Bank geographic diversification and funding stability

Sebastian Doerr

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Abstract

The recent banking turmoil has renewed attention on banks' branch network and deposit taking activity. This paper provides novel evidence that the geographic diversification of banks' deposit base improves their funding stability and thereby fosters liquidity creation. First, I establish that banks with greater diversification have higher dispersion in deposit growth rates *across their branches*; and lower volatility in deposit growth rates *over time*. Subsequently, banks benefit from lower deposit rates. These patterns are consistent with diversification improving funding stability. Second, I show that deposit diversification enables banks to engage in increased liquidity creation and small business lending, with positive effects for real economic activity. The funding stability channel of geographic diversification is distinct from previous findings on the benefits of diversification on banks' asset side. It also highlights benefits of branch networks for bank lending that go beyond information acquisition.

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1 Introduction

The rapid disappearance of physical bank branches is one of the most striking developments in the banking sector over the last decades. In the US, the number of bank branches has declined from almost 100,000 in 2009 to less than 75,000 today. In OECD countries, it declined by about 30 percent over the past 15 years. An active literature investigates the importance of branches for local information acquisition and how it affects lending to informationally opaque firms, eg small businesses and startups.[1] However, while the total number of branches has declined, the average number of branches per bank has increased. Through consolidation, the number of commercial banks in the US declined at a faster pace than branches, from about 7,000 in 2009 to about 4,000 today. And not only did the average number of branches per bank increase,[2] but banks have steadily expanded the geographic footprint of their deposits base over the last decades.

This paper studies how the structure of branch networks, in particular their geographic distribution, affects banks' funding stability. Moreover, it investigates how the geographic diversification of banks' deposit base affects their asset side, ie their liquidity creation and lending. It thereby provides novel evidence on the consequences of branch closures and contributes to the long-standing debate on the costs and benefits of bank diversification, one of the central questions in finance.[3]

I argue that banks with a geographically diversified branch network – and hence deposit base – have greater funding stability. The reason is lower exposure to idiosyncratic deposit withdrawals at each branch. As long as withdrawal shocks are imperfectly correlated, a bank with greater geographic diversification should have a lower correlation in branch-level deposit growth rates *across its branches*. And it should experience less volatile deposit growth *over time*. Since more stable funding

[1] See Agarwal and Hauswald (2010); Nguyen (2019); Bonfim et al. (2021) and Amberg and Becker (2024), among others. Related work studies the causes of bank branch closures, in particular the rise of information technology (IT) in the financial sector, and its implications (see Haendler (2023); Jiang et al. (2023); Koont (2023)).

[2] According to data from the FDIC's Historical Bank Data, the average number of branches per bank increased from 12 in 2009 to 18 in 2023. According to data from the Summary of Deposits, the median bank had three branches in 2009 and five in 2023.

[3] On bank diversification, see Demsetz and Strahan (1997); Acharya et al. (2006); Deng et al. (2007); Goetz et al. (2013, 2016); Doerr and Schaz (2021); Levine et al. (2021) and Gelman, Goldstein and MacKinlay (2023), among others.

allows banks to invest more in illiquid assets, greater diversification should enable more liquidity creation and lending. Finally, to the extent that deposit withdrawals affect bank health, greater funding stability is expected to reduce bank funding costs by lowering bank risk.[4]

To test these hypotheses, I measure the degree of geographic diversification of US banks' deposits with disaggregated branch-level data. For each bank I construct a Herfindahl-Hirschman Index (HHI) of the geographic concentration of its deposits across branches in each year between 1994 and 2019. Banks with lower deposit concentration, ie, those that raise deposits in several branches, are classified as more diversified. Banks that raise a large share of their deposits in just a few branches are classified as more concentrated. Over the sample period, the diversification of banks' deposit base has steadily increased.

To identify the causal effect of geographic diversification on funding stability and liquidity creation I construct an instrumental variable (IV). Following Goetz et al. (2013, 2016) and Levine et al. (2021), the IV is based on a gravity model of bank expansion combined with an index of interstate banking deregulation. The instrumental variable approach exploits exogenous variation in banks' deposit shares, and hence geographic diversification, across counties and over time.

To construct the instrument, in a first step I predict banks' deposit shares in each county with a gravity model. The model is based on the distance between banks' headquarters (HQ) and branch counties, as well as the counties' relative market size. The standard gravity model predicts that deposit shares are lower in counties that are further away from the headquarters. The reason is that transaction and information costs as well as agency conflicts increase with distance. For example, headquarters might find it more costly to monitor branch managers in more distant locations.[5] Deposit shares are also predicted to be higher in larger destination

[4]See Flannery (1994); Deng et al. (2007), and Levine et al. (2021). While deposits represent a relatively stable and dependable source of funding (Stein, 1998; Kashyap et al., 2002; Hanson et al., 2015), banks can be subject to sudden and large deposit withdrawals (Diamond and Dybvig, 1983), as the recent banking turmoil has made abundantly clear (Acharya et al., 2023; Metrick, 2024). More generally, Gilje et al. (2016) find that geographically concentrated deposit inflows spur banks' mortgage lending in other counties, while Kundu et al. (2023) provide evidence on the importance of county- and state-level idiosyncratic deposit shocks for aggregate bank lending. Becker (2007) and Doerr et al. (2023) show how an increase in local deposits due to population aging spurs bank lending and risk-taking.

[5]A long-standing literature documents that informational frictions within organizations, for

markets. The first step of the gravity model exploits the quasi-exogenous location of bank headquarters, which is mostly determined by historical factors.

In a second step, predicted deposit shares are adjusted with an index of staggered interstate banking deregulation. Even after de-jure deregulation following the Interstate Banking and Branching Efficiency Act in 1994, states used different policy tools to restrict out-of-state banks from opening branches. They did so to different degrees and relaxed these constraints over time in a staggered fashion. The gravity model, which is unaware of this regulation, thus predicts deposit shares that are too high in more regulated states.

Following Rice and Strahan (2010), Célerier and Matray (2019), and Li (2022), I construct a state-level deregulation index that varies over time. It reflect the ease of opening branches for out-of-state banks. The index is scaled to lie between zero and one, where one measures maximum ease. I then multiply predicted deposit shares with the index. Predicted deposit shares in states with more stringent branching restrictions are hence downward adjusted.[6] Finally, I reconstruct the HHI for each bank-year cell from these adjusted deposit shares.

The instrument thus draws on two plausibly exogenous sources of variation in banks' ability to expand their branch network. First, the geographic distance between the headquarters location and the destination branch. And second, the staggered removal of interstate banking regulation across states.[7]

The analysis begins with an investigation of the relationship between geographic diversification and deposit volatility. In OLS and IV regressions I find a strong positive effect of bank diversification on the standard deviation in deposit growth across a bank's branches. Banks with a geographically more diversified deposits hence see a decline in the correlation in deposit growth rates across their branches.[8]

example agency frictions between the headquarters and divisional/branch managers, increase with distance (see, among others, Stein (2002), Berger et al. (2005), Giroud (2013), and Levine et al. (2020)).

[6]This adjustment assumes that deposit shares decline linearly with the index. For robustness, I also predict deposit shares with a gravity equation that directly includes the index, as well as its interaction with the distance variable. This specification allows for possible non-linearities.

