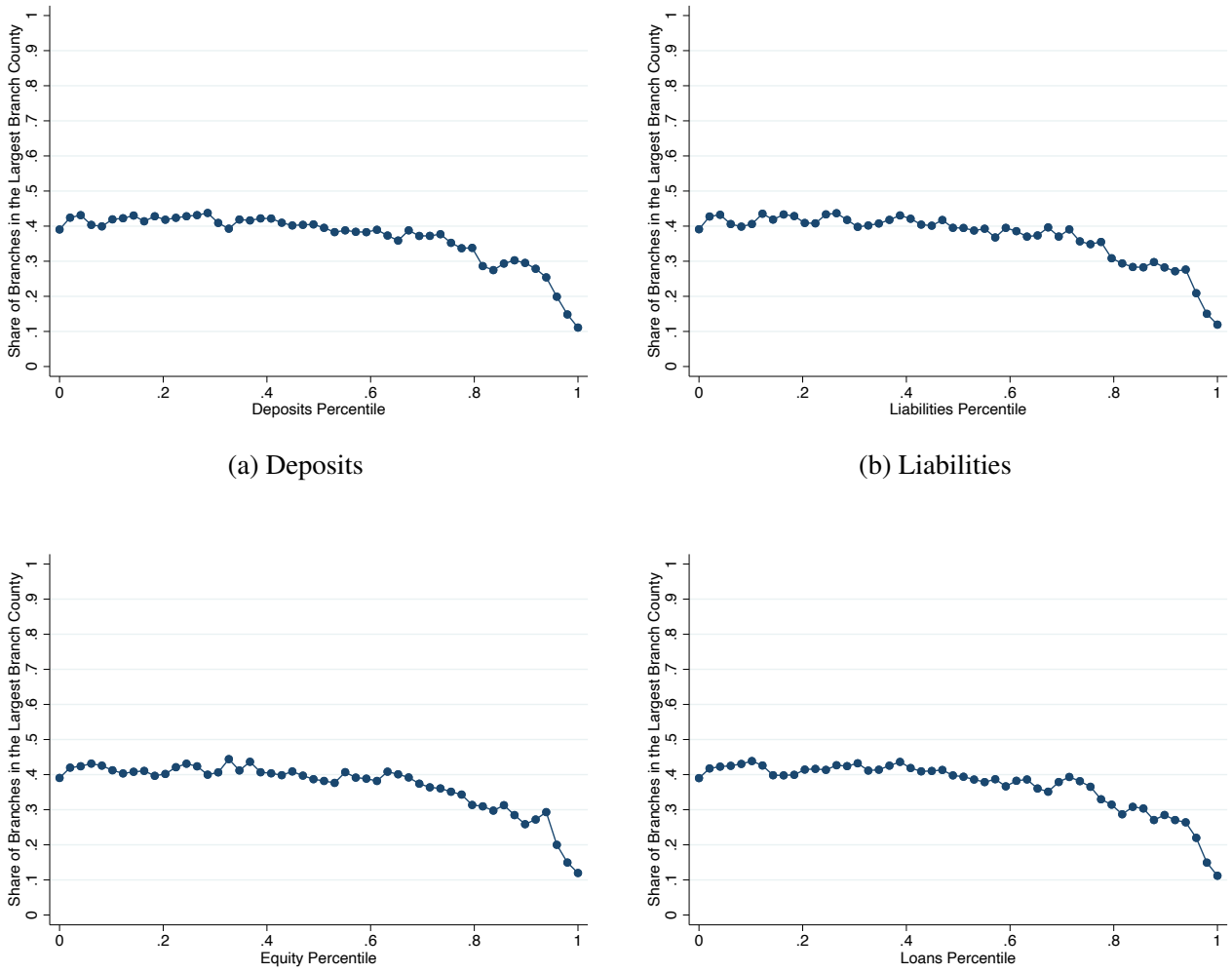


(a) All Counties (b) Largest Deposit Counties

Note: This figure compares each county's share of deposits within a bank to its share of branches. Figure D.14a includes all counties, while Figure D.14b 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.

and is corroborated by the independent geographic distribution of physical bank branches. We therefore interpret the geographic concentration documented in Section 4.1 as an economically meaningful feature of banks' funding geography rather than an artifact of SOD reporting.

Figure D.15: Geographic Concentration of Branches Across Bank Characteristics



(a) Deposits

(b) Liabilities

(c) Equity

(d) Loans

Note: This figure uses Summary of Deposits (SOD) data from 1994 to 2019 to illustrate the relationship between the geographic concentration of bank branches and bank size, measured by deposits (Figure D.15a), total liabilities (Figure D.15b), book equity (Figure D.15c), and loans (Figure D.15d). In each panel, banks are sorted by the relevant size measure, and we plot the average branch share in the county where the bank has its largest presence against the corresponding percentile of deposits, liabilities, equity, or loans.

Appendix E Effects of Natural Disasters

Section 4.2 establishes that natural disasters generate persistent declines in local deposits and that banks exposed to disasters in important deposit markets experience declines in total funding. This section provides additional evidence on this relationship. We first describe the geography and distribution of the disaster variation and then examine the robustness and persistence of the local deposit response. We then study the economic channels through which disasters reduce deposits, distinguishing declines in local economic activity from geographic reallocation through migration. Finally, we examine the response of total bank deposits and present the Capital One/Hibernia experience around Hurricane Katrina as a case study of the mechanism underlying our shock construction.

E.1 Natural Disaster Exposure in the Data

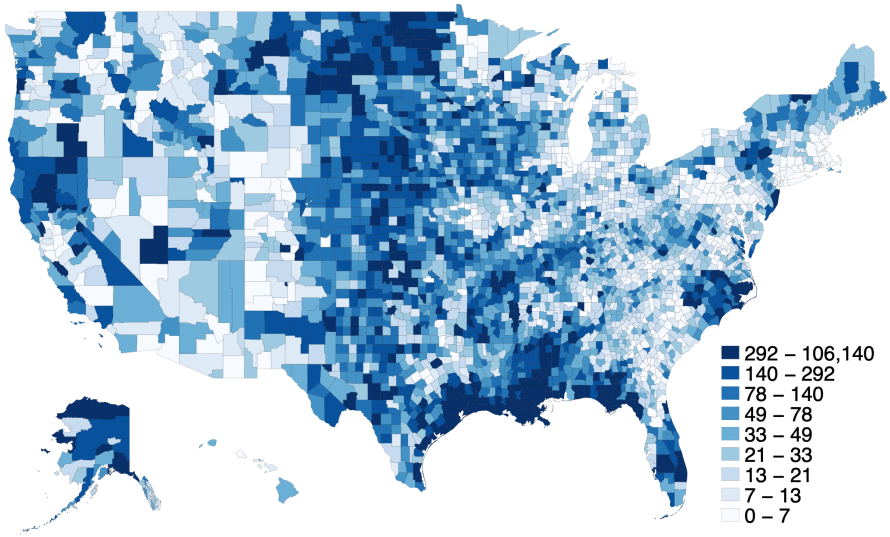
Before turning to the deposit response, we describe the disaster variation underlying the shock construction. Table E.1 reports the frequency and distribution of property damage by hazard type in SHELDUS. Floods, hurricanes, tornadoes, wildfires, hail, wind, and severe storms account for much of the observed disaster exposure, while the distribution of damages is strongly right-skewed: most county-year events are small, but a limited number of events generate very large losses. Figure E.1 maps average annual property damage per capita across counties from 1994 to 2019. Disaster exposure is geographically dispersed rather than concentrated in a single region, providing variation across the deposit markets of different banks. Table F.2 reports additional summary statistics for the bank-level variables and aggregate shocks used throughout the appendix.

Table E.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.

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



Note: This figure illustrates average annual natural-disaster-induced property damage per capita across counties from 1994 to 2019.

E.2 Robustness and Persistence of the Deposit Response

The baseline estimates in Table 2 show that natural disasters reduce subsequent county deposit growth. A one-standard-deviation disaster shock, corresponding to approximately $2,500 in property damage per capita, is associated with a 0.09 to 0.11 percentage-point decline in deposit growth. The coefficient is negative and statistically significant across increasingly demanding fixed-effect specifications and remains stable as county, year, and state-by-year fixed effects are introduced.

We conduct two additional exercises to assess this relationship. First, Table E.2 controls for lagged disaster shocks. The estimated effect remains negative and significant, indicating that the baseline relationship is not generated by persistence in prior disaster exposure.

Second, we conduct a placebo exercise in which we replace actual disaster exposure with randomly generated shocks. Figure E.2 reports the distribution of coefficients obtained from 1,000 placebo simulations estimated using the specification of Table 2. The placebo estimates are centered close to zero, whereas the coefficient estimated using actual disaster damages lies well outside the placebo distribution. None of the 1,000 placebo draws produces an estimate exceeding the actual coefficient in magnitude.

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

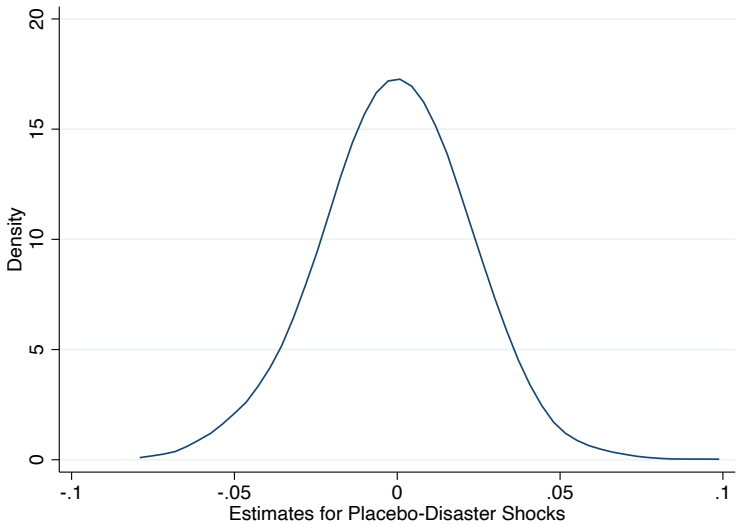
Dep Var: Deposit Growth (%)	(1)	(2)	(3)
Disaster Shock$_{c,t-1}$	-0.0910***	-0.0949***	-0.0972***
	(0.0269)	(0.0277)	(0.0286)
Disaster Shock$_{c,t-2}$		-0.0962***	-0.0986***
		(0.0292)	(0.0301)
Disaster Shock$_{c,t-3}$			-0.0541
			(0.0330)
County FE	✓	✓	✓
State-Year FE	✓	✓	✓
# Obs	79,886	79,886	79,886
R^2	0.2033	0.2035	0.2036

Notes: 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 estimates of β_k from

$$\Delta \ln(Deposits)_{c,t} \times 100 = \sum_{k=1}^{3} \beta_k \times \text{Disaster Shock}_{c,t-k} + \theta_c + \theta_{s(c\in s),t} + \varepsilon_{c,t},$$

where c and t indicate county and year, respectively. The dependent variable is deposit growth in percent, defined as the first difference of the natural logarithm of total deposits held by all banks in county c and year t, multiplied by 100. Disaster Shock$_{c,t-k}$ is the standardized dollar amount of property damage per capita from natural disasters in county c and year $t-k$. θ_c and $\theta_{s(c\in s),t}$ are county and state-year fixed effects, respectively. Standard errors clustered at the county level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Figure E.2: Disaster Shock and Deposit Growth: Placebo Test



Mean	Std Dev	Min	P1	P5	P25	P50	P75	P95	P99	Max
-0.0006	0.0215	-0.0691	-0.0535	-0.0376	-0.0138	-0.0008	0.0138	0.0327	0.0519	0.0889

Notes: This figure reports the kernel density of coefficients from 1,000 placebo simulations in which the disaster shock is randomly drawn from a standard normal distribution and the specification of Table 2 is re-estimated. The actual estimate from column 6 of Table 2 is -0.4666, which lies outside the range plotted here; none of the 1,000 placebo draws exceeds it in magnitude.

The effect of disasters on deposits is also persistent. Figure 3 reports Jordà local projections tracing the response of deposits following a disaster shock. The decline remains negative even ten years after the initial shock. This persistence distinguishes the response from a short-lived change in liquidity demand or the timing of disaster-related transfers. Instead, it is consistent with disasters producing lasting changes in the economic resources that support deposits in affected areas.

E.3 Why Do Natural Disasters Reduce Deposits?

Natural disasters can reduce local deposits through several channels. Destruction of productive capital may cause businesses to close, reducing business deposits directly and household deposits indirectly through lower employment and income. Households and firms may draw down savings to finance uninsured losses, reconstruction, or consumption following an income shock. Disasters can also induce migration. The migration channel is particularly important for interpreting our results: if households simply relocate and their deposits are reassigned to branches near their new residences, county deposits could fall without any corresponding reduction in total bank funding.

We therefore examine local business activity, employment, household income, and migration separately.

E.3.1 Business Activity

We begin with local business activity using County Business Patterns data from 1994 to 2019. Panel A of Table E.3 relates the number of establishments in a county to lagged disaster-related property damages per capita. Disaster exposure is associated with a decline in the number of local establishments. A one-standard-deviation increase in property damages is associated with approximately a 0.06% decline in establishments.

Business closures can reduce local deposits through two related channels. Firms themselves maintain deposit accounts used for payroll, payments, and other operating expenses, so closure can directly reduce business deposits. Businesses also employ local households, meaning that establishment closures can reduce wages and household deposits indirectly through employment.