[7]The IV also addresses bias stemming from measurement error in diversification. For example, differences across banks in how they assign online deposits to individual branches could lead to measurement error in county-level deposit shares and diversification, thereby a downward-biasing OLS estimates (Pancost and Schaller, 2022).

[8]The positive effect of diversification on the standard deviation in growth rates across branches

This finding suggests that banks reduce their exposure to branch-specific deposit withdrawal shocks.

Does higher variation in deposit growth rates across branches translate into lower overall volatility in bank deposits? Regression results suggest they do: more diversified banks experience significantly lower volatility in deposit growth rates over time. A one standard deviation increase in diversification reduces the volatility in deposit growth rates over time by 4.8 basis points, or 12% of the mean volatility. I find the dampening effect of diversification on deposit volatility to be especially pronounced during periods of heightened macroeconomic uncertainty or risk, further suggesting that deposit diversification enhances banks' overall resilience. Taken together, these results imply that more diversified banks benefit from greater funding stability.

I examine alternative explanations that could account for the link between the geographic diversification of banks' deposit base and funding stability. First, I contrast deposit with asset diversification. The latter can bring benefits through lower exposure to idiosyncratic shocks to economic output (Levine et al., 2021; Doerr and Schaz, 2021; Gelman et al., 2023). While asset diversification is mainly about credit risk and not funding liquidity risk, it could be correlated with deposit diversification. I find that controlling for the diversification of banks' loan portfolio across counties does not affect the positive effect of deposit diversification on funding stability.[9] Second, I control for banks' deposit market power (Drechsler et al., 2017), which benefits banks through more stable funding when the policy rate changes (Li et al., 2023). While my results confirm that banks' deposit market power has a negative effect on deposit volatility, it does not materially affect the estimated effects of deposit diversification on funding stability. Third, I show that bank branch density, defined as the number of branches over total deposits (Benmelech et al., 2023), does not account for the effects of geographic diversification on funding stability; nor does incorrectly accounting for online deposits.[10] Finally, the positive effect

remains similar in sign, size, and significance when I control for the total number of branches.

[9]Regression results show that asset diversification has an economically very small effect on deposit volatility across branches and time, compared to deposit diversification. This is to be expected: asset diversification is fundamentally about credit risk. It operates by reducing banks' exposure to idiosyncratic shocks to the quality of its assets (eg mortgages). Deposit diversification, which is about funding liquidity risk, reduces banks' exposure to branch-specific shocks to deposit in- and outflows. There is hence no obvious reason why asset diversification should substantially affect funding stability.

[10]First, I find that the positive effect of diversification on dispersion in deposit growth rates across branches remains economically and statistically significant when I drop cyber branches and

of diversification on dispersion in deposit growth rates across branches is present both for rate-setting branches and branches whose deposit rates are determined by a centralized rate-setting policy. This finding suggests that the link is not due to expanding banks being better at setting rates to smooth their deposit flows.[11]

With granular branch-level data on deposit rates I then show that greater diversification benefits banks through lower deposit rates. A one standard deviation increase in diversification reduces rates on time and savings deposit by around 3 to 4 basis points (ca 3–6% of the mean). This finding is consistent with the argument that greater diversification of a bank's deposit base increases funding stability and thereby lowers bank risks, benefitting banks through lower funding costs.[12] Importantly, the negative effect of diversification on deposit rates remains robust to the inclusion of branch county*time fixed effects. The effect of diversification is hence not capturing unobservable time-varying factors at the branch county level, such as diversified banks operating branches in counties with more stable deposit flows or greater deposit market concentration. Results also remain similar when I exploit within-branch variation with branch fixed effects. This precludes the possibility that the link between diversification and lower rates is driven by banks that expand because they benefit from lower funding costs to begin with.

In a second step, I analyze to what extent greater geographic diversification allows banks to create liquidity on their asset side. Stable funding is essential for liquidity creation, a core function of banks (Berger and Bouwman, 2009). Banks combine money creation on the liability side, in particular in the form of deposits, with investing in assets that have relatively long-run cash flows (Strahan, 2008). Such assets include loans to firms and households. When deciding on how to allocate funds between more liquid shorter-term and less liquid longer-term assets,

the HQ branch, which usually account for the lion's share of online deposits. Second, I show that controlling for the share of deposits held in cyber branches and the HQ branch does not affect the size, sign, or significance of the estimated coefficient on diversification in two-stage least squares (2SLS) regression, but that it reduces the coefficient size in OLS regressions. To the extent that the share of cyber/HQ deposits correlates with unobservable bank characteristics, in particular IT adoption, this finding suggests that the IV purges the estimation from such unobservable confounding factors.

[11]Results are also robust to controlling for bank HQ state*year fixed effects.

[12]Previous work has shown that banks' asset diversification reduces exposure to idiosyncratic shocks to output, which lowers funding costs (Levine et al., 2021) and bank risk (Goetz et al., 2016). My results provide a complementary but distinct channel through which diversification can reduce bank risk and funding costs.

a bank needs to assess its funding liquidity risk. If, for whatever reason, depositors decide to withdraw funds today, the bank needs to liquidate its assets to meet those withdrawals. But liquidating illiquid assets early is costly. A bank subject to greater funding liquidity risk can hence invest less in illiquid assets.

Drawing on the metrics developed in Berger and Bouwman (2009) I find that greater geographic diversification leads to a significant increase in liquidity creation. I confirm this finding with bank balance sheet data on assets of different liquidity. The effect of diversification on banks' C&I loan growth (classified as an illiquid asset by Berger and Bouwman (2009)) is significantly larger than its effect on real estate loan growth (semi-liquid). And it is much larger than its statistically insignificant effect on growth in security holdings (liquid). These patterns are consistent with the argument that an increase in banks' geographic diversification leads to more liquidity creation, driven by greater funding stability. Supporting this argument, the positive effect of diversification on liquidity creation remains economically and statistically significant when I control for asset-side diversification, deposit market power, and branch density.

To further shed light on the link between diversification and bank lending, I use bank-county-year data on small business lending. Small business lending is inherently risky and illiquid. Banks usually retain small business loans on their balance sheet. It thus should benefit from stable deposit funding and lower funding costs (Drechsler et al., 2017; Supera, 2022). In support of my hypotheses, I find that greater diversification leads to a significant increase in banks' small business lending.

Exploring the diversification-lending nexus with granular bank-county data offers two advantages. First, the rich data set allows me to saturate models with borrower county*year fixed effects, thus removing confounding demand effects. Conceptually, the analysis compares growth rates in small business lending in the same county and year for two banks with different levels of diversification. Second, I can exclude all branch counties when investigating the effect of diversification on lending. This avoids any confounding effects of shocks that affect both banks' local deposit growth and investment opportunities. It also precludes that results are driven by banks' informational advantage in counties where they operate branches (Agarwal and Hauswald, 2010). The positive effect of diversification on small business lending in no-branch counties suggests that the structure of bank branch networks has implications for bank lending that go beyond the ability to gather soft information locally.

Lastly, I study the impact of banks' geographic diversification on local economic activity. I show that counties with greater exposure to diversified banks experience significantly faster firm growth. These effects are concentrated in more bank-dependent industries and among small firms, consistent with the argument and results that diversification spurs banks' C&I and small business lending.

In sum, this paper presents a novel channel through which diversification can improve banks' funding stability and stimulate lending to the real economy. Greater diversification of banks' deposit base reduces deposit volatility over time. More stable funding in turn reduces banks' cost of financing and allows them to engage in more liquidity creation and lending, spurring real activity among bank-dependent firms.

Related literature and contribution

The main contribution of this paper is to propose and test a novel channel through which the diversification of banks' deposit base can improve funding stability and promote bank lending and liquidity creation. Previous work has focused on the consequences of banks' geographic diversification for their valuation (Deng and Elyasiani, 2008; Goetz et al., 2013), individual and systemic risk (Demsetz and Strahan, 1997; Acharya et al., 2006; Goetz et al., 2016; Chu et al., 2020), funding costs (Levine et al., 2021), or lending (Doerr and Schaz, 2021; Gelman et al., 2023). Other work has focused on the importance of bank branches for the gathering of soft information and local lending, especially to small firms (Berger et al., 2005; Nguyen, 2019; Bonfim et al., 2021; Amberg and Becker, 2024). To the best of my knowledge, this paper is the first to show that the funding stability channel plays an important role in assessing the benefits of geographic diversification. It further highlights that the benefits of branch networks go beyond integrating local credit markets and mitigating contracting frictions (Agarwal and Hauswald, 2010; Gilje et al., 2016).

Diversification, risk, and agency conflicts. A large literature investigates whether banks' geographic diversification affects their corporate valuations. The literature discusses two main channels. On the one hand, diversification could reduce banks' exposure to idiosyncratic local shocks. On the other hand, agency conflicts within the organization could lead to an inefficient allocation of resources and increased risk-taking. Early work finds mixed evidence. Some studies find that geographically diversified banks or banks that expand geographically choose riskier loans (Demsetz and Strahan, 1997; Acharya et al., 2006), which is associated with lower returns and valuations. Others find that risk declines and valuations rise with banks' geographic diversification (Deng and Elyasiani, 2008; Aldasoro et al., 2022).

Earlier studies, however, faced the challenge of obtaining exogenous variation in banks' geographic footprint. Goetz et al. (2013, 2016) revisit the topic with an instrumental variable approach. Goetz et al. (2013) show that increases in geographic diversification causally reduce bank valuations, likely because increased agency conflicts allow insiders to extract rents. Goetz et al. (2016) find that geographic expansion reduces bank risk without affecting loan quality. This finding suggests that asset-side diversification reduces exposure to idiosyncratic shocks. However, the decrease in banks' individual risk is associated with an increase in their contribution to systemic risk, as banks' asset similarity increase (Chu et al., 2020).

Diversification and funding. Other work studies how banks' geographic diversification affects their access to funding. Levine et al. (2021) use bank-level data and an IV (based on Goetz et al. (2013, 2016)) to show that geographic diversification lowers banks' funding costs. The underlying mechanism relates to banks' improved ability to weather idiosyncratic shocks to their assets: the effects of diversification on funding costs are stronger when banks expand into states whose output is less correlated with the banks' state or the overall US economy. For a global sample of banks, Doerr and Schaz (2021) show that banks with a more diversified syndicated loan portfolio are better able to attract wholesale funding during financial crises.

Diversification and lending. A set of papers studies whether diversification helps banks to maintain lending during shock episodes. While not explicitly focusing on diversification, Cortés and Strahan (2017) show that integrated banks are better able to respond to an increase in local loan demand. The reason is that they can bid up deposit rates and hence attract funding in other areas. Doerr and Schaz (2021) focus on bank lending during financial crises in borrower countries. They show that diversified banks maintain higher loan supply due to their better ability to raise funding. Finally, Gelman et al. (2023) show that banks with greater asset diversification are less exposed to idiosyncratic shocks and have a more stable stream of earning. They thus lend more in normal and turbulent times.

Bank branches and small business lending. When banks screen and monitor opaque borrowers, they need to obtain soft information to overcome information asymmetries. One way to do so is through branches. Berger et al. (2005) provide evidence that closer proximity to a branch enables better loan monitoring of opaque borrowers. Agarwal and Hauswald (2010) show that local lenders are better able to lend to riskier borrowers. As small businesses tend to be informationally opaque, branch closures have negative effects on small firms (Nguyen, 2019; Bonfim et al., 2021; Jiménez et al., 2022; Amberg and Becker, 2024). In light of the rise of information technology (IT) in the banking sector, recent papers study the effects of IT on branch closures, information processing, and lending (Petersen and Rajan, 2002; Jiang et al., 2023; Ahnert et al., 2024; Haendler, 2023; Koont, 2023).

2 Hypotheses development

Banks provide liquidity to customers by issuing deposits. They invest the float (ie, the deposit balance) in loans, securities, and other assets. By investing deposits in less liquid assets, banks create liquidity but expose themselves to funding liquidity risk. If sufficiently many depositors decide to withdraw their funds early, the bank has to liquidate some of its illiquid assets. This is costly and can lead to bank failures (Diamond and Dybvig, 1983; Strahan, 2008). While a bank has different ways of managing funding liquidity risk, a simple example illustrates how geographic diversification of the deposit base can enhance funding stability.

Suppose a bank has only one branch. It raises deposits D to invest them into more and less liquid assets. Illiquid assets have a relatively higher payoff in the long run but a lower payoff if they need to be liquidated in the short run. With probability p the bank branch faces deposit withdrawals of amount d in the short run. The higher the expected withdrawal pd, the more funds the bank needs to allocate towards the liquid asset that can be sold at a higher price in the short run.

Now suppose a bank has two branches that raise $D/2$ each. The bank still raises a total of D. If shocks across branches are uncorrelated, then the probability of a withdrawal of amount d is only p^2. The probability of a withdrawal of $d/2$ is $(1-p)*p$. The bank can hence invest more in the illiquid asset, as, in expectation, it has to liquidate fewer assets early to meet withdrawals. This example readily extends to more branches with imperfectly correlated shocks.

These considerations suggest that a bank with greater geographic diversification of its deposit base should experience less volatile deposit growth *over time*. However, it should have a greater standard deviation (reflecting lower correlation) in branch-level deposit growth *across its branches*. Moreover, since greater funding stability allows the bank to invest more in the illiquid asset, banks with greater diversification should engage in more liquidity creation. Finally, to the extent that large enough deposit withdrawals threaten bank health – as investors stand to lose some of their funds – greater funding stability is expected to reduce bank risk. This should reduce funding costs (Flannery, 1994; Levine et al., 2021).

Two important assumptions underlie the preceding arguments. First, deposit growth rates across branches need to be imperfectly correlated. Otherwise the standard deviation in deposit growth rates across a bank's branches would equal zero. There would be no diversification benefit from geographic expansion. As I will show below, for the average bank the standard deviation in deposit growth rates across its branches is 11.8% (with a median of 9.3%), relative to a mean (median) branch-level deposit growth rate of 5.2% (3.9%). These numbers suggest far from perfect correlation.

The second assumption is that regional shocks to banks' deposit base need to be large enough to affect bank lending. Consistent with this argument, Gilje et al. (2016) show that local deposit inflows spur banks' mortgage lending in other areas. Kundu et al. (2023) provide evidence on the importance of county-level idiosyncratic 'granular deposit shocks' for total bank lending. Becker (2007) shows how an increase in local deposits due to population aging spurs bank lending, while Doerr et al. (2023) show that it leads to more risk-taking. Doerr et al. (2022) further find that rising inequality in a state increases the cost of deposit funding for banks headquartered in that state, with implications for lending. And as the banking turmoil of 2023 has made clear, banks can be subject to sudden and large local deposit withdrawals that threaten bank health (Acharya et al., 2023; Metrick, 2024).