Panel B of Table E.3 confirms that local business activity is positively associated with local bank deposits. The decline in establishments following a disaster therefore provides one mechanism through which destruction of local productive activity can translate into lower deposit balances.

E.3.2 Employment and Household Income

We next examine employment. Panel C of Table E.3 relates county employment to lagged disaster-related property damage. A one-standard-deviation increase in property damages is associated with approximately a 0.16% decline in county employment.

Table E.3: Economic Effects of Natural Disasters

	Panel A: Effect of Disasters on Business						
Dep Var: $ln(\#Establishment)_{c,t}$	(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						
Dep Var: $ln(Deposits)_{c,t}$	(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						
Dep Var: $ln(Employment)_{c,t}$	(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

Notes: This table uses County Business Patterns data, spanning 1994 to 2019, and reports estimates of β from

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

where c denotes the county and t the year. The dependent variable $Y_{c,t}$ is ln(# Establishments) in Panel A, ln($Deposits$) in Panel B, and ln($Employment$) in Panel C. The independent variable $X_{c,t-1}$ is Disaster Shock$_{c,t-1}$, the standardized dollar amount of property damage per capita from natural disasters in county c and year $t-1$, in Panels A and C, and ln(# Establishments)$_{c,t-1}$ in Panel B. Standard errors clustered at the county level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

We complement this evidence with household-income data. Table E.4 documents a negative relationship between disaster damages and household income. Taken together, the establishment, employment, and income results indicate that disasters generate persistent losses in local economic activity. Lower employment and household income provide a natural channel through which disasters reduce household savings and bank deposits.

These findings are consistent with the broader literature documenting persistent economic losses following major natural disasters. For our purposes, the important implication is that the decline in local

Table E.4: Disasters and Household Income

Dep Var: HH Income	(1)	(2)	(3)	(4)
Disaster Shock$_{s,t-1}$	-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

Notes: This table uses annual survey data on household family income from the Current Population Survey (CPS), spanning 1994 to 2019, and reports estimates of β from

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

where h denotes the household, s the state, and t the year. The dependent variable, HH Income$_{h,s,t}$, is total family income for household h in state s in year t. Poisson pseudo maximum likelihood (PPML) is used to estimate the specification, as HH Income is right-skewed. Disaster Shock$_{s,t-1}$ is the standardized dollar amount of property damage per capita from natural disasters in state s and year $t-1$. Standard errors clustered at the state level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

deposits occurs alongside a decline in the underlying economic activity and income that generate those deposits.

E.3.3 Migration

Migration provides an alternative mechanism. Households may leave disaster-affected counties and update their addresses with their financial institutions. Their deposits may then be attributed to branches closer to their new residences. In this case, measured deposits in the affected county would decline even if the total deposits held by the bank remained unchanged.

We examine this possibility using IRS migration data from 1994 to 2018. Table E.5 reports the results. Natural disasters increase population outflows from affected counties. A one-standard-deviation increase in property damage is associated with a 0.04 percentage-point increase in population outflow, measured relative to the prior year's population. We also observe a 0.01 percentage-point decline in population inflow. Net population outflow, estimated separately in column (3) of Table E.5, increases by approximately 0.03 percentage points following a one-standard-deviation disaster shock.

Thus, migration is part of the response to natural disasters. This finding alone, however, does not determine whether disasters generate a genuine funding loss for banks. If households simply move from one county to another while retaining accounts at the same multi-market bank, the geographic distribution of the bank's deposits may change while its total deposits remain approximately unchanged.

Table E.5: Disasters and Migration

Dep Var:	(1) Outflow	(2) Inflow	(3) Net Outflow
Disaster Shock$_{c,t-1}$	0.0431***	-0.0122***	0.0275***
	(0.0076)	(0.0036)	(0.0051)
County FE	✓	✓	✓
Year FE	✓	✓	✓
# Obs	78,321	78,321	78,321
R^2	0.7969	0.7941	0.4680

Notes: This table uses IRS Statistics of Income (SOI) annual data on migration, spanning 1994 to 2018, and reports estimates of β from

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

where c denotes the county and t the year. $Y_{c,t}$ is outflow per capita in column (1), inflow per capita in column (2), and net outflow (outflow minus inflow) per capita in column (3). Disaster Shock$_{c,t-1}$ is the standardized dollar amount of property damage per capita from natural disasters in county c and year $t-1$. Standard errors clustered at the county level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

We therefore examine the response of total bank deposits directly below.

E.3.4 Other Channels

Several additional mechanisms may contribute to the decline in deposits. Households and businesses may draw down savings to cover property losses not reimbursed by insurance or to finance reconstruction and consumption during the recovery period. Disasters can also increase the demand for physical cash when electricity, communications, or payment infrastructure is disrupted. More broadly, natural disasters may affect health, mortality, and well-being in ways that reduce economic activity and household resources.

We do not attempt to separately identify each of these mechanisms. They all imply that a disaster can reduce the stock of deposits available to banks rather than merely changing the branch at which those deposits are reported. The bank-level analysis below provides a direct test of this distinction.

E.4 Do Disasters Reduce Total Bank Funding?

The migration results make it important to distinguish a decline in deposits in the affected county from a decline in the total deposits of banks exposed to that county. If migration were the dominant mechanism and depositors simply moved their accounts between branches of the same multi-market bank, county deposits could decline without producing a bank funding shock.

We test this implication by relating bank-level disaster exposure, $\Gamma_{b,t}$, to subsequent bank deposits.

Table 3, reported in the main text, examines total deposits and several deposit categories separately: demand deposits, transaction savings deposits, and savings deposits. Banks with greater exposure to disasters in their important deposit markets experience significantly larger declines in total deposits. The decline is concentrated in savings deposits, the only category for which the response is statistically significant.

This bank-level result is the direct test against pure within-bank reallocation. If depositors merely moved after a disaster and their balances were reassigned to another branch of the same multi-market bank, deposits in the affected county could fall but the bank's total deposits would not. Instead, total deposits fall at the exposed bank. The same conclusion holds after aggregation: Table 4 shows that the aggregate granular funding shock, Γ_t^*, predicts lower aggregate deposit growth. Together, these results are inconsistent with pure geographic reallocation as the explanation for the deposit decline. Disaster exposure produces a net loss of deposit funding at exposed banks that remains visible in aggregate deposits.

E.5 Long-Term Local Effects: Hurricane Katrina

The local economic consequences of natural disasters can persist long after the initial destruction. We illustrate this persistence with two visual examples from New Orleans following Hurricane Katrina. These examples complement the county-level evidence on establishments, employment, income, and migration by making the persistence of local economic disruption visible at the neighborhood level.

Six Flags New Orleans was severely damaged by Hurricane Katrina in August 2005 and subsequently closed permanently. The park had been an important employer and anchor for surrounding commercial activity. Its closure illustrates how the destruction of a major local establishment can affect not only the immediate workforce but also nearby businesses that depended on visitors and local activity. Figure E.3 compares the site before and after the hurricane.

The Lower Ninth Ward provides a second illustration of persistent local disruption. The neighborhood experienced catastrophic flooding following levee failures, resulting in widespread destruction of homes and displacement of residents. Figure E.4 shows aerial images before the hurricane and in 2005, 2008, and 2015, illustrating the slow recovery of the neighborhood over the subsequent decade.

These examples are not intended as quantitative estimates of the disaster's aggregate effects. Rather, they illustrate the persistence underlying our empirical results: natural disasters can destroy productive and residential capacity in affected locations, with consequences for local employment, income, population, and the deposits generated by economic activity in those locations.

Figure E.3: Hurricane Katrina and Six Flags New Orleans



(a) Before

(b) After

(c) Before

(d) After

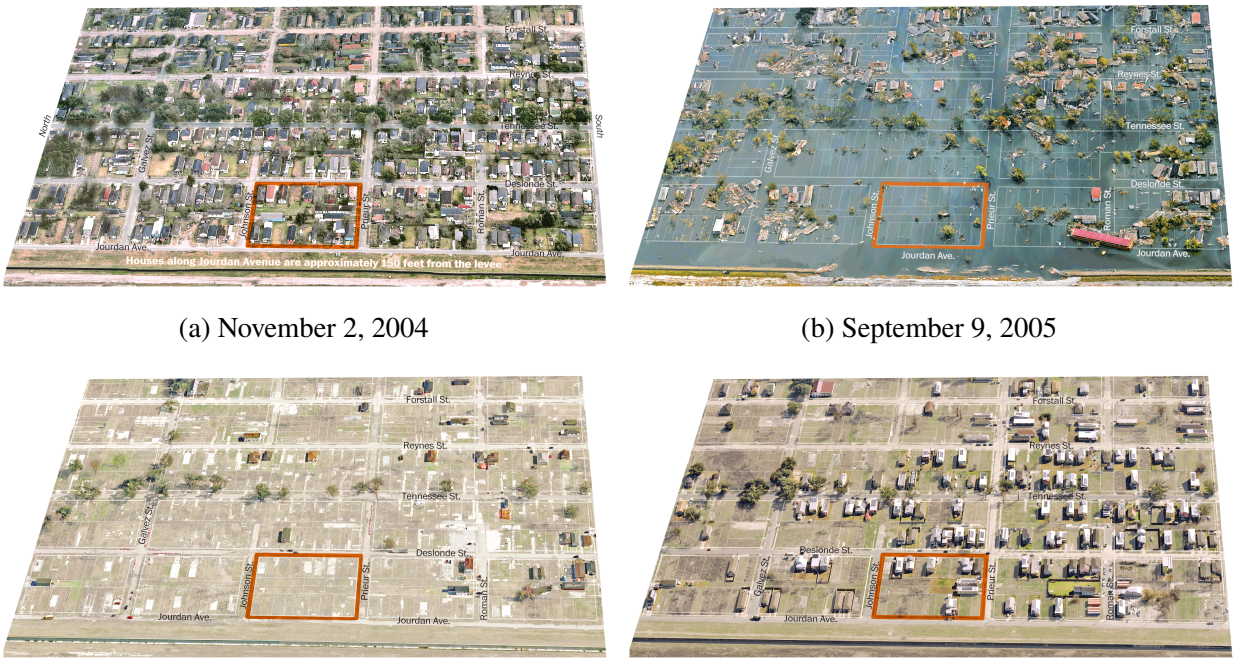
Note: This figure displays images of the Six Flags New Orleans, before and after Hurricane Katrina. Panels (a) and (c) present photos before the hurricane. Panels (b) and (d) present photos after the hurricane. The images in panel (a), (b), and (c) are reproduced from the New Orleans Advocate. The image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

E.6 Hibernia/Capital One and Hurricane Katrina

The experience of Hibernia National Bank around Hurricane Katrina provides a concrete illustration of how a local disaster can become a bank-level funding shock when deposits are geographically concentrated. Hibernia National Bank was headquartered in New Orleans and operated primarily in Louisiana and Texas. In 2005, Capital One entered retail banking through its acquisition of Hibernia. At the time, Hibernia had a substantial presence in Louisiana, reporting approximately 21% of the state's deposit market.

Figure E.5 compares the geographic distribution of Hibernia's deposits with disaster damages in 2005. The figure shows substantial overlap between counties that supplied large shares of the bank's deposits and locations experiencing severe disaster damage. This is precisely the interaction captured by the bank-level shock: a disaster matters more for a bank when it strikes a county that supplies a larger

Figure E.4: Hurricane Katrina and the Lower Ninth Ward, New Orleans



(a) November 2, 2004

(b) September 9, 2005

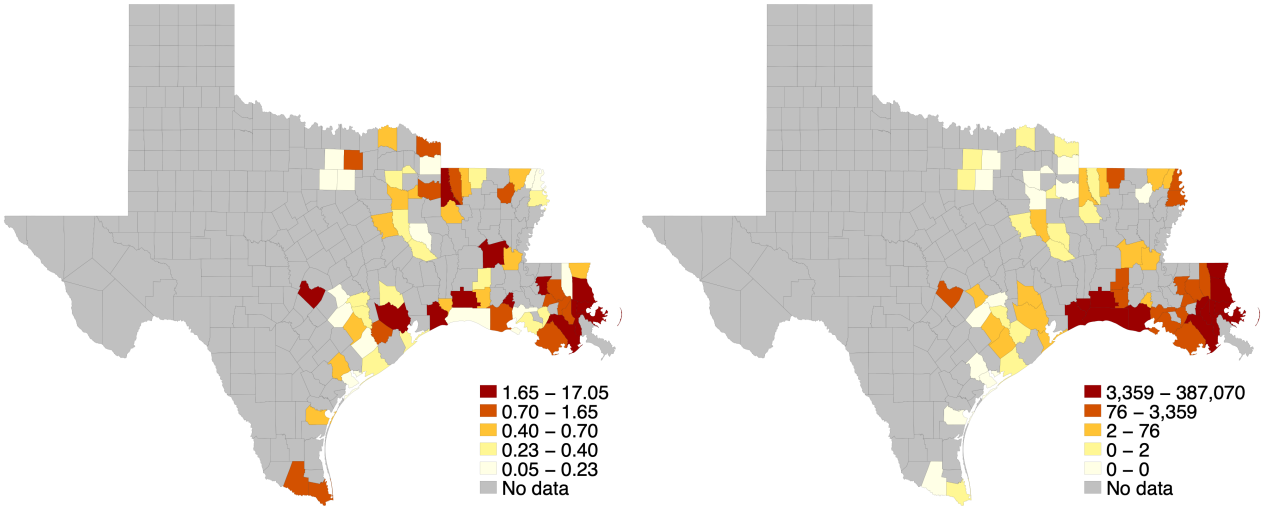
(c) January 20, 2008

(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).

share of the bank's deposits.