3 Data and descriptive statistics

This section first discusses the data and construction of the main variables. It then presents summary statistics.

3.1 Data

Data sources. The analysis combines different data sources on bank deposits, deposit rates, and balance sheet items.

Bank deposits: The Federal Deposit Insurance Corporation's (FDIC) Summary of Deposits (SOD) provides branch-level information on the geographic distribution of bank deposits. To eliminate noise stemming from banks and branches with a small number of observations I require at least three years of observations per branch and at least two branches per bank.

Bank data: The US Call Reports, provided by the Federal Reserve Bank of Chicago, contain quarterly data on the income statements and balance sheets of all US commercial banks. I collect information on banks' total deposits, total assets, the share of non-interest income out of total operating income, return on assets (defined as net income over assets), the ratio of total securities over total assets, and the equity ratio (defined as total equity over total assets). I also construct the log difference in banks' C&I lending, real estate lending, and security holdings. In addition, I obtain data on bank liquidity creation as a share of banks' gross total assets (available up until 2016) from Berger and Bouwman (2009). They classify business loans and leases as illiquid assets, residential mortgages and consumer loans as semi-liquid assets, and cash, securities, and other marketable assets as liquid.[13]

[13] Berger and Bouwman (2009) first classify all bank assets and off-balance sheet activities as liquid, semi-liquid, or illiquid, based on the ease, cost, and time for customers to obtain liquid funds from the bank, and the ease, cost, and time for banks to dispose of their obligations in order to meet these liquidity demands. Second, they assign weights to the activities classified in step 1, with greater weights on more liquid assets. And third, they construct a measure of asset liquidity creation by combining the activities as classified in Step 1 and as weighted in Step 2.

To account for outliers, growth rates and ratios are winsorized at the 1^{st} and 99^{th} percentile in each year.

Deposit rates: Data on deposit rates are obtained from RateWatch, which collects weekly branch-level data on deposit rates on new accounts by product from 2000 onward. Following the literature, I restrict the sample to branches that actively set rates and focus on the two most commonly offered deposit products, money market deposit accounts with an account size of $25,000 and 12-month certificates of deposit with an account size of $10,000. As discussed in Drechsler et al. (2017), these products are representative of savings and time deposits. The data is collapsed to the branch-quarter level by taking the simple average.

Mortgages and small business loans: Data on mortgage and small business loan originations at the bank-county-year level are obtained from the Federal Financial Institutions Examination Council (FIEC). The underlying mortgage loan data are obtained from the Home Mortgage Disclosure Act (HMDA) database on the near universe of residential mortgages. The underlying small business loan data is from the Community Reinvestment Act (CRA) database, which contains information on loans with commitment amounts below $1 million originated by financial institutions with more than $1 billion in assets. The granular lending data cover the years from 2004 onward.

County data: Data on the distance in miles between counties is provided by the NBER's county distance database. Data on annual county population is provided by the US Census Bureau's Annual Estimates of the Population for Counties (obtained via GeoFRED). Data on county-level firm growth and employment is provided by the Business Dynamic Statistics, with a breakdown by either 2-digit NAICS sector or firm size bucket for each county.

Deregulation index: Information on state-level interstate branching laws is obtained from Rice and Strahan (2010) and Li (2022). Even after de-jure deregulation following the Interstate Banking and Branching Efficiency Act in 1994, most states used policy tools to protect domestic banks from outside competition. Over time, states relaxed these constraints. The regulation of local banking markets took one or more of the following forms: 1) minimum age of the targeted bank; 2) de-novo branching without an explicit agreement by state authorities; 3) acquisition of individual branches without acquiring the entire bank; and 4) a cap on the total amount of state-wide deposits controlled by a single bank or bank holding company. The yearly state-level index *deregulation* ranges from 0 to 4 to capture each dimension of state level branching restrictions (see also Célerier and Matray (2019) and Doerr (2021)). States with a value of zero regulate their banking sector in all four dimensions. States with a value of four are fully deregulated.

Variable construction. I use the FDIC's SOD to construct banks' geographic diversification as one minus the Herfindahl-Hirschman Index (HHI):

$$\text{diversification}_{b,t} = 1 - \underbrace{\sum_i \left(\frac{\text{deposits}_{i(b,c),t}}{\text{deposits}_{b,t}} \right)^2}_{HHI}. \tag{1}$$

The variable $deposits_{i(b,c),t}$ denotes the total amount of deposits of bank b in branch i, located in county c, in year t. $Deposits_{b,t}$ are the total amount of deposits of bank b in year t. To create the diversification measure, I invert the scale of the HHI. A value of zero ($diversification = 0$) implies no diversification (all deposits are held in one branch), while higher values reflect increasing diversification of banks' deposit base.

To compute the standard deviation in deposit growth rates across branches, for each branch I first compute the log difference in deposits $\Delta deposits_{i(b,c),t}$ in branch i of bank b and located in branch county c from year $t-1$ to year t. To account for episodes of extreme deposit volatility, deposit growth is winsorized at the 1^{st} and 99^{th} percentile in each year. I then take the standard deviation across branch-level deposit growth rates for each bank-year cell, denoted by $sd(\Delta deposits_{i,t})$. In doing so, I weight each branch by its total deposits to account for the fact that deposit volatility among larger branches is more important for overall funding volatility than deposit flows at smaller branches.[14]

To compute the volatility in banks' deposit growth over time, I use Call Reports data to first compute the log difference in total deposits $\overline{\Delta deposits_{b,t}}$ (as well as time and demand deposits) for each bank in each quarter. Similar to the branch-level analysis, I require at least three years of data per bank. Growth rates are again

[14]Results are similar when using the unweighted standard deviation. I also compute dispersion across branches that are not classified as cyber branches or the headquarters branch to address the rising importance of online deposits. Results are shown below.

winsorized at the 1^{st} and 99^{th} percentile in each year. I then take the standard deviation across quarters for each bank-year cell, denoted by $\overline{sd(\Delta deposits_{b,t})}$.

Finally, I use the CRA data on small business loans to construct the growth rate in amounts and originations at the bank-county-year level, as well as the share of small business lending by bank b in county c out of total small business lending in county c in year t. To account for outliers, I winsorize growth rates at the 1^{st} and 99^{th} percentile in each year.

3.2 Descriptive statistics

The bank-year sample comprises 8,996 unique banks over a period from 1995 to 2019. Table 1 shows that for the average bank, diversification equals 0.615, with a standard deviation of 0.22. It has increased steadily over time, from less than 0.5 in 1994 to over 0.63 in 2019. The mean of the standard deviation in deposit growth rates across branches equals 0.12. The standard deviation in deposit growth over time averages 4.1%. The average rate on CDs (ie, time deposits) is 1.54%, compared to 0.74% for money market accounts (ie, savings deposits). Liquidity creation equals 7.3% of total assets for the average bank.

4 Diversification and funding stability

This section first explains the empirical strategy to analyze the link between diversification and funding stability. In particular, it discusses the instrumental variable strategy. It then reports results and investigates alternative explanations.