Figure E.5: Capital One Deposit Share and Damages Per Capita in 2005



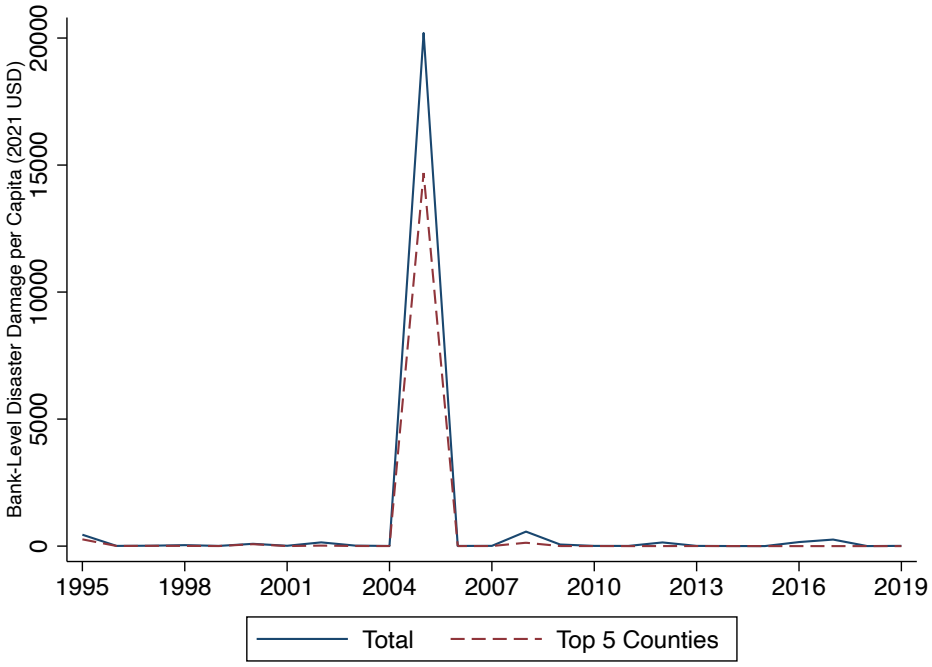
(a) Deposit Share

(b) Damage per Capita

Note: This figure reports the geographic distribution of Capital One's (formerly Hibernia National Bank) deposit shares and property damage per capita in 2005.

Figure E.6 plots Hibernia/Capital One's bank-level funding shock over time, constructed using all deposit counties and using only the five largest deposit counties. The shock is close to zero in most years but rises sharply in 2005, coinciding with Hurricane Katrina, and most of the spike is generated by the five largest deposit counties.

Figure E.6: Time-Series Bank-Level Shock for Capital One

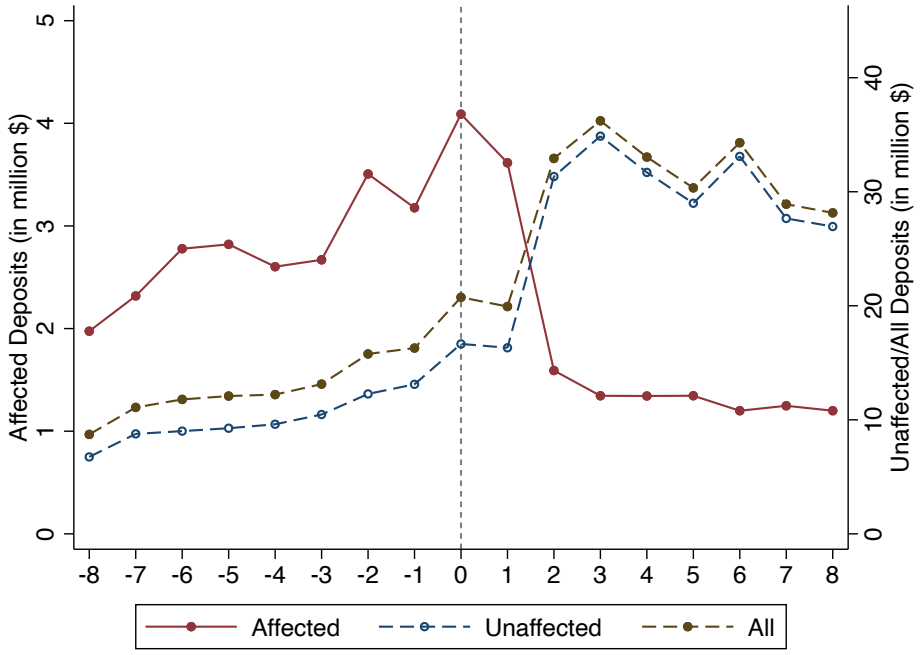


Note: This figure reports the bank-level funding shock for Capital One (Hibernia), all counties vs. top 5 deposit counties.

Figure E.7 compares deposit growth in counties heavily affected by Katrina with deposit growth in less affected counties. Deposits in affected counties initially increased following the hurricane, consistent with insurance proceeds and government assistance flowing into the region. Deposit growth subsequently fell relative to unaffected counties and remained depressed for several years, consistent with Capital One's contemporaneous warning that the temporary inflow of disaster-related funds could reverse as rebuilding began.

The Hibernia episode therefore illustrates each step of the empirical construction. The bank raised a disproportionate share of its deposits in a small number of counties; a major natural disaster struck those counties; the resulting bank-level funding shock rose sharply; and deposit growth subsequently weakened in the affected funding markets.

Figure E.7: Capital One Deposit Growth for Affected and Unaffected Counties



Note: This figure reports Capital One's total deposits, 2000–2014, split between counties affected and unaffected by Hurricane Katrina. Deposit data are reported as of June 30 of each year. Year 0 corresponds to the June 30, 2006 reporting date.

Appendix F Properties of the Bank-Level Funding Shock

Section 4.4 provides summary evidence that the bank-level funding shock, $\Gamma_{b,t}$, behaves like an idiosyncratic shock rather than a proxy for persistent bank characteristics or common banking-sector conditions. This section presents the underlying tests in greater detail. We examine whether observable bank characteristics predict subsequent funding shocks, whether the shocks are persistent within banks, and whether they contain substantial common variation across banks.

F.1 Predictability from Bank Characteristics

A first concern is that $\Gamma_{b,t}$ may systematically vary with observable bank characteristics. For example, banks of different sizes, capitalization, liquidity, or funding structures may operate in systematically different geographic markets. If these characteristics predict subsequent disaster exposure, the funding shock could partly reflect persistent differences across banks rather than idiosyncratic variation generated by the interaction of deposit geography with natural disasters.

We examine this possibility in Table F.1. We regress $\Gamma_{b,t}$ on a range of lagged bank characteristics, including bank size, loans, equity, cash holdings, demand deposits, hedging activity, dividends, and operating income. We first enter the characteristics individually and then jointly. We also include specifications with bank and year fixed effects.

The individual characteristics have little explanatory power for subsequent funding shocks, and including them jointly does not materially change this conclusion. Even with the full set of bank characteristics together with bank and year fixed effects, the specification explains only approximately 7% of the variation in $\Gamma_{b,t}$.

This result is useful for interpreting the source of identifying variation. Banks clearly differ in their balance sheets and geographic footprints, but those observable characteristics have limited ability to predict when a bank will subsequently experience a large funding shock. Most of the variation in $\Gamma_{b,t}$ therefore arises from the interaction between predetermined geographic deposit exposures and the realized timing and location of natural disasters rather than from readily observable persistent bank characteristics.

F.2 Persistence of Bank-Level Funding Shocks

We next examine whether $\Gamma_{b,t}$ is persistent over time. Persistent bank-level shocks could indicate that the measure captures slowly moving differences in bank geography or exposure rather than discrete realizations of idiosyncratic disasters.

Table F.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(Assets)$_{b,t-1}$	-0.0107								-0.0078	-0.1013
	(0.0085)								(0.0142)	(0.0700)
Loan/Assets$_{b,t-1}$		-0.0149*							-0.0200**	0.0239
		(0.0088)							(0.0096)	(0.0202)
Equity/Assets$_{b,t-1}$			0.0004						0.0020	-0.0015
			(0.0115)						(0.0110)	(0.0199)
Cash/Assets$_{b,t-1}$				-0.0043					-0.0091*	-0.0015
				(0.0047)					(0.0054)	(0.0116)
Deposits/Assets$_{b,t-1}$					0.0055				0.0043	0.0036
					(0.0095)				(0.0146)	(0.0125)
Hedge/Assets$_{b,t-1}$						0.0062***			0.0045	-0.0033
						(0.0016)			(0.0033)	(0.0024)
Div/Assets$_{b,t-1}$							-0.0072		-0.0093	-0.0181**
							(0.0068)		(0.0073)	(0.0090)
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

Notes: This table uses the Spatial Hazard Events and Losses Database for the United States (SHELDUS) and bank call report data and reports estimates of β from

$$\Gamma_{b,t} = \beta \times \text{Bank Characteristic}_{b,t-1} + \theta_b + \theta_t + \varepsilon_{b,t},$$

where b and t indicate bank and year, respectively. The data span from 1998 to 2019. The dependent variable is the bank-level disaster shock $\Gamma_{b,t}$. The independent variable, Bank Characteristic$_{b,t-1}$, is the natural logarithm of total bank assets in column (1); the average loan balance divided by total assets in column (2); total equity divided by total assets in column (3); total cash holdings divided by total assets in column (4); total deposits divided by total assets in column (5); net derivatives held for hedging divided by total assets in column (6); total dividends on common stock divided by total assets in column (7); and operating income divided by total assets in column (8). Column (9) includes all eight bank characteristics jointly, and column (10) further adds bank and year fixed effects, θ_b and θ_t. All variables are standardized. Standard errors clustered at the bank level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Following the original analysis, we estimate a bank-specific AR(1) coefficient for $\Gamma_{b,t}$ for each bank and examine the cross-sectional distribution of the resulting coefficients.

Panel F.1a of Figure F.1 reports the distribution. The estimates are concentrated around zero, and the average bank-specific AR(1) coefficient is -0.03. Thus, a bank experiencing a large funding shock in one period is not systematically more likely to experience another large shock in the following period.

The low persistence is consistent with the source of variation underlying $\Gamma_{b,t}$. A bank's deposit geography determines which local disasters matter for its funding, but the timing and location of major natural disasters change over time. Consequently, exposure to a disaster in one period does not imply continued exposure in subsequent periods.

F.3 Common Variation across Banks

Finally, we examine whether the bank-level funding shocks move together across institutions. This test is important because a shock that is highly correlated across banks could simply be capturing a common macroeconomic or banking-sector factor rather than bank-specific exposure to local disasters.

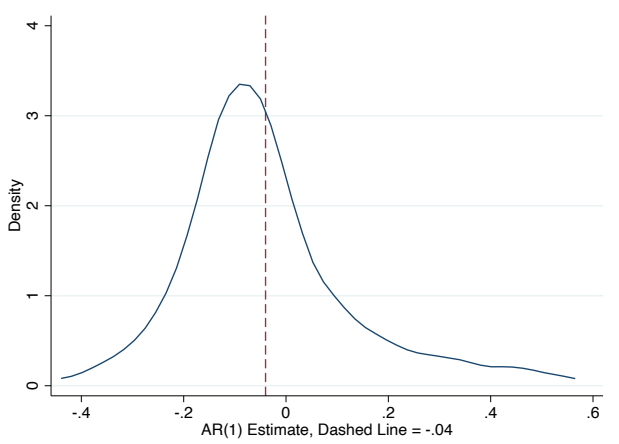
For each pair of banks, we measure the degree of comovement between their funding-shock series and report the distribution of the resulting pairwise R^2 values. Panel F.1b of Figure F.1 presents the results.

The distribution is concentrated close to zero. The average pairwise R^2 is approximately 0.08, indicating that the shock experienced by one bank explains relatively little of the variation in the shock experienced by another bank.

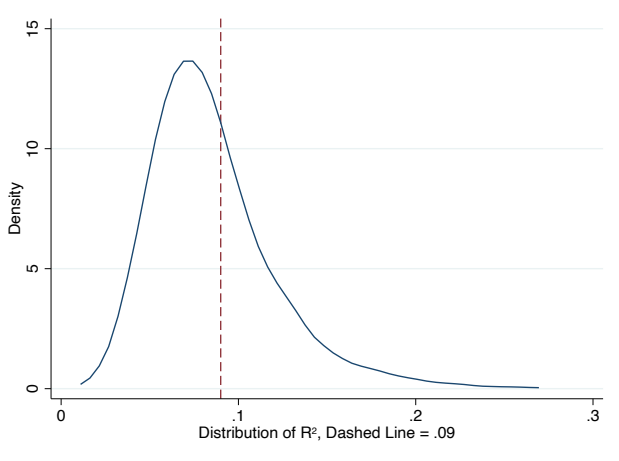
This low cross-bank correlation follows naturally from heterogeneity in deposit geography. Two banks can be exposed very differently to the same disaster because they raise different shares of their deposits from the affected county. Conversely, even banks of similar size or with similar balance sheets may experience different shocks because their important deposit markets are located in different parts of the country.

Taken together, the three exercises indicate that $\Gamma_{b,t}$ has the properties required of the bank-specific variation underlying our empirical design. Observable bank characteristics explain little of its variation, the shock exhibits essentially no serial persistence, and shocks are only weakly correlated across banks. These findings are consistent with $\Gamma_{b,t}$ capturing idiosyncratic exposure generated by the interaction of predetermined deposit geography with the realized location and timing of natural disasters.

Figure F.1: Spatial and Temporal Properties of Bank-Level Funding Shocks



(a) AR(1) Estimates for Bank-Level Funding Shocks



(b) Pairwise R^2 for Bank-Level Funding Shocks

Note: This figure reports the temporal and cross-bank properties of the bank-level funding shock, $\Gamma_{b,t}$. Panel (a) reports the distribution of bank-specific AR(1) coefficients for $\Gamma_{b,t}$. The average AR(1) coefficient is -0.03. Panel (b) reports the distribution of pairwise R^2 values across banks' funding-shock series. The average pairwise R^2 is 0.08.

Table F.2: Summary Statistics: Bank-Level Variables & Other Aggregate Shocks

	# Obs	Mean	SD	P25	P50	P75
Panel A. Bank × Year						
Ln(Assets)	10,894	14.051	1.747	12.744	13.706	15.060
Loan/Assets	10,894	0.640	0.132	0.564	0.654	0.733
Equity/Assets	10,894	0.101	0.028	0.082	0.096	0.114
Cash/Assets	10,894	0.052	0.042	0.026	0.038	0.061
Deposits/Assets	10,894	0.789	0.098	0.744	0.810	0.860
Hedge/Assets	10,894	-0.046	0.377	0.000	0.000	0.000
Dividend/Assets	10,894	0.002	0.003	0.000	0.001	0.003
Operating Income/Assets	10,894	0.017	0.006	0.013	0.016	0.020
Panel B. Year						
Oil Shock	97	0.01	0.83	-0.24	0.00	0.33
Monetary Shock	97	-0.01	0.04	-0.01	-0.00	0.00
Uncertainty Shock	97	0.02	0.16	-0.10	0.02	0.12
Term Spread	97	1.10	0.74	0.60	1.08	1.55
Government Expenditure Shock	97	4.40	2.51	2.97	4.34	6.17
Γ_t^{Gabaix}	97	-0.00	0.01	-0.00	0.00	0.00
ln(Total Home Loss)	75	21.18	1.19	20.15	21.25	21.86
ln(Total Business Loss)	75	20.30	1.40	18.93	19.98	21.24

Notes: This table reports summary statistics for variables explored in the paper. Panel A reports bank-year variables, where bank financial data are from Call Reports (1994–2018); see Section C for definitions. Panel B reports quarterly aggregate variables. Oil Shock is the quarterly average of the oil supply surprise series from Känzig (2021). Monetary Shock is the quarterly average of tight-window monetary policy shocks from Vats (2020). Uncertainty Shock is the percentage change in the economic policy uncertainty index from Baker et al. (2016). Term Spread is 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 Shock is the percentage change in total government expenditure. Γ_t^{Gabaix} is the granular residual constructed as in Gabaix (2011). ln(Total Home Loss) and ln(Total Business Loss) are the natural logarithms of the aggregate dollar amounts of losses verified by the Small Business Administration under the SBA Disaster Loan Program.

Appendix G Regional Identification and Robustness

This section provides additional evidence on the regional design used to estimate χ. We first examine the bank-county lending response underlying the regional first stage, using the out-of-state funding shocks that are aggregated into the county-level instrument $z_{c,t}$. We then report the reduced-form relationship between $z_{c,t}$ and county output and examine whether that relationship could reflect direct exposure to disasters elsewhere rather than the funding of banks that lend in the county. Finally, we examine heterogeneity in the regional elasticity and whether the pooled estimate of χ provides a useful summary for the aggregation exercise.

G.1 Bank-County Transmission of Funding Shocks

The regional instrument has two components,

$$z_{c,t} = \underbrace{\sum_b \omega_{b,c,t-1}\Gamma_{b,s(c),t-1}}_{\text{lending-share weighted}} - \underbrace{\frac{1}{N_{c,t}}\sum_b A_{b,s(c),t-1}}_{\text{equal-weighted placebo}},$$

where $\omega_{b,c,t-1}$ is bank b's lagged share of small-business lending in county c, $\Gamma_{b,s(c),t-1}$ is bank b's deposit-weighted exposure to disaster damage originating outside the state $s(c)$ containing county c, $A_{b,s(c),t-1}$ is the corresponding unweighted out-of-state disaster exposure, and $N_{c,t}$ is the number of banks serving county c in year t. The instrument $z_{c,t}$ is $\tilde{z}_{c,t}$ standardized to zero mean and unit variance across county-years. The first component is aggregated across banks using lending-share weights, while the placebo is aggregated using equal weights. In particular, the construction is not the lending-share-weighted average of the bank-level difference $\Gamma_{b,s(c),t-1} - A_{b,s(c),t-1}$. Because the set of deposit markets excluded from these exposures depends on the destination state, the same bank's exposure can differ across the states in which it lends.

We begin by examining the bank-county lending response before aggregation to the county level. Our preferred bank-county specifications, Columns 3, 4, and 6–8 of Table G.1, include county-by-year fixed effects. Although $A_{b,s(c),t-1}$ varies across banks before aggregation, it enters $z_{c,t}$ only through its equal-weighted mean across banks serving a given county-year. This placebo component is therefore constant across banks within a county-year and is absorbed exactly by the county-by-year fixed effects. The within-county-year variation identifying the lending response consequently comes from differences in $\Gamma_{b,s(c),t-1}$ across banks. Its coefficient is unchanged, up to rescaling, if the county-year placebo is netted out before estimation. Columns 1, 2, and 5 report less saturated specifications to show the stability of the estimate; the absorption argument applies to the specifications with county-by-year fixed effects.

The bank-county setting therefore provides a particularly clean test of the credit-supply channel underlying the regional instrument. County-by-year fixed effects absorb local credit demand, local economic conditions, and the direct effects of disasters common to all banks operating in the same county and year, while bank-by-county fixed effects absorb persistent differences across lending relationships. Identification comes from comparing banks serving the same local economy but experiencing different out-of-state funding exposure because of the geography of their deposit bases.

Table G.1 reports the results. The coefficient on $\Gamma_{b,s(c),t-1}$ is negative and statistically significant across all specifications. In the preferred specification with county-by-year and bank-by-county fixed effects, the coefficient is -1.2716, implying that a one-standard-deviation increase in out-of-state funding exposure lowers bank-county small-business lending growth by approximately 1.27 percentage points. Banks therefore reduce lending when their funding sources outside the destination state are adversely affected. These estimates validate the bank-level component that generates the identifying variation in $z_{c,t}$, while the county-level first stage in Table H.2 establishes the relevance of the resulting instrument for county loan growth.

Columns 7 and 8 further distinguish bank funding transmission from the direct local consequences of disasters. The lending response remains negative and statistically significant both in counties without a contemporaneous disaster and in counties directly affected by disasters. The response in unaffected counties is particularly informative: the funding shock originates outside the destination state and reduces lending in a county that did not itself experience a disaster. The bank-county evidence therefore supports the interpretation that the identifying variation operates through the funding conditions of banks serving the county rather than through local disaster exposure or local credit demand.

Table G.1: Bank-County Lending Responses to Out-of-State Funding Shocks

Dep Var: Lending Growth (%)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Gamma_{b,c,t-1}$	-0.9102***	-1.1317***	-1.3036***	-1.1976***	-0.7879***	-1.2716***	-2.7877***	-1.2400***
	(0.1415)	(0.1472)	(0.1598)	(0.1637)	(0.1530)	(0.1731)	(0.6955)	(0.1899)
County FE		✓						
Year FE		✓						
County × Year FE			✓	✓		✓	✓	✓
Bank FE				✓				
Bank × County FE					✓	✓	✓	✓
# Obs	613,931	613,931	613,931	613,931	613,931	613,931	116,071	476,063
R^2	0.0001	0.0099	0.1178	0.1240	0.0728	0.1902	0.3102	0.2036
Sample	All Counties	All Counties	All Counties	All Counties	All Counties	All Counties	Unaffected Counties	Affected Counties

Notes: This table uses small business lending data collected under the Community Reinvestment Act (CRA) and reports estimates of β from

$$\Delta \ln(Lending)_{b,c,t} \times 100 = \beta \times \Gamma_{b,c,t-1} + \theta_{b,c} + \theta_{c,t} + \varepsilon_{b,c,t},$$

where b, c, and t indicate bank, county, and year, respectively. The data span from 1998 to 2019. The dependent variable is lending growth in percent, defined as the change in the natural logarithm of small business lending originated by bank b in county c and year t, multiplied by 100. $\theta_{b,c}$ and $\theta_{c,t}$ are bank-county and county-year fixed effects, respectively. $\Gamma_{b,c,t-1}$ is the bank's standardized funding shock reaching county c from elsewhere, which is the deposit-weighted average of disaster damage per capita across the counties where bank b raises deposits, excluding all counties in county c's home state. Column (7) restricts the sample to counties not affected by a disaster in year $t-1$, and column (8) restricts the sample to counties affected by a disaster in year $t-1$. Standard errors clustered at the bank-county level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

As a robustness check on the bank-county lending response, Table G.2 re-estimates the preferred specification after excluding specialized credit-card banks under two alternative classifications. The coefficient on the out-of-state funding shock remains negative and statistically significant under both exclusions. The baseline bank-county credit-supply response therefore does not appear to be driven by specialized credit-card institutions.

Table G.2: Small Business Lending and Funding Shocks: Exclusion of Credit Card Banks

Dep Var: Lending Growth (%)	(1)	(2)
$\Gamma_{b,c,t-1}$	-0.9665***	-1.2335***
	(0.1735)	(0.1679)
County × Year FE	✓	✓
Bank × County FE	✓	✓
# Obs	529,661	613,616
R^2	0.2054	0.1902

Notes: This table uses small business lending data collected under the Community Reinvestment Act (CRA) and reports estimates of β from

$$\Delta \ln(Lending)_{b,c,t} \times 100 = \beta \times \Gamma_{b,c,t-1} + \theta_{b,c} + \theta_{c,t} + \varepsilon_{b,c,t},$$

where b, c, and t indicate bank, county, and year, respectively. The data span from 1998 to 2019. The dependent variable is lending growth in percent, defined as the change in the natural logarithm of small business loans originated by bank b in county c and year t, multiplied by 100. $\theta_{b,c}$ and $\theta_{c,t}$ are bank-county and county-year fixed effects, respectively. $\Gamma_{b,c,t-1}$ is the bank's standardized funding shock reaching county c from elsewhere, which is the deposit-weighted average of disaster damage per capita across the counties where bank b raises deposits, excluding all counties in county c's home state. We drop credit card banks from the sample: column (1) drops banks with at least $1 billion in loans under $100K where these loans constitute at least 75% of total loans, following Adams et al. (2023), and column (2) drops banks with at least 99% of loans under $100K and an average loan amount below $15K, following Board of Governors of the Federal Reserve System (2010). Standard errors clustered at the bank-county level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Having established that the bank-county lending response is robust to the composition of the CRA sample, we next examine whether the lending-share- weighted aggregation of these funding shocks into $z_{c,t}$ predicts county output.

G.2 Regional Reduced Form

Having established that the underlying bank-county funding shocks shift loan supply, we next examine whether their lending-share-weighted aggregation, $z_{c,t}$, predicts county output. Table G.3 reports this reduced-form relationship underlying the regional 2SLS estimates.

The coefficient on $z_{c,t}$ is negative and statistically significant in every specification, moving from -0.0997 in the specification without fixed effects to -0.1249 in the specification with county and

year fixed effects, so a one-standard-deviation increase in $z_{c,t}$ lowers county GDP growth by roughly 0.10 to 0.12 percentage points. Counties whose lenders experience larger funding shocks therefore experience lower subsequent output growth, and this relationship remains after absorbing persistent county differences and common national shocks.

Table G.3: Regional Reduced Form: Funding Shock and County Output Growth

Dep Var: GDP Growth (%)	(1)	(2)	(3)	(4)
$z_{c,t-1}$	-0.0997***	-0.1099***	-0.1126***	-0.1249***
	(0.0348)	(0.0371)	(0.0371)	(0.0400)
Constant	3.4479***			
	(0.0301)			
County FE		✓		✓
Year FE			✓	✓
# Obs	54,275	54,275	54,275	54,275
R^2	0.0001	0.0389	0.0876	0.1258

Notes: This table reports reduced-form regressions of county GDP growth on the standardized county-level funding shock $z_{c,t-1}$ across fixed-effect specifications. The dependent variable is GDP growth in percent, defined as the log difference of GDP multiplied by 100. $z_{c,t-1}$ is the county's exposure to out-of-state funding shocks hitting the banks that lend there, weighted by banks' lagged county lending shares and net of the equal-weighted component (Section 4.3). Column (1) includes no fixed effects; column (2) adds county fixed effects; column (3) adds year fixed effects; column (4) includes both county and year fixed effects. The sample consists of county-year observations from 2002 to 2019. Standard errors clustered by county are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

G.3 Alternative Out-of-State Exposure

The regional design requires that $z_{c,t}$ affect county output through the funding of banks that lend in county c, rather than through direct exposure to disasters elsewhere. Excluding disasters within county c's state removes the most immediate geographic connection, but counties remain connected to locations outside their states through real economic networks. If the deposit markets of banks lending in county c systematically overlap with economically connected locations, $z_{c,t}$ could partly capture direct disaster spillovers rather than credit supply.

We therefore examine whether the reduced-form relationship can be explained by alternative measures of out-of-state disaster exposure. Table G.4 augments the baseline specification reported in Table G.3. Columns 1 through 4 add employment-, GDP-, population-, and establishment-weighted measures of out-of-state disaster exposure, respectively. Columns 5 through 8 instead add measures based on trade, migration, geographic distance, and social connectedness, while column 9 includes all of these controls jointly.