4.1 Empirical strategy and identification

Figure 1 previews the effects of geographic diversification on funding stability. It provides a binned scatter plot at the bank-year level. In panel (a) the vertical axis shows the standard deviation in deposit growth rates across branch counties. The horizontal axis shows banks' geographic diversification of deposits. Greater diversification is associated with higher dispersion in branch-level deposit growth rates for a given bank. In panel (b), the vertical axis shows the standard deviation of each banks' deposit growth rate over time, while the horizontal axis again shows diversification. Diversification has a negative correlation with the volatility in banks' deposit growth rates over time, suggesting more stable funding among diversified banks.

Ordinary least squares regressions. To investigate the effects of banks' geographic diversification on funding stability, I estimate regressions at the bank-year level:

$$y_{b,t} = \beta \; diversification_{b,t} + controls_{b,t} + \theta_b + \tau_t + \varepsilon_{b,t}. \tag{2}$$

The dependent variable $y_{b,t}$ denotes either bank b's standard deviation of deposit growth rates *across branches* in each year ($sd(\Delta deposits)_{b,t}$); or the standard deviation of the deposit growth rate *over time* ($\overline{sd(\Delta deposits)_{b,t}}$). Geographic diversification is defined in Equation (1). Since bank size has been shown to be correlated with geographic diversification, all regressions control for the log of banks' total assets. Other yearly bank-level controls include the share of wholesale funding out of total liabilities, the share of non-interest income, return on assets, securities over assets, and the equity ratio. Bank fixed effects are denoted by θ_b and year fixed effects by τ_t. In robustness tests, the regression also includes HQ state*year fixed effects to account for unobservable trends within each bank's HQ state. Standard errors are clustered at the bank level.

Based on the hypotheses developed in Section 2, for $sd(\Delta deposits)_{b,t}$ we expect $\beta > 0$: a bank with greater diversification should see greater dispersion (implying lower correlation) in deposit growth rates across its branches. And we expect $\beta < 0$ for $\overline{sd(\Delta deposits)_{b,t}}$: more diversified banks should have a lower volatility of deposit growth rates over time.

Instrumental variable strategy. Geographic diversification is based on the distribution of deposits across branches, but banks' deposit shares are potentially endogenous to unobservable bank or county characteristics. For example, banks that have more stable funding to begin with could use it to finance their geographic expansion, leading to reverse causality. Alternatively, more ardent adoption of information technology could lead to branch closures and changes in deposit dynamics. Another concern is measurement error. For example, differences across banks in how they assign online deposits to individual branches could lead to mis-measured county-level deposit shares and thereby a downward bias in OLS estimates (Pancost and Schaller, 2022).

To address these identification concerns and establish causality, I build on Goetz et al. (2013, 2016) and Levine et al. (2021) and develop an instrumental variable. It is based on deposit shares predicted with a gravity model of bank expansion and an index of staggered interstate banking deregulation. I first estimate the following 'zero stage' regression to predict deposit shares:

$$deposit\ share_{b,c,t} = \gamma_1\ ln(distance_{B,c}) + \gamma_2\ ln\left(\frac{population_{c,t}}{population_{B,t}}\right) + \epsilon_{b,c,t}, \quad (3)$$

where b denotes bank, B the bank headquarters county, and c the destination (branch) county. The dependent variable is share of deposits of bank b in county c, $\frac{\text{deposits}_{b,c,t}}{\text{deposits}_{b,t}}$. The variable *ln(distance)* is the distance between the bank headquarters county and the branch county, while $\frac{population_{c,t}}{population_{B,t}}$ measure the size of the branch county relative to the headquarters county. Following Goetz, Laeven and Levine (2016) I use a fractional logit model to estimate Equation (3). It ensures that the predicted deposit share lies between 0 and 1. Denote the resulting predicted deposit share as $\widehat{deposit\ share}_{b,c,t}$.

The gravity model predicts $\gamma_1 < 0$, as the cost of expanding increases in the distance to the HQ county.[15] The underlying argument is that transaction and information costs increase with distance, and so do agency conflicts between the headquarters and branch managers (Demsetz and Strahan, 1997; Acharya et al., 2006; Goetz et al., 2013).[16] A large literature in corporate finance investigates how informational frictions within organizations increase with distance (see, among others, Giroud (2013)). For example, rent-seeking divisional managers want to

[15]The gravity model is also consistent with the structural analyses in Ji et al. (2023) and Oberfield et al. (2024), who show that banks tend to open branches in more populous regions, or in regions that are nearer to the headquarters.

[16]Recent scandals, such as the Wells Fargo cross-selling scandal in 2016, illustrate how branch managers' incentives can deviate from those of the headquarters and lead to agency conflicts within an organization. Another example is the HSBC money laundering scandal in India, in which the HSBC India branch allegedly engaged in wide-spread money laundering activity without the knowledge of its headquarters.

extract extra compensation and over-report their costs (Scharfstein and Stein, 2000; Marin et al., 2024). Brickley et al. (2003) and Berger et al. (2005) argue that greater distance lowers the ability of a bank's headquarters to monitor its subsidiaries and branch managers (see also Liberti and Petersen (2019) for a summary). Similar arguments are presented in Deng and Elyasiani (2008). Building on seminal work by Stein (2002), Levine et al. (2020) show that the costs of communicating soft information within banks increase with distance, as do transaction and monitoring costs (Herpfer et al., 2023; Heitz et al., 2023). For market size, the gravity model predicts $\gamma_2 > 0$, as deposit shares are expected to be higher in relatively larger markets (Ji et al., 2023).

Table 2 reports results for the zero stage regression. In a fractional logit regression, column (1) shows a strong and significant negative effect of distance on banks' deposit share in a given county. Market size enters positively, suggesting that banks hold a higher share of deposits in larger markets. Columns (2)–(5) run OLS regressions and add different fixed effects to assess whether effects are sensitive to unobservable home or host market characteristics. Column (2) first shows that results are similar in OLS and logit regressions. Column (3) adds year fixed effects to account for common trends, while columns (4) and (5) add host state fixed effects and home state fixed effects. Column (6) instead includes home state*host county fixed effects and compares deposit shares by banks located in the same state operating branches in the same 'foreign' county. Accounting for any of these unobservable characteristics does not materially affect the coefficients of interest. For column (6), this result suggests that banks headquartered in state B that are physically closer to branch county c have higher deposit shares in county c than banks headquartered in state B but located farther away from county c.[17]

The gravity model does not take into account that states impose restrictions on entry by out-of-state banks. Rice and Strahan (2010) show that even after de-jure deregulation following the Interstate Banking and Branching Efficiency Act (IBBEA) in 1994, most states used up to four different policy tools to protect domestic banks from outside competition. Over time, states relaxed these constraints

[17] As I show in the Online Appendix (see Table OA1), the estimated effect of distance on deposit shares (in terms of coefficient estimate and R-squared) is similar when I split the sample into different time periods, contrast larger with smaller banks, or focus on branches within a 100 mile radius around the headquarters. Moreover, in all regressions distance explains the lion's share of the variation in deposit shares across regions.

(see the discussion in Section 3.1). The state-level index $deregulation_{s,t}$ captures the extent of branching restrictions in each year. States with a value of zero regulate their banking sector along all four dimensions. States with a value of four are classified as fully deregulated.

Figure 2, panel (a) shows the dynamic process of deregulation across the four dimensions over the sample period. The height of each bar denotes the average value of the index in a year. The shaded areas show the average value for each sub-component of the index, where a value closer to 1 means that more states have deregulated their banking sector for the specific requirement. The average index, as well as the average of its sub-components, steadily increased over time, implying greater deregulation. Panel (b) shows the dispersion in the index across states in each year by providing values for the 25^{th} percentile, the mean, and the 75^{th} percentile. For most of the sample period the inter-quartile range equals 2, indicating substantial variation in the deregulation index across states.