The real-activity-weighted disaster measures are themselves related to county output growth when introduced individually, consistent with their capturing economically meaningful channels through which disasters elsewhere affect local economic activity. At the same time, controlling for these channels, as well as for trade, migration, geographic distance, and social connectedness, leaves the estimated effect of $z_{c,t}$ virtually unchanged. The reduced-form relationship therefore does not appear to reflect a county's broader exposure to disaster-affected parts of the country.

Table G.4: Regional Reduced-Form Robustness: Alternative Out-of-State Controls

Dep Var: GDP Growth (%)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$z_{c,t-1}$	-0.1108***	-0.1120***	-0.1125***	-0.1101***	-0.1184***	-0.1241***	-0.1178***	-0.1032**	-0.1282***
	(0.0389)	(0.0387)	(0.0390)	(0.0389)	(0.0397)	(0.0390)	(0.0388)	(0.0407)	(0.0410)
Employment-Weighted Damage$_{t-1}$	-0.4595***								-7.1487
	(0.1623)								(4.3738)
GDP-Weighted Damage$_{t-1}$		-0.4110*							10.9238***
		(0.2136)							(2.1284)
Population-Weighted Damage$_{t-1}$			-0.3783***						6.5127***
			(0.1274)						(2.0994)
Establishment-Weighted Damage$_{t-1}$				-0.5444***					-10.3814***
				(0.1676)					(2.4906)
Trade-Weighted Damage$_{t-1}$					0.0297				0.0049
					(0.0374)				(0.0398)
Migration-Weighted Damage$_{t-1}$						-0.0102			-0.0891*
						(0.0287)			(0.0512)
Distance-Weighted Damage$_{t-1}$							-0.4003*		-0.4822*
							(0.2078)		(0.2879)
Social-Connectedness-Weighted Damage$_{t-1}$								0.0673*	0.1109
								(0.0385)	(0.0690)
County FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
# Obs	48,280	48,280	48,280	48,280	48,280	48,280	48,280	48,280	48,280
R^2	0.1413	0.1413	0.1414	0.1414	0.1412	0.1412	0.1413	0.1413	0.1427

Notes: This table reports reduced-form regressions of county GDP growth on the standardized county-level funding shock $z_{c,t-1}$. Columns (1)–(4) each add a real-activity-weighted out-of-state disaster-damage variable as a control. Employment-Weighted Damage, GDP-Weighted Damage, Population-Weighted Damage, and Establishment-Weighted Damage are county property damage per capita occurring *outside the county's state*, weighted by the county's national share of employment, GDP, population, or establishments, respectively. Columns (5)–(8) each add a network-weighted out-of-state disaster-exposure variable as a control. Trade-Weighted Damage, Migration-Weighted Damage, Distance-Weighted Damage, and Social-Connectedness-Weighted Damage are constructed analogously, replacing the real-activity weights with trade, migration, distance, and social-connectedness weights. Column (9) includes all controls jointly. The dependent variable is GDP growth in percent, defined as the log difference of GDP multiplied by 100. The corresponding baseline reduced-form specification is reported in Table G.3. All control variables are lagged one year and standardized. All specifications include county and year fixed effects. Standard errors clustered by county are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Appendix H Aggregate Shock Robustness

The main text establishes that the granular funding shock, Γ_t^*, predicts aggregate lending, deposits, and GDP, and that its aggregate effects are driven by the largest banks in the banking system. This appendix provides additional evidence on the interpretation and robustness of the aggregate shock. We proceed in sequence. First, we examine whether the predictive content of Γ_t^* is absorbed by other aggregate macroeconomic shocks. Second, we distinguish the funding shock from the direct effects of aggregate disaster intensity. Third, we ask whether the aggregate relationship is specific to the funding side of bank balance sheets rather than the geography of bank lending. Fourth, we examine the major disaster episodes underlying the largest realizations of the shock. Fifth, we consider alternative constructions of the aggregate shock based on deposit-measurement adjustments and the geographic distribution of bank branches. Finally, we extend the aggregate analysis to the longer historical sample beginning in 1981.

H.1 Other Aggregate Macroeconomic Shocks

A natural concern is that the predictive content of the granular funding shock Γ_t^* reflects other aggregate shocks that happen to coincide with the disaster episodes underlying its construction. Table H.1 examines this possibility by augmenting the baseline aggregate GDP regression with several prominent sources of aggregate fluctuations. Specifically, we consider oil-supply shocks, monetary-policy shocks, economic-policy uncertainty, the term spread, government-expenditure shocks, and the firm-level granular residual of Gabaix (2011). Each control is introduced separately and then jointly to assess whether the estimated relationship between Γ_t^* and aggregate GDP growth is absorbed by these alternative sources of macroeconomic variation.

The estimated effect of the granular funding shock is remarkably stable across specifications. The baseline coefficient is -0.2952 and remains negative and statistically significant when each macroeconomic shock is added separately. When all six controls are included jointly, the coefficient is -0.2906, almost identical to the baseline estimate. None of the alternative aggregate shocks is individually significant, nor do they materially increase the explanatory power of the regression beyond what is already captured by Γ_t^*. The aggregate relationship between the granular funding shock and GDP growth therefore does not appear to reflect these alternative sources of macroeconomic fluctuation.

Table H.1: Horse Race: Granular Shock & Other Macroeconomic Shocks

Dep Var: GDP Growth (%)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Γ^*_{t-1}	-0.2952**	-0.3109***	-0.2738**	-0.2859**	-0.2957**	-0.3156***	-0.3010**	-0.2906**
	(0.1203)	(0.1119)	(0.1282)	(0.1225)	(0.1207)	(0.1204)	(0.1260)	(0.1241)
Oil Shock$_{t-1}$		0.3645						0.3273
		(0.3532)						(0.3297)
MP Shock $_{t-1}$			0.3799					0.3430
			(0.2887)					(0.2882)
Uncertainty Shock$_{t-1}$				-0.2449				-0.2184
				(0.2304)				(0.2434)
Term Spread$_{t-1}$					0.0109			-0.0525
					(0.1243)			(0.1141)
Govn't Exp Shock$_{t-1}$						-0.1394		-0.0668
						(0.2017)		(0.1882)
Γ^{Gabaix}_{t-1}							0.1121	0.0238
							(0.1244)	(0.1297)
Constant	1.1007***	1.1041***	1.1035***	1.0973***	1.1006***	1.1005***	1.1008***	1.1036***
	(0.1170)	(0.1172)	(0.1157)	(0.1073)	(0.1168)	(0.1119)	(0.1110)	(0.1061)
# Obs	97	97	97	97	97	97	97	97
R^2	0.0126	0.0320	0.0337	0.0213	0.0126	0.0154	0.0144	0.0585

Notes: This table uses quarterly GDP series from 1994Q3 to 2018Q4 matched with other macroeconomic variables and reports estimates of β_1 and the vector β_2 from

$$\Delta \ln(GDP)_t \times 100 = \alpha + \beta_1 \times \Gamma^*_{t-1} + \beta_2 \times \text{Macro-Shock}_{t-1} + \varepsilon_t,$$

where t indicates quarter-year. Γ^*_{t-1} is the standardized granular funding shock, and Macro-Shock$_{t-1}$ is 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 the 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 et al. (2016). Column (5) uses the term spread, 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 total government expenditure. Column (7) uses the standardized granular residual of Gabaix (2011), defined as the sum of the top 100 firms' idiosyncratic productivity shocks weighted by each firm's share of sales in GDP. The idiosyncratic productivity shock is computed as the log difference of sales per employee, controlling for industry-level mean productivity growth. All macroeconomic shocks are standardized. Newey-West heteroskedasticity- and autocorrelation-robust standard errors (8 lags) are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

H.2 Major Disaster Episodes Underlying the Aggregate Funding Shock

The construction of Γ_t^* implies that large realizations of the aggregate funding shock should coincide with major disasters affecting locations that are important sources of bank funding. Table H.2 identifies the disaster episodes underlying the largest values of the raw aggregate bank funding shock and reports the corresponding insurance payouts.

Table H.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 4a. The table reports the natural disasters, states affected by the disasters, and the insurance payout associated with these disasters.

The largest movements in the aggregate funding shock coincide with familiar disaster episodes, including Hurricanes Katrina, Sandy, Harvey, Ike, Ivan, Wilma, and Floyd, as well as major floods, wildfires, and the Nisqually earthquake. These episodes also correspond to the largest insurance payouts in the sample, indicating that the aggregate funding shock is concentrated around economically important disaster events rather than isolated local incidents. The table therefore provides a narrative description of the raw aggregate shock Γ_t: the periods in which the shock is largest are precisely those in which severe disasters disrupted important sources of bank funding.

H.3 Bank Size and Funding-Shock Transmission

The large-bank placebo in Section 6.2 establishes that the aggregate predictive content of Γ_t^* depends on the banks whose size makes the banking system granular. That result does not require large banks to be more sensitive than small banks to a given funding shock. Granularity alone implies that shocks to large institutions receive greater aggregate weight and therefore need not average out.

Table H.3 asks whether bank-level transmission also differs with bank size. Using the out-of-state bank-county funding shock developed in Section 5, we estimate the lending response separately across bank-size categories while absorbing county-by-year and bank-by-county fixed effects. The specification therefore compares funding-induced changes in lending while holding fixed contemporaneous conditions in the local credit market and persistent differences across bank-county relationships.

The estimates show a pronounced difference across the size distribution. Small banks exhibit no statistically significant lending response, while the response becomes negative among medium and large banks and is largest and statistically significant among systemically important banks. For SIBs, a one-standard-deviation out-of-state funding shock reduces small-business lending growth by approximately 1.9 percentage points at banks with assets between $50 billion and $250 billion and by approximately 8.8 percentage points at banks with assets of $250 billion or more. Thus, the banks whose size gives their idiosyncratic shocks disproportionate aggregate weight also exhibit the strongest lending response to the underlying funding shock.

This result strengthens, but is not required for, the granular interpretation of the aggregate evidence. The large-bank placebo establishes that aggregate predictive content disappears when the institutions responsible for granularity are removed from Γ_t^*. Table H.3 shows that these same institutions also exhibit particularly strong credit-supply responses when their funding conditions deteriorate. Large banks therefore matter along two distinct margins in the data: their size prevents idiosyncratic funding shocks from averaging out, and their lending responds strongly to those shocks.

Table H.3: Small Business Lending and Funding Shocks by Bank Size

Dep Var: Lending Growth (%)	(1)	(2)	(3)	(4)
	Non-SIB		SIB	
	A < $5B	$5B ≤ A < $50B	$50B ≤ A < $250B	A ≥ $250B
$\Gamma_{b,c,t-1}$	-0.4235	-1.3140***	-1.9445***	-8.7639***
	(0.7602)	(0.2479)	(0.6372)	(2.2447)
County-Bank FE	✓	✓	✓	✓
County-Year FE	✓	✓	✓	✓
# Obs	89,733	147,819	129,697	149,933
R^2	0.3866	0.3496	0.3950	0.3221

Notes: This table uses small business lending data collected under the Community Reinvestment Act (CRA), matched with bank call report data, and reports estimates of β from

$$\Delta \ln(Lending)_{b,c,t} \times 100 = \beta \times \Gamma_{b,c,t-1} + \theta_{c,t} + \theta_{b,c} + \varepsilon_{b,c,t},$$

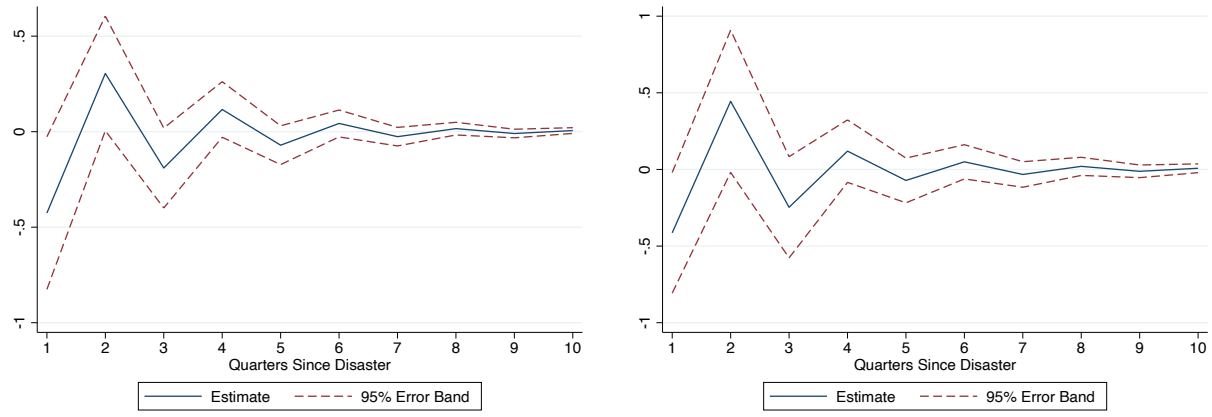
estimated separately for each bank-size group. b, c, and t indicate bank, county, and year, respectively. The data span from 1997 to 2019. The dependent variable is lending growth in percent, defined as the change in the natural logarithm of small business loans originated by bank b in county c and year t, multiplied by 100. $\theta_{b,c}$ and $\theta_{c,t}$ are bank-county and county-year fixed effects, respectively. $\Gamma_{b,c,t-1}$ is the bank's standardized bank-level funding shock reaching county c from elsewhere: the deposit-weighted average of disaster damage per capita across the counties where bank b raises deposits, excluding all counties in county c's home state. Bank size is measured by total assets, in billions of dollars, as of the end of the prior year. Columns (1) and (2) split non-systemically important banks (Non-SIB), with assets below $50 billion, into two subgroups at a $5 billion cutoff. Columns (3) and (4) split systemically important banks (SIB), defined as banks with assets of $50 billion or more under Title I of the Dodd-Frank Act, into two subgroups at a $250 billion cutoff. 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.4 Granular Funding Shocks versus Aggregate Disaster Exposure

The next concern is more specific to the construction of Γ_t^*. Because the shock is built from natural disasters, a positive realization of Γ_t^* could reflect the direct effect of greater disaster activity on aggregate output rather than the transmission of funding disruptions through banks. We therefore compare the aggregate response to the granular funding shock with the response to aggregate disaster intensity itself and then control directly for aggregate disaster losses.

Figure H.1 reports the response of GDP growth to the granular funding shock using the VAR specifications discussed in the main text. Figure H.2 repeats the same exercise after replacing Γ_t^* with aggregate disaster-related property damage.

Figure H.1: Long-Run Response of GDP Growth to Granular Funding Shocks



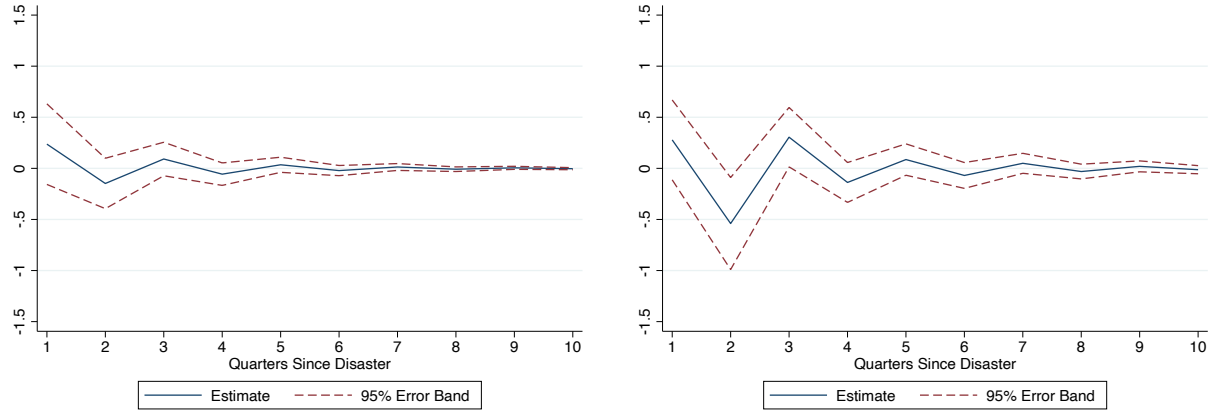
(a) Impulse Response Function from VAR(1,1) (b) Impulse Response Function from VAR(2,2)

Notes: This figure uses the quarterly series of GDP growth and the granular funding shock from 1994Q3 to 2019Q4. Panel (a) presents the orthogonalized impulse response function (IRF) estimated from a VAR(1,1) model, and Panel (b) presents the IRF from a VAR(2,2) model, each including GDP growth and the granular funding shock. GDP growth is in percent, defined as the log difference of GDP multiplied by 100. The IRF shows the response of GDP growth to a granular funding shock. The solid blue line plots the IRF over 10 steps, and the dashed red lines plot the 95% confidence interval.

The two responses differ. GDP responds negatively to the granular funding shock on impact in Figure H.1, whereas the response to aggregate disaster damage in Figure H.2 is economically small and , apart from a short-lived negative response, statistically indistinguishable from zero over most of the reported horizon. Periods with more severe disasters therefore do not, by themselves, generate the aggregate response associated with Γ_t^*.

Table H.4 provides a complementary regression-based test by controlling directly for aggregate home and business losses verified by the Small Business Administration. If the aggregate response to Γ_t^* merely reflected the direct destruction caused by disasters, these measures should absorb much of its explanatory power.

Figure H.2: 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)

Notes: This figure uses the quarterly series of GDP growth and the aggregate disaster shock from 1994Q3 to 2019Q4. GDP growth is in percent, defined as the log difference of GDP multiplied by 100. The aggregate disaster shock is total property damage, in hundreds of thousands of dollars, from disasters in the preceding quarter. Panel (a) presents the orthogonalized impulse response function (IRF) estimated from a VAR(1,1) model, and Panel (b) presents the IRF from a VAR(2,2) model, each including GDP growth and the aggregate disaster shock. The IRF shows the response of GDP growth to a disaster shock. The solid blue line plots the IRF over 10 steps, and the dashed red lines plot the 95% confidence interval. Consistent with a funding-shock rather than generic-disaster interpretation of Γ^*, the direct effect of aggregate disaster intensity on GDP growth shown here is economically small and, apart from a short-lived negative response, statistically insignificant over most of the horizon.

Table H.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}	-0.1910**		-0.1811**		-0.1799**		-0.1799**
	(0.0797)		(0.0810)		(0.0809)		(0.0810)
ln(Total Home Loss)$_{t-1}$		0.1318	0.1118			-0.0158	-0.0068
		(0.1763)	(0.1733)			(0.6175)	(0.6177)
ln(Total Business Loss)$_{t-1}$				0.1381	0.1169	0.1534	0.1235
				(0.1782)	(0.1761)	(0.6254)	(0.6296)
Constant	1.0551***	1.0500***	1.0548***	1.0500***	1.0548***	1.0500***	1.0548***
	(0.1243)	(0.1210)	(0.1225)	(0.1227)	(0.1238)	(0.1229)	(0.1239)
# Obs	75	75	75	75	75	75	75
R^2	0.0076	0.0029	0.0097	0.0032	0.0099	0.0032	0.0099

Notes: This table uses quarterly GDP series from 2001Q1 to 2019Q4, the period for which disaster loss data are available, and reports estimates of β_1, β_2, and β_3 from

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

where t indicates quarter-year. Γ^*_{t-1} is the standardized granular deposit shock. Total Home Loss and Total Business Loss are the standardized aggregate dollar amounts of losses collected by the Small Business Administration under the SBA Disaster Loan Program. Newey-West heteroskedasticity- and autocorrelation-robust standard errors (8 lags) are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

The estimated coefficient on Γ^*_{t-1} remains remarkably stable across specifications. The baseline estimate of -0.1910 changes only modestly when home losses or business losses are added individually

and remains −0.1799 when both controls are included jointly. The loss variables themselves are economically small and statistically insignificant throughout. Thus, controlling directly for the amount of disaster-related property destruction does not materially alter the estimated relationship between the granular funding shock and aggregate GDP growth.

Taken together, Figures H.1–H.2 and Table H.4 indicate that the aggregate response associated with Γ_t^* is not simply a generic consequence of periods in which natural disasters are more severe. Instead, the relevant variation comes from the interaction of disasters with the uneven geographic distribution of bank funding.

H.5 Robustness to Shock Construction

The aggregate funding shock is constructed by combining the geographic distribution of bank deposits with the geographic distribution of natural disasters. Its construction therefore depends on the geographic assignment of deposits in the SOD. Appendix Section D.1 describes the relevant SOD reporting conventions and how banks assign deposits to branch locations in practice.

We examine the sensitivity of the aggregate results to this measurement in two complementary ways. First, we reconstruct Γ_t^* after removing observations associated with the principal sources of potential geographic mismeasurement. Second, we construct an alternative aggregate shock using the geographic distribution of physical bank branches rather than reported deposits. The latter provides an independent measure of banks' geographic funding footprints that does not rely on the assignment of deposit balances across branch locations.

Table H.5 addresses the first concern. Motivated by the deposit-geography exercises in Appendix Section D, we reconstruct the aggregate shock after successively excluding tax-driven deposits, banks involved in mergers and acquisitions, non-local deposits, headquarters branches, operational branches, and banks' largest lending counties. The final columns combine all of these adjustments into a single shock and then repeat the exercise with year fixed effects.

The estimated relationship remains robust across these alternative shock constructions. The coefficient on Γ_{t-1}^* remains negative and statistically significant after each individual adjustment and remains significant when all adjustments are imposed jointly. Although the estimated magnitude declines somewhat once all exclusions are combined, the aggregate funding shock continues to predict aggregate GDP growth, indicating that the main results are not driven by any single feature of the deposit assignment.

Table H.6 provides an independent robustness exercise by constructing the aggregate shock from the geographic distribution of physical branches rather than deposits. Because branch locations are directly observed, this construction is not subject to the same deposit-assignment concerns as the baseline measure.

Table H.5: 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} Excluding:	Tax State	M&A Banks	Non-Local Deposits	HQ	Operating Branch	Lending County	All	All
Γ^*_{t-1}	-0.3310**	-0.2030**	-0.2537**	-0.2667**	-0.2835**	-0.2476*	-0.2066***	-0.2548*
	(0.1636)	(0.0904)	(0.1058)	(0.1115)	(0.1217)	(0.1298)	(0.0696)	(0.1520)
Constant	1.1113***	1.1092***	1.1105***	1.1102***	1.1098***	1.1125***	1.1098***	
	(0.1047)	(0.1042)	(0.1032)	(0.1024)	(0.1016)	(0.1049)	(0.1041)	
Year FE								✓
# Obs	101	101	101	101	101	101	101	100
R^2	0.0162	0.0059	0.0093	0.0102	0.0119	0.0084	0.0064	0.0077

Notes: This table uses quarterly GDP series from 1994Q3 to 2019Q4 and reports estimates of β from

$$\Delta \ln(GDP)_t \times 100 = \alpha + \beta \times \Gamma^*_{t-1} + \varepsilon_t,$$

where t indicates quarter-year. Γ^*_{t-1} is the granular deposit shock in the prior quarter, reconstructed after dropping different components of the underlying data. Column (1) excludes 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 total deposits reported at the main office. Column (4) excludes the bank's headquarters branch. Column (5) excludes the largest operating branch in each state. Column (6) excludes counties that represent the bank's largest lending locations. Column (7) applies all exclusions from columns (1) through (6) jointly. Column (8) repeats the column (7) specification with year fixed effects. Newey-West heteroskedasticity- and autocorrelation-robust standard errors (8 lags) are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

The branch-based shock produces qualitatively similar results. The lagged shock remains negative and statistically significant in both the baseline specification and the richer lag structure, and the relationship continues to hold after adding year fixed effects. The similarity between the deposit-based and branch-based results indicates that the aggregate findings do not depend on the particular way deposits are geographically assigned. Instead, they reflect the broader geographic concentration of banks' funding bases.

H.6 Historical Aggregate Evidence

The aggregate analysis in the main text uses the 1994–2019 sample to maintain consistency with the modern Summary of Deposits (SOD) series used to construct the funding shock. The historical SOD data, however, allow us to examine whether the aggregate relationship predates the baseline sample.

Figure D.4 shows that geographic deposit concentration was already present before 1994. Table H.7 extends the aggregate shock analysis to the full 1981–2019 period and reports estimates for the entire sample as well as separately for the pre-1994 and post-1994 periods. The historical estimates are presented separately because the historical SOD series are reported differently before 1994 and measured deposit concentration exhibits a discrete change around the transition associated with the Riegle–Neal Interstate Banking and Branching Efficiency Act.

Table H.6: Branch-Based Granular Shock and Aggregate Fluctuations

Dep Var: GDP Growth (%)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Γ^*_t	-0.2493**						-0.2632***	-0.4495**
	(0.1081)						(0.0965)	(0.2077)
Γ^*_{t-1}		-0.2994**					-0.3548***	-0.5931***
		(0.1336)					(0.1163)	(0.1891)
Γ^*_{t-2}			0.2302*				0.2054**	0.0359
			(0.1257)				(0.0950)	(0.3526)
Γ^*_{t-3}				0.2184			0.2031	0.0742
				(0.3277)			(0.2988)	(0.6392)
Γ^*_{t-4}					-0.0293		-0.0631	-0.1899
					(0.1381)		(0.1205)	(0.4229)
Γ^*_{t-5}						-0.3778**	-0.4296***	-0.5598
						(0.1498)	(0.1553)	(0.4657)
Constant	1.1155***	1.1113***	1.0777***	1.1262***	1.1076***	1.1120***	1.1217***	
	(0.1016)	(0.1048)	(0.1105)	(0.1160)	(0.1079)	(0.1147)	(0.1189)	
Year FE								✓
# Obs	102	101	100	99	98	97	97	96
R^2	0.0092	0.0133	0.0079	0.0074	0.0001	0.0222	0.0654	0.0816

Notes: This table uses quarterly GDP series from 1994Q3 to 2019Q4 and reports estimates of β_h from

$$\Delta \ln(GDP)_t \times 100 = \alpha + \beta_h \times \Gamma^*_{t-h} + \varepsilon_t,$$

where t indicates quarter-year and h indicates the lag. Γ^*_{t-h} is the branch-based granular deposit shock at lag h. Newey-West heteroskedasticity- and autocorrelation-robust standard errors (8 lags) are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

The aggregate relationship is present throughout the extended sample. The estimated responses remain negative across both the historical and modern periods, although their magnitudes differ because of the change in the SOD reporting series after 1994. The historical estimates therefore provide evidence that the aggregate relationship is not unique to the modern sample, while reinforcing our decision to estimate the main specifications over the internally consistent 1994–2019 period rather than combine the two reporting regimes into a single continuous series.