The staggered deregulation index is used to adjust predicted deposit shares obtained from the zero stage regression in Table 2, column (1). I first re-scale the index to lie in the range of $[0, 1]$, where a higher value means a state is more deregulated. I then multiply predicted deposit shares ($\widehat{deposit\ share}_{b,c,t}$) with the deregulation index to obtain the *adjusted deposit share* in each bank-county-year cell.[18] Predicted deposit shares in states with more stringent branching restrictions are hence downward adjusted.[19] In the final step, I recompute diversification according to Equation (1), but based on the adjusted predicted deposit shares.

Although unobservable factors could be correlated with headquarter-branch distance in the gravity model, the cross-state and cross-time variation in branching prohibitions provides a quasi-exogenous change to the ability of banks to enter other states. To build intuition, consider three cases for a bank headquartered in San Francisco County (CA). First, the gravity models predicts a higher deposit share in

[18]If s equals a bank's headquarter state, then $deregulation_{s,t} = 1$, since banks face no restrictions on expanding in their own state.

[19]This adjustment assumes that deposit shares decline linearly with the index. As an alternative, I also predict deposit shares by including the index, as well as its interaction with the distance variable, directly in Equation (3). This specification allows for possible non-linearities. It also accounts for the fact that, unlike in the pre-IBBEA period, deregulation did restrict but not prohibit out-of-state banks from opening branches. The HHI obtained from both methods is highly correlated and results remain qualitatively and quantitatively similar, see Figure OA2 and Table OA9.

Santa Barbara County (CA) than in the further away Los Angeles County (CA). Second, while the gravity model predicts a similar deposit share in two counties outside California that are equally far away from San Francisco, the deregulation adjustment leads to a higher predicted deposit share if the county is in Nevada (average deregulation index of 2.46) vs Oregon (average of 2.11). And third, as the deregulation index varies over time, the predicted deposit share in the same county in Oregon is higher in 2015 (index = 4) than in 2000 (index = 1).

In sum, the instrument exploits two plausibly exogenous sources of variation in the ability of a bank to expand its branch network: first, the geographic distance between the HQ location and the destination branch, and second the staggered removal of interstate bank regulations across states. The identifying assumption is thus that the HHI, constructed from deposit shares predicted with the gravity model and adjusted for the staggered removal of branching restrictions, identifies variation in banks' observed HHI that is plausibly exogenous to other (unobservable) county or bank characteristics.

The predicted variables have a strong correlation with actual deposit shares and the HHI. The correlation between actual and predicted deposit shares at the bank-county-year level is 0.91, and a regression of actual on predicted deposit shares yields an R-squared of 0.83. For the bank-year level HHI, the correlation between actual and predicted values is 0.89, with an R-squared of 0.78.

4.2 Results on funding stability

This section reports results on the link between diversification and funding stability. As discussed, as long as deposit withdrawal shocks are imperfectly correlated across branches, better-diversified banks should have a greater standard deviation (ie, lower correlation) in deposit growth rates *across its branches*. In turn, lower exposure to individual withdrawal shocks at each branch imply the bank should experience less volatile deposit growth *over time*.

Table 3 reports results for Equation (2) and shows a strong positive effect of bank diversification on the standard deviation in deposit growth across banks' branches. Column (1) reports a positive coefficient on *diversification*, significant at the 1% level. Column (2) adds the full set of bank-level control variables. There is only a modest change in the size of the estimated coefficient, suggesting that diversification does not capture other observable bank characteristics. Finally, column (3) adds bank and year fixed effects to account for any unobservable time-invariant bank-level characteristics as well as any common trends. Even when exploiting only within-bank variation, there is a positive and highly significant association between a bank's diversification and its dispersion in deposit growth rates across branches.

Columns (4)–(6) report 2SLS results for the same specifications. Irrespective of whether one controls just for size (column 4), other bank characteristics (column 5), or bank and year fixed effects (column 6), greater diversification leads to a significant increase in the standard deviation of deposit growth rates across branches.[20] The first-stage F-statistics safely exceed 100, so there is no weak instrument problem.[21]

In terms of magnitude, an increase in diversification (which ranges from zero to one) by one standard deviation (0.22 units) leads to an increase in the standard deviation of deposit growth rates across branches of 4.5 basis points in column (6). This increase corresponds to 38% of the mean and 45% of the standard deviation of the dependent variable.

The results in Table 3 suggest that greater diversification leads to lower exposure to local withdrawal shocks. Does lower correlation in growth rates across branches translate into lower volatility in bank deposits over time? Table 4 uses the standard deviation of the deposit growth rate *over time* ($\overline{sd(\Delta deposits)_{b,t}}$) as dependent variable and shows that the answer is yes. Column (1) shows a negative and statistically significant association between diversification and the volatility in deposit growth rates at the bank-level. Controlling for bank characteristics in column (2) and including bank and year fixed effects in column (3) confirms this result. Column (4) reports 2SLS results. It shows that diversification has a negative and statistically significant effect on deposit volatility. A one standard deviation increase in diversification reduces the volatility in deposit growth rates over time by 4.8 basis points, or 12% of the mean volatility. Finally, columns (5) and (6) look

[20]Coefficient estimates are larger in magnitude in 2SLS than OLS regressions. This could reflect measurement error in *diversification*, stemming from eg differences across banks in how they assign online deposits to individual branches. Such measurement error leads to a downward bias in OLS regressions (Pancost and Schaller, 2022).

[21]In the Online Appendix, Table OA4 shows that results are robust to the inclusion of bank HQ state*year fixed effects; and to using the IV based on the gravity model that directly includes the deregulation index (see Table OA9).

at the volatility in savings and time deposits separately. Diversification leads to a significant decline in the volatility of both deposit types by a similar magnitude.

Taken together, these results suggest that more diversified banks see greater dispersion in deposit growth rates across branches, reflecting lower exposure to local shocks. They thereby benefit from lower volatility in deposit growth rates over time. These patterns are consistent with greater funding stability.

4.3 Assessing alternative explanations

This section examines competing explanations for the link between diversification and funding stability.

Asset diversification. Diversification on the asset side lowers exposure to idiosyncratic shocks to economic output, reducing credit risk. Levine et al. (2021) show that banks with greater cross-state dispersion of its bank subsidiaries (in terms of total assets) benefit from lower funding costs. Doerr and Schaz (2021) show that banks with a geographically more diversified syndicated loan portfolio are better able to raise funding during times of distress. Gelman et al. (2023) show that greater asset diversification leads to a more stable stream of earnings.

Asset diversification is fundamentally about credit risk. It operates by reducing banks' exposure to idiosyncratic shocks to the quality of its assets (eg mortgages). Deposit diversification is about funding liquidity risk. It reduces banks' exposure to branch-specific shocks to deposit in- and outflows. There is no obvious reason why asset diversification should substantially increase the dispersion in deposit growth rates across branches or lower volatility in deposit growth rates over time. Yet banks' geographic diversification on the asset and liability side could be correlated. I use data on mortgage loans and small business loans (amounts, both origination and purchase) at the bank-county-year level and construct $asset\ diversification_{b,t}$ following Equation (1).