Table H.7: Granular Shock and Aggregate Fluctuations: 1981–2019

Dep Var: GDP Growth (%)	(1) All	(2) All	(3) All	(4) All	(5) All	(6) All	(7) All	(8) <1994	(9) >1994	(10) All	(11) <1994	(12) >1994
Γ^*_t	-0.2765*						-0.2577**	0.0169	-0.3747**	-0.4658**	-0.1378	-0.5773*
	(0.1494)						(0.1193)	(0.0678)	(0.1521)	(0.2235)	(0.1514)	(0.3246)
Γ^*_{t-1}		-0.2634**					-0.2844**	-0.4908**	-0.3087***	-0.4938***	-0.6112**	-0.5411**
		(0.1298)					(0.1279)	(0.1959)	(0.1106)	(0.1621)	(0.2711)	(0.2449)
Γ^*_{t-2}			0.5394***				0.5283***	0.7740***	0.3604***	0.2016	0.4120	0.0527
			(0.1186)				(0.1196)	(0.0857)	(0.0919)	(0.2916)	(0.9785)	(0.3476)
Γ^*_{t-3}				-0.0391			-0.0460	-0.2470***	0.0252	-0.3979	-0.6496	-0.2839
				(0.1940)			(0.1726)	(0.0676)	(0.3208)	(0.3503)	(0.9809)	(0.6675)
Γ^*_{t-4}					-0.1600		-0.1706	-0.0729	-0.2869	-0.4932	-0.4428	-0.5842
					(0.1813)		(0.1521)	(0.1074)	(0.2747)	(0.2982)	(1.0048)	(0.4246)
Γ^*_{t-5}						-0.3219***	-0.3402***	-0.3708**	-0.2546	-0.6688**	-0.7537	-0.5588
						(0.1201)	(0.1154)	(0.1801)	(0.1714)	(0.2935)	(1.0624)	(0.4148)
Constant	1.2674***	1.2580***	1.2300***	1.2772***	1.2645***	1.2736***	1.2779***	1.6742***	1.0819***			
	(0.1037)	(0.1041)	(0.1129)	(0.1081)	(0.1060)	(0.1100)	(0.1136)	(0.1707)	(0.1179)			
Year FE										✓	✓	✓
#Obs	154	153	152	151	150	149	149	45	100	148	44	100
R^2	0.0097	0.0088	0.0371	0.0002	0.0034	0.0137	0.0764	0.1631	0.0583	0.0933	0.1810	0.0769

Notes: This table uses historical Summary of Deposits (SOD) data to extend the aggregate analysis to 1981–2019 and reports estimates of β_h from

$$\Delta \ln(GDP)_t \times 100 = \alpha + \sum_h \beta_h \times \Gamma^*_{t-h} + \theta_t + \varepsilon_t,$$

where Γ^*_{t-h} is the granular funding shock at lag h. The dependent variable is GDP growth in percent, defined as the log difference of GDP multiplied by 100. Columns (1)–(6) include the shock and each lag individually over the full sample; column (7) includes them jointly. Columns (8) and (9) re-estimate the joint specification separately for the pre-1994 and post-1994 subperiods. Columns (10)–(12) repeat the joint specification for the full sample and the two subperiods with year fixed effects θ_t, in which case the constant is omitted as it is absorbed by the fixed effects. The pre- and post-1994 SOD series are reported differently and are therefore not directly comparable. Newey-West heteroskedasticity- and autocorrelation-robust standard errors (8 lags) are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Appendix I Additional Evidence on Financial Frictions and Transmission

This section provides additional evidence on the financial frictions studied in Section 8. The organizing question is whether funding shocks are transmitted more strongly when substitution is limited on either side of the credit relationship. We first report the detailed specifications underlying the bank-side results, examining banks' reliance on deposit funding, capital constraints, and the allocation of scarce balance-sheet capacity across lending markets. We then examine an additional bank-side substitution margin, the ability to release balance-sheet capacity through securitization, before turning to borrowers' ability to replace credit withdrawn by an affected bank.

I.1 Bank Constraints and Credit Allocation

Table 13 in the main text summarizes three margins through which bank constraints shape the transmission of funding shocks: reliance on deposit funding, capitalization, and the allocation of credit across core and non-core markets. The tables below report the underlying specifications across progressively richer sets of fixed effects. Together, these exercises ask whether the same funding shock produces a larger lending response when banks have less capacity to replace funding or absorb the shock on their balance sheets, and whether constrained banks respond by reallocating credit across markets.

Reliance on deposit funding. Table I.1 examines banks' reliance on deposit funding. Banks that depend more heavily on deposits have less scope to replace a deposit outflow with alternative liabilities, so the same funding shock should produce a larger lending response when deposit dependence is high. Consistent with this prediction, the interaction between high deposit reliance and the funding shock is negative and statistically significant across specifications. In the preferred specification with county-by-year and bank-by-county fixed effects, the interaction coefficient is -1.1922. The result therefore reflects differential transmission among banks facing the same local economic conditions rather than differences in the markets served by deposit-dependent banks.

Table I.1: Small Business Lending and Funding Shocks by Reliance on Deposit Funding

Dep Var: Lending Growth (%)	(1)	(2)	(3)	(4)	(5)	(6)
High Core-Dep Share$_{b,t-1} \times \Gamma_{b,c,t-1}$	-0.4747	-0.8314***	-1.1385***	-1.0145***	-0.3344	-1.1922***
	(0.3005)	(0.3065)	(0.3238)	(0.3324)	(0.3270)	(0.3521)
High Core-Dep Share$_{b,t-1}$	0.9486***	1.2648***	1.4553***	5.4393***	5.4160***	5.4328***
	(0.2185)	(0.2245)	(0.2320)	(0.3926)	(0.4052)	(0.4269)
$\Gamma_{b,c,t-1}$	-0.6896***	-0.6759***	-0.7204***	-0.7073***	-0.6683***	-0.6779**
	(0.2277)	(0.2310)	(0.2443)	(0.2559)	(0.2540)	(0.2695)
Constant	4.7101***					
	(0.1337)					
County FE		✓				
Year FE		✓				
County × Year FE			✓	✓		✓
Bank FE				✓		
Bank × County FE					✓	✓
# Obs	575,000	575,000	575,000	575,000	575,000	575,000
R^2	0.0001	0.0106	0.1208	0.1273	0.0723	0.1924

Notes: This table uses small business lending data collected under the Community Reinvestment Act (CRA) matched with the SNL bank regulatory data and reports estimates of β_1, β_2, and β_3 from

$$\Delta \ln(Lending)_{b,c,t} \times 100 = \beta_1 \times \text{High Core-Dep Share}_{b,t-1} \times \Gamma_{b,c,t-1} + \beta_2 \times \text{High Core-Dep Share}_{b,t-1} + \beta_3 \times \Gamma_{b,c,t-1} + \theta_{c,t} + \theta_{b,c} + \varepsilon_{b,c,t}.$$

b, c, and t denote bank, county, and year, respectively. The data span from 1998 to 2019. The dependent variable is lending growth in percent, defined as the change in the natural logarithm of small business loans originated by bank b in county c and year t, multiplied by 100. $\theta_{b,c}$ and $\theta_{c,t}$ are bank-by-county and county-by-year fixed effects, respectively; the fixed effects included vary by column, as reported below. High Core-Dep Share$_{b,t-1}$ is an indicator equal to one if bank b's ratio of core deposits (demand and time deposits) to total deposits in year $t-1$ is above the year-$t-1$ cross-sectional median. $\Gamma_{b,c,t-1}$ is the bank's standardized funding shock reaching county c from elsewhere: the deposit-weighted average of disaster damage per capita across the counties where bank b raises deposits, excluding all counties in county c's home state. Standard errors clustered at the bank-county level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Capital constraints. Table I.2 applies the same sequence of specifications to bank capitalization. Banks with thinner capital buffers have less capacity to absorb a funding shock while maintaining lending, so the same shock should generate a larger response when capital is scarce. The interaction between the funding shock and an indicator for a below-median Tier 1 capital ratio is negative and statistically significant throughout. In the preferred specification, the interaction coefficient is -13.0968. The lending response is therefore substantially stronger at less-capitalized banks, consistent with capital constraints limiting their ability to absorb funding shocks on the balance sheet.

Table I.2: Small Business Lending and Funding Shocks by Bank Constraint

Dep Var: Lending Growth (%)	(1)	(2)	(3)	(4)	(5)	(6)
Low Tier 1 Ratio$_{b,t-1} \times \Gamma_{b,c,t-1}$	-10.5114***	-13.9343***	-14.0113***	-13.0742***	-9.4000***	-13.0968***
	(0.7063)	(0.7320)	(0.7425)	(0.7985)	(0.7893)	(0.8404)
Low Tier 1 Ratio$_{b,t-1}$	0.7887***	0.6563***	0.5424**	-2.4254***	-1.3130***	-2.0652***
	(0.2173)	(0.2229)	(0.2314)	(0.4279)	(0.4532)	(0.4790)
$\Gamma_{b,c,t-1}$	-0.4602***	-0.5606***	-0.7221***	-0.6581***	-0.3578**	-0.7118***
	(0.1467)	(0.1502)	(0.1631)	(0.1681)	(0.1595)	(0.1777)
Constant	4.5436***					
	(0.1502)					
County FE		✓				
Year FE		✓				
County × Year FE			✓	✓		✓
Bank FE				✓		
Bank × County FE					✓	✓
# Obs	575,000	575,000	575,000	575,000	575,000	575,000
R^2	0.0005	0.0113	0.1213	0.1276	0.0723	0.1927

Notes: This table uses small business lending data collected under the Community Reinvestment Act (CRA) matched with the SNL bank regulatory data and reports estimates of β_1, β_2, and β_3 from

$$\Delta \ln(Lending)_{b,c,t} \times 100 = \beta_1 \times \text{Low Tier 1 Ratio}_{b,t-1} \times \Gamma_{b,c,t-1} + \beta_2 \times \text{Low Tier 1 Ratio}_{b,t-1} + \beta_3 \times \Gamma_{b,c,t-1} + \theta_{c,t} + \theta_{b,c} + \varepsilon_{b,c,t}.$$

b, c, and t denote bank, county, and year, respectively. The data span from 1998 to 2019. The dependent variable is lending growth in percent, defined as the change in the natural logarithm of small business loans originated by bank b in county c and year t, multiplied by 100. $\theta_{b,c}$ and $\theta_{c,t}$ are bank-by-county and county-by-year fixed effects, respectively; the fixed effects included vary by column, as reported below. Low Tier 1 Ratio$_{b,t-1}$ is an indicator equal to one if bank b's Tier 1 capital ratio in year $t-1$ is below the year-$t-1$ cross-sectional median. $\Gamma_{b,c,t-1}$ is the bank's standardized funding shock reaching county c from elsewhere: the deposit-weighted average of disaster damage per capita across the counties where bank b raises deposits, excluding all counties in county c's home state. Standard errors clustered at the bank-county level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Allocation across core and non-core markets. Table I.3 turns from the magnitude of the lending response to the allocation of scarce balance-sheet capacity across markets. When a funding shock tightens a bank's constraint, the bank need not contract lending uniformly. It may instead preserve credit where relationships or informational advantages are more valuable. We classify a county as non-core when the bank does not maintain a physical branch there. The interaction between non-core status and the funding shock is negative and statistically significant across specifications, indicating that banks contract lending more heavily in markets where they lack a physical presence.

Table I.3: Core vs. Non-Core Markets by the Presence of a Branch

Dep Var: Lending Growth (%)	(1)	(2)	(3)	(4)	(5)	(6)
$NC_{b,c,t-1} \times \Gamma_{b,c,t-1}$	-1.2332***	-1.3426***	-1.2551***	-1.3305***	-1.3551***	-1.4470***
	(0.2591)	(0.2612)	(0.2810)	(0.2771)	(0.2753)	(0.3006)
$NC_{b,c,t-1}$	9.3482***	10.3004***	10.0547***	10.1119***	40.9738***	38.1818***
	(0.1667)	(0.1857)	(0.1942)	(0.2155)	(0.8015)	(0.8572)
$\Gamma_{b,c,t-1}$	-0.0503	-0.1503	-0.3978**	-0.1869	0.2038	-0.1374
	(0.1756)	(0.1775)	(0.2010)	(0.2001)	(0.1766)	(0.2080)
Constant	-1.4292***					
	(0.1095)					
County FE		✓				
Year FE		✓				
County × Year FE			✓	✓		✓
Bank FE				✓		
Bank × County FE					✓	✓
# Obs	575,000	575,000	575,000	575,000	575,000	575,000
R^2	0.0016	0.0123	0.1222	0.1284	0.0763	0.1952

Notes: This table uses small business lending data collected under the Community Reinvestment Act (CRA) and reports estimates of β_1, β_2, and β_3 from

$$\Delta \ln(Lending)_{b,c,t} \times 100 = \beta_1 \times NC_{b,c,t-1} \times \Gamma_{b,c,t-1} + \beta_2 \times NC_{b,c,t-1} + \beta_3 \times \Gamma_{b,c,t-1} + \theta_{c,t} + \theta_{b,c} + \varepsilon_{b,c,t}.$$

b, c, and t denote bank, county, and year, respectively. The data span from 1998 to 2019. The dependent variable is lending growth in percent, defined as the change in the natural logarithm of small business loans originated by bank b in county c and year t, multiplied by 100. $\theta_{b,c}$ and $\theta_{c,t}$ are bank-by-county and county-by-year fixed effects, respectively; the fixed effects included vary by column, as reported below. $\Gamma_{b,c,t-1}$ is the standardized out-of-state bank-county funding shock. $NC_{b,c,t-1}$ is an indicator equal to one if bank b does not have a branch in county c in year $t-1$. 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 I.4 shows that this result is not specific to branch presence. We alternatively classify a county as non-core when the bank's small-business lending market share is below its median local market share. The interaction between non-core status and the funding shock remains negative and statistically significant across specifications. Under both definitions, banks therefore protect lending more strongly in markets where their local relationships are more important, consistent with an endogenous reallocation of scarce balance-sheet capacity following a funding shock.

Table I.4: Core vs. Non-Core Markets by the Share of Lending

Dep Var: Lending Growth (%)	(1)	(2)	(3)	(4)	(5)	(6)
$NC_{b,c,t-1} \times \Gamma_{b,c,t-1}$	-1.2749***	-1.4185***	-1.4329***	-1.4558***	-1.1252***	-1.4602***
	(0.3103)	(0.3183)	(0.3319)	(0.3300)	(0.3252)	(0.3388)
$NC_{b,c,t-1}$	59.3298***	60.1339***	58.3510***	68.2227***	127.3054***	129.7244***
	(0.3305)	(0.3364)	(0.3386)	(0.3745)	(0.5604)	(0.5611)
$\Gamma_{b,c,t-1}$	-0.5968***	-0.7356***	-0.9617***	-0.6431***	-0.4590***	-0.4995***
	(0.1622)	(0.1665)	(0.1839)	(0.1878)	(0.1605)	(0.1801)
Constant	-16.9098***					
	(0.1509)					
County FE		✓				
Year FE		✓				
County × Year FE			✓	✓		✓
Bank FE				✓		
Bank × County FE					✓	✓
# Obs	575,000	575,000	575,000	575,000	575,000	575,000
R^2	0.0696	0.0804	0.1823	0.1984	0.2091	0.3165

Notes: This table uses small business lending data collected under the Community Reinvestment Act (CRA) and reports estimates of β_1, β_2, and β_3 from

$$\Delta \ln(Lending)_{b,c,t} \times 100 = \beta_1 \times NC_{b,c,t-1} \times \Gamma_{b,c,t-1} + \beta_2 \times NC_{b,c,t-1} + \beta_3 \times \Gamma_{b,c,t-1} + \theta_{c,t} + \theta_{b,c} + \varepsilon_{b,c,t}.$$

b, c, and t denote bank, county, and year, respectively. The data span from 1997 to 2019. The dependent variable is lending growth in percent, defined as the change in the natural logarithm of small business loans originated by bank b in county c and year t, multiplied by 100. $\theta_{b,c}$ and $\theta_{c,t}$ are bank-by-county and county-by-year fixed effects, respectively; the fixed effects included vary by column, as reported below. $\Gamma_{b,c,t-1}$ is the standardized out-of-state bank-county funding shock. $NC_{b,c,t-1}$ is an indicator equal to one if bank b's small-business lending market share in county c in year $t-1$ is below its year-$t-1$ cross-sectional median market share. Standard errors clustered at the bank-county level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

I.1.1 Securitization and Balance-Sheet Capacity

The preceding results examine banks' ability to absorb funding shocks through their liabilities, capital, and the allocation of lending across markets. A further margin operates through the asset side of the balance sheet. Banks can reduce the balance-sheet capacity required to support new lending when loans can be sold after origination. Conforming mortgages can be sold to Fannie Mae and Freddie Mac, whereas jumbo mortgages are generally ineligible for purchase by the government-sponsored enterprises. Jumbo lending should therefore remain more sensitive to the originating bank's funding position (Loutskina and Strahan, 2009).

Table I.5 compares jumbo and non-jumbo mortgage originations following the same bank-county funding shock. The increasingly saturated specifications progressively narrow the identifying comparison. Column 2 introduces county-by-year and bank-by-county fixed effects. Column 3 absorbs the entire bank-by-county-by-year cell, so identification comes from differences between jumbo and non-jumbo lending exposed to the same bank funding shock in the same local market and year. Column 4 additionally includes jumbo-by-bank-by-county fixed effects, absorbing persistent differences in the importance of jumbo lending within each bank-county relationship.

The interaction between jumbo status and the funding shock is negative and statistically significant throughout. In the most saturated specification, the interaction coefficient is -3.4320. Jumbo mortgage origination therefore contracts more than conforming origination following the same funding shock. The response is stronger precisely for loans that are more difficult to move off the originating bank's balance sheet, consistent with securitization providing an additional margin through which banks can absorb funding shocks.

Table I.5: Jumbo vs. Non-Jumbo Mortgage Loans and Funding Shocks

Dep Var: Lending Growth (%)	(1)	(2)	(3)	(4)
$\text{Jumbo}_j \times \Gamma_{b,c,t-1}$	-3.1350***	-3.1350***	-3.1350***	-3.4320***
	(0.2494)	(0.2530)	(0.2494)	(0.2912)
Jumbo_j	1.6836***	1.6836***	1.6836***	
	(0.1276)	(0.1294)	(0.1276)	
$\Gamma_{b,c,t-1}$	2.6284***	1.4828***		
	(0.1862)	(0.2089)		
Constant	1.8836***			
County × Year FE		✓		
County × Bank FE		✓		
County × Bank × Year FE			✓	✓
County × Bank × Jumbo FE				✓
# Obs	2,732,554	2,732,554	2,732,554	2,732,554
R^2	0.0001	0.0576	0.5297	0.5481

Notes: This table uses Home Mortgage Disclosure Act (HMDA) data and reports estimates of β_1 and β_2 from

$$\Delta \ln(Lending)_{b,c,t,j} \times 100 = \beta_1 \times Jumbo_j \times \Gamma_{b,c,t-1} + \beta_2 \times Jumbo_j + \theta_{b,c,t} + \theta_{b,c,j} + \varepsilon_{b,c,t,j}.$$

b, c, t, and j denote bank, county, year, and loan type (jumbo or non-jumbo), respectively. The data span from 1995 to 2019. The dependent variable is lending growth in percent, defined as the change in the natural logarithm of mortgage lending originated by bank b in county c, year t, and loan type j, multiplied by 100. $\Gamma_{b,c,t-1}$ is the bank's standardized out-of-state funding shock reaching county c from elsewhere. $Jumbo_j$ is an indicator equal to one for jumbo mortgages and zero for non-jumbo mortgages. $\theta_{b,c,t}$ are bank-by-county-by-year fixed effects, and $\theta_{b,c,j}$ are bank-by-county-by-loan-type fixed effects. Standard errors clustered at the bank-county level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Taken together, the bank-side evidence points to a common mechanism. Funding shocks produce larger lending responses when banks have less capacity to replace funding, draw on capital buffers, or release balance-sheet capacity through securitization. When capacity becomes scarce, banks also reallocate credit across markets, contracting lending more heavily where their local relationships and informational advantages are weaker. The transmission of a funding shock therefore depends not only on the size of the initial funding loss but on the margins available to the bank for absorbing it.

I.2 Borrower Constraints and Credit Substitution

The borrower side of the transmission mechanism depends on the ability to replace credit withdrawn by an affected bank. A contraction in bank lending need not reduce a firm's total financing if the firm can borrow from another lender or substitute toward other sources of external finance. The same contraction can have substantially larger effects when these alternatives are limited. We examine this substitution margin in two complementary ways. The CRA data allow us to ask whether banks allocate funding-induced lending contractions differently across smaller and larger businesses, while matched Dealscan–Compustat data allow us to examine whether exposure to funding-shocked banks translates into financing and real outcomes for firms with different access to alternative finance.

We first examine the allocation of the initial credit contraction across borrowers. Table I.6 compares lending to businesses with gross revenue below $1 million with lending to larger businesses. The increasingly saturated fixed effects narrow the comparison to borrowers of different sizes exposed to the same bank in the same local market. Column 3 includes bank-by-county-by-year fixed effects, absorbing the bank's funding shock and all contemporaneous conditions common to borrowers in the same bank-county-year. Column 4 additionally includes firm-size-by-bank-by-county fixed effects, absorbing persistent differences in the composition of lending across borrower size within each bank-county relationship.

The interaction between small-firm status and the funding shock is negative and statistically significant throughout. In the most saturated specification, the interaction coefficient is -1.0285, implying that the same funding shock produces a larger decline in lending to smaller businesses than to larger businesses served by the same bank in the same county and year. This evidence identifies how banks allocate the contraction in credit supply across borrowers; it does not by itself establish that smaller firms experience an equivalent decline in total financing, since they may replace credit from the affected bank elsewhere. It nevertheless shows that smaller businesses bear a disproportionate share of the initial bank-lending contraction.

Table I.7 examines the next step in the transmission mechanism: whether exposure to funding-shocked banks is associated with changes in firms' financing and real activity when substitution is more

difficult. We use Dealscan to identify the banks connected to each borrowing firm and combine their funding shocks into a firm-level measure of bank exposure. We then match these firms to Compustat and use firm age as a proxy for access to alternative finance. Younger firms tend to have shorter credit histories, fewer established financing relationships, and more limited access to external finance (Hadlock and Pierce, 2010; Petersen and Rajan, 1994). The specification compares the response of younger and older firms to bank funding shocks while absorbing firm fixed effects and industry-by-young-by-year conditions.

The results show substantially stronger responses among younger firms. A one-standard-deviation increase in exposure to bank funding shocks is associated with an additional 13.3 percent decline in debt for younger firms relative to older firms. Book assets decline by an additional 10.0 percent, employment by 12.2 percent, and capital expenditure by 20.2 percent. The interaction is statistically significant at the 10 percent level for debt and at the 5 percent level for assets, employment, and capital expenditure. By contrast, the coefficients on bank funding exposure for older firms are small and statistically insignificant across all four outcomes. The differential effects therefore extend beyond bank borrowing to firms' balance sheets, employment, and investment.

The two exercises capture different stages of the borrower-side transmission mechanism. The CRA evidence shows that banks direct a larger share of the initial lending contraction toward smaller businesses. The Dealscan–Compustat evidence shows that exposure to funding-shocked banks is associated with larger financing and real responses among younger firms, for whom replacing bank finance is more difficult. Together, the results are consistent with credit substitution limiting the transmission of bank funding shocks: when borrowers have fewer financing alternatives, a contraction in bank credit is more likely to translate into reductions in total financing and real activity.

Combined with the bank-side evidence in Section 8, these results point to substitution frictions on both sides of the credit relationship. Funding shocks generate larger lending contractions when banks have less capacity to replace funding or release balance-sheet capacity, and those contractions have larger consequences when borrowers have fewer alternatives to the affected banks. These exercises do not assign particular components of the missing intercept to individual frictions. Rather, they identify the microeconomic margins along which funding shocks propagate most strongly.

Table I.6: Small vs. Large Recipients of Small Business Loans and Funding Shocks

Dep Var: Lending Growth (%)	(1)	(2)	(3)	(4)
$\text{Small}_s \times \Gamma_{b,c,t-1}$	-1.3522***	-1.3522***	-1.3522***	-1.0285***
	(0.2911)	(0.3071)	(0.2911)	(0.3230)
Small_s	-0.9709***	-0.9709***	-0.9709***	
	(0.1473)	(0.1553)	(0.1473)	
$\Gamma_{b,c,t-1}$	0.6510***	0.4679*		
	(0.2404)	(0.2390)		
Constant	3.9996***			
	(0.1228)			
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	0.0001	0.1637	0.5349	0.5671

Notes: This table uses small business lending data collected under the Community Reinvestment Act (CRA) and reports estimates of β_1 and β_2 from

$$\Delta \ln(Lending)_{b,c,t,s} \times 100 = \beta_1 \times Small_s \times \Gamma_{b,c,t-1} + \beta_2 \times Small_s + \theta_{b,c,t} + \theta_{b,c,s} + \varepsilon_{b,c,t,s}.$$

b, c, t, and s denote bank, county, year, and firm size (small or large), respectively. The data span from 1997 to 2019. The dependent variable is lending growth in percent, defined as the change in the natural logarithm of small business lending originated by bank b in county c, year t, to firms of size s, multiplied by 100. $\Gamma_{b,c,t-1}$ is the bank's standardized out-of-state funding shock reaching county c from elsewhere. $Small_s$ is an indicator equal to one for loans to firms with gross revenue below $1 million. $\theta_{b,c,t}$ are bank-by-county-by-year fixed effects, and $\theta_{b,c,s}$ are bank-by-county-by-firm-size fixed effects. 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 I.7: Bank-Borrower Lending Relationship and Real Effects

	(1)	(2)	(3)	(4)
	Debt	Size	Employment	CapEx
$\text{Young}_f \times \sum_b \Gamma_{b,t-1}$	-0.1329*	-0.0995**	-0.1216**	-0.2023**
	(0.0734)	(0.0503)	(0.0568)	(0.0857)
$\sum_b \Gamma_{b,t-1}$	-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

Notes: This table uses Dealscan data matched with Compustat data and reports β_1 and β_2 from

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

where f and t indicate borrowing firm and year, respectively. The dependent variable $y_{f,t}$ is the natural logarithm of total debt in column (1), the natural logarithm of the book value of assets in column (2), the natural logarithm of employment in column (3), and the natural logarithm of capital expenditure in column (4). Firm age is defined as the years elapsed since IPO, and $Young_f$ is an indicator equal to one for firms with age below the sample median firm age. $\Gamma_{b,t-1}$ refers to standardized bank-specific funding shocks, measured using the deposit-weighted average of disaster damage per capita. $\sum_b \Gamma_{b,t-1}$ is the standardized sum of bank funding shocks across the lead banks of firm f identified using the Dealscan database. $\theta_{i,g,t}$ and θ_f are industry-by-young-by-year and firm fixed effects, respectively. Industries refer to the 38 Fama-French industries. Standard errors clustered at the firm level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.