Table 5 shows that deposit diversification still has a significant positive effect on dispersion in growth rates across branches (column 1), and a significant negative effect on the volatility in bank-level overall deposit growth rates (column 2), after controlling for banks' geographic diversification of their loan portfolio. Asset diversification has an economically small effect on deposit volatility across branches and time, compared to deposit diversification, consistent with the argument that asset diversification does not have a direct link to funding stability.

Deposit market power. Building on Drechsler et al. (2017), Li et al. (2023) show that banks with greater deposit market power (DMP) benefit from more stable funding when the Fed funds rate changes.[22] I first compute the variable *Branch HHI* as the sum of squared deposit market shares for all bank branches operating in a given county: $Branch\ HHI_{c,t} = \sum_b \left(\frac{deposits_{b,c,t}}{deposits_{c,t}}\right)^2$. I then use *Branch HHI* to measure banks' deposit market power as $\text{DMP}_{b,t} = \sum_c \frac{\text{deposits}_{b,c,t}}{\text{deposits}_{b,t}} \times \text{Branch HHI}_{c,t}$. The variable measures bank b's average market power in setting deposit rates, where higher values imply that a large share of bank deposits is held in counties with relatively low competition. Note that the correlation between *DMP* and *diversification* is relatively low, with a correlation coefficient of 0.087. Table 5, columns (3)–(4) show that deposit diversification still has a significant positive effect on dispersion in growth rates across branches (column 3) and a significant negative effect on volatility in bank-level deposit growth rates over time (column 4), after controlling for banks' average deposit market power. The negative coefficient on *DMP* in column (4) is in line with Li et al. (2023).

Bank branch density. Benmelech et al. (2023) show that lower bank branch density, defined as the number of bank branches to total deposits, is associated with steeper stock price declines during the banking turmoil of early 2023. Withdrawals of deposits by large depositors (both corporations and tech-savvy households) likely drive the link. Columns (5)–(6) in Table 5 thus control for the number of branches over total deposits of each bank (*branch density*). Results remain unaffected.

Rate setting. If expanding banks improve their ability to set deposit rates at the branch level, they might be better able to smooth local deposit flows. To test for this channel, I use Equation (2) but separate branches into those that are rate set-

[22] Note that the analysis in Li et al. (2023) is about changes in deposit volatility in response to changes in the policy rate, while deposit diversification works through an increase in general funding stability.

ters and those that are followers in the RateWatch dataset. Followers are branches whose deposit rates are determined by a centralized rate-setting policy (Begenau and Stafford, 2023). Table 6 shows that diversification increases dispersion in deposit growth rates across both rate setting and follower branches. Column (1) first replicates the baseline finding for dispersion across all branches (pooling rate setters and followers) for the smaller sample of branches that is covered both in the RateWatch and FDIC data. Columns (2) and (3) report results separately for follower and rate setter branches. For both types, diversification has a positive and highly significant effect on dispersion in deposit growth rates. Columns (4) and (5) confirm this finding in 2SLS regressions. The significant effect of diversification on deposit dispersion among follower branches suggests that the link is not explained by changes in banks' rate setting practices across branches.[23]

Online deposits. Over the last decades, banks have increasingly adopted information technology, leading to a rise in the importance of online deposits. FDIC guidelines instruct banks to allocate online deposits to the branch closest to the depositor location. But anecdotal evidence suggest that banks at times allocate online deposits to so-called cyber branches or their headquarters branch. While the IV addresses measurement error in deposit shares and diversification, a remaining concern is that my measure of dispersion in deposit growth rates across branches could be biased due to differences in accounting for online deposits across banks.

I address this concern in two ways (see Table OA2). First, I re-compute the dispersion in deposit growth rates across branches after dropping the headquarters branch and branches classified as cyber branches. The effect of diversification on the dispersion in deposit growth rates across branches remains positive and economically and statistically significant in OLS and 2SLS regressions (columns 1 and 2). Second, for each bank I compute the share of total deposits held in cyber branches and the headquarter branch in each year. This share proxies for banks' reliance on online deposits, or more broadly for the effects of their adoption of IT/online banking on deposit taking activity. Controlling for the share of online deposits does not affect the size, sign, or significance of the estimated coefficient on diversification in 2SLS regression. It reduces the coefficient size in OLS regressions, but it remains

[23] In addition, columns (1) and (2) in Table OA4 show that there is a small and insignificant effect of diversification on dispersion in time and demand deposit rates across branches.

positive and significant (columns 3–6). The stability of the coefficient in 2SLS regressions, together with the decline in OLS regressions, suggests the following: to the extent that the share of cyber/HQ deposits proxies for unobservable omitted bank characteristics that correlate with diversification, in particular IT adoption, the IV purges my estimation from such confounding factors.

Macroeconomic volatility. My results suggest that the benefits of a diversified branch network go beyond benefits from diversification on the asset side. To further investigate whether deposit diversification enhances banks' overall resilience, I investigate the effects of diversification on deposit volatility over time in Equation (2) during periods of macroeconomic turmoil. I interact *diversification* with three indicator variables that measure macroeconomic conditions: the Chicago Board Options Exchange's CBOE Volatility Index (VIX), a measure of the stock market's expectation of volatility; the Excess Bond Premium (EBP) from Gilchrist and Zakrajšek (2012), a measure of investor sentiment in the corporate bond market and predictor of recessions; and real GDP growth from FRED. For the VIX and EBP I define a dummy that takes on a value of one if the VIX/EBP value lies in the top quartile of the distribution; for GDP growth a dummy that takes on a value of one if it is in the bottom quartile. In other words, a realization of one reflects years of heightened macroeconomic uncertainty or risk.

Table OA3, columns (1)–(3) report OLS results. In each column, more diversified banks have more stable funding in general (negative coefficient on *diversification*). Deposit volatility is relatively lower for diversified banks during periods of macroeconomic turmoil, as indicated by the negative and significant coefficient on the interaction terms. Columns (4)–(6) confirm these results in 2SLS regressions, although coefficients on the interaction terms are generally less precisely estimated.

Number of branches and depositor characteristics. Table OA10, columns (1) and (2) report baseline results on funding stability, but control for the total number of branches of each bank in each year. Results remain similar, suggesting that diversification – ie, the structure of the branch network – matters above and beyond the number of branches. Table OA5 shows that controlling for proxies of banks' average depositor base does not affect results. For each bank-year cell, I compute the weighted exposure to the average county in which a bank raises deposits in terms of income per capita, the share of the population of age 65 and above, and the share of the population with a bachelor degree or higher. Weights are given by local deposit shares. These characteristics have been shown to correlate with depositor behavior.

4.4 Funding costs

Geographic diversification reduces banks' exposure to deposit withdrawals. As withdrawal shocks could lead to losses among investors, the funding stability channel could provide a complementary explanation for why geographic diversification reduces bank risk (Goetz et al., 2016) and funding costs (Levine et al., 2021).

To investigate the link between deposit diversification and funding costs, I use granular data on deposit rates at the branch level and estimate bank-county-quarter regressions:

$$rate_{i(b,c),t} = \delta \; diversification_{b,t} + controls_{b,t} + \iota_i + \theta_b + \tau_{c,t} + \varepsilon_{i,t}. \tag{4}$$

The dependent variable is the average deposit rate on savings or time deposits offered by branch i, belonging to bank b and located in county c, in quarter t. Diversification is defined in Equation (1), and bank-level controls include the log of total assets, the share of non-interest income, return on assets, ratio of total securities over total assets, and the equity ratio. Standard errors are clustered at the bank level. If diversification reduces bank risk, we expect $\delta < 0$. Note that it is not necessary for local branches to set rates independently or have market power in local deposit markets. Lower funding risk should benefit the bank as a whole and hence operate across branches.

A benefit of the disaggregated bank-county level analysis is that I can include granular fixed effects. Branch county*year fixed effects ($\tau_{c,t}$) account for any unobservable time-varying factors that vary at the county level and could affect deposit rates, such as deposit market concentration, income growth, or investment opportunities. In addition, these fixed effects rules out that effects are driven by diversified banks operating branches in counties with more stable deposit flows. Regressions with branch fixed effects (ι_i) exploit within-branch variation. This addresses the concern that banks expand because of lower funding costs.

Table 7 shows that higher diversification decreases deposit rates at the branch level. Columns (1)–(3) use deposit rates on savings deposits as dependent variable. Column (1), with bank controls as well as bank and year fixed effects, shows that in OLS regressions, diversification is negatively correlated with rates on savings deposits. The coefficient is significant at the 1% level. Controlling for branch county*time fixed effects and branch fixed effects in column (2) does not change this pattern, suggesting that the change in rates is not explained by local deposit market power.[24] A 2SLS regression in column (3) confirms this pattern. The coefficient is less precisely estimated but similar in magnitude.

Similar patterns are obtained for rates on time deposits in columns (4)–(6). OLS regressions without and with branch and county*year fixed effects show a negative significant coefficient on diversification (columns 4 and 5). Moreover, the 2SLS regression in column (6) yields a negative coefficient significant the 5% level. In column (6), a one standard deviation increase in diversification (0.22 units) reduces the interest rate on time deposits by 3.2 basis points. For savings deposits in column (3), the respective decline is 4.1 basis points.

These results are consistent with the interpretation that greater geographic diversification reduces bank risk – and thus benefits banks through lower funding costs. While similar results are obtained in Levine et al. (2021), they highlight how bank diversification on the asset side, which reduces exposure to idiosyncratic shocks and thus credit risk, lowers deposit rates. My results instead show that greater diversification of a bank's deposit base, which increases funding stability, reduces banks' funding costs.

5 Diversification, liquidity creation, and lending

A core function of banks is liquidity creation (Berger and Bouwman, 2009). They combine stable money creation on the liability side with assets that have relatively long-run cash flows (Strahan, 2008). Bank deposits represent a uniquely stable and dependable source of funding that cannot be easily replaced with wholesale funding (Stein, 1998; Kashyap et al., 2002; Hanson et al., 2015). A large literature conse-

[24]Further ruling out banks' market power as an explanatory factor, Table OA6 shows that results remain identical when I control for each bank's share in total county deposits.

quently investigates how deposits and funding stability matter for banks' ability to engage in maturity transformation and liquidity creation.[25] What is absent from the literature is an investigation of the effects of geographic diversification of banks' deposit base on liquidity creation.

5.1 Liquidity creation

Table 8 shows that greater geographic diversification of banks' deposit base – which the previous sections have shown to reduce funding volatility and costs – allows banks to create more liquidity on their asset side. I estimate variations of Equation (2) with different outcome variables. All regressions report 2SLS results.

Column (1) uses the Berger and Bouwman (2009) asset liquidity creation measure and shows that greater diversification leads to significantly more liquidity creation. The estimated coefficient is large in economic magnitude: a one standard deviation increase in diversification (0.22 units) increases liquidity creation over assets by 1.2 percentage points, relative to a mean liquidity creation of 7.7% of banks' total assets.

Unpacking the measure, column (2) shows that the effect of diversification on banks' C&I loan growth (illiquid) is greater than its effect on real estate loan growth (column 3, semi-liquid) and much greater than its (insignificant) effect on growth in security holdings (column 4, liquid). This relative ordering is consistent with increased liquidity creation by more diversified banks.[26]

[25] Gatev et al. (2009) show that transactions deposits help banks hedge liquidity risk from unused loan commitments, especially during periods of tight liquidity. Exploiting quasi-experimental variation in liquidity risk, Choudhary and Limodio (2022) shows that banks with a stronger exposure to liquidity risk lower their supply of long-term finance. Focusing on banks' deposit market power, Li et al. (2023) provide similar evidence: deposit market power enhances banks' funding stability, allowing them to extend loans with longer maturity. Exploiting a tax reform that induced households to substitute bank bonds with deposit, Carletti et al. (2021) show that a greater reliance on deposits leads to an increase in long-term loans. Drechsler et al. (2017) further show that deposit outflows, and in particular time deposit outflows (Supera, 2022), lead to a decline banks' small business lending, which is inherently risky and illiquid. This list is far from exhaustive. See Strahan (2008) for a survey on the relation between deposits and liquidity creation; and Calomiris and Jaremski (2016) for a survey with a focus on deposit insurance.

[26] Table OA8 further shows that diversification increases the share of loans over assets by more for loans with a maturity of five years or more, relative to loans with a maturity of one to five years or those with a maturity of one year or less. This is, diversified banks do more maturity transformation.

The Online Appendix examines the robustness of the link between deposit diversification and liquidity creation. Table OA7 shows that the effect of diversification on liquidity creation (and the relative effect on its sub-components) is robust to controlling for banks' assets side diversification, deposit market power, or branch density. Table OA10, columns (3)–(6) show that it is robust to controlling for the number of branches. Moreover, columns (5)–(8) in Table OA4 show that the results remain unaffected by the inclusion of bank HQ state*year fixed effects that account for eg changes in state-level bank regulation or state-level shocks to deposits.

5.2 Small business lending

To further shed light on the link between diversification and bank lending, I use granular data on small business lending at the bank-county-year level. As discussed in Drechsler et al. (2017) and Supera (2022), among others, small business lending is inherently risky and illiquid. It is usually retained on balance sheet and dependent on banks' access to deposits. It thus benefits from stable and cheaper deposit funding. I estimate the following regression:

$$\Delta\ lending_{b,c,t} = \kappa\ diversification_{b,t} + controls_{b,t} + \tau_{c,t} + \varepsilon_{i,t}. \quad (5)$$

The dependent variable is the growth rate of small business lending by bank b in county c in year t. Diversification is defined in Equation (1), and bank-level controls include the log of total assets, the share of non-interest income, return on assets, ratio of total securities over total assets, and the equity ratio. Standard errors are clustered at the bank level. We expect that $\kappa > 0$.

Exploring the diversification-lending nexus with granular bank-county data offers two advantages. First, I can exclude all branch counties to avoid any effects of shocks that affect both banks' local deposit growth and investment opportunities in counties where they have branches.[27] Excluding branch counties also precludes that results are driven by banks' informational advantage in counties where they operate branches (Agarwal and Hauswald, 2010). Second, the rich data set allows me to saturate models with county*year fixed effects ($\tau_{c,t}$), thus removing confounding

[27]Excluding branch counties reduces the number of observations by around 25%. Results remain qualitatively similar when including branch counties.

demand effects. Conceptually, the analysis compares growth rates in small business lending in the same county and year for two banks with different levels of diversification.

Table 9 shows that greater diversification leads to a significant increase in banks' small business lending. For loan amounts, column (1) reports a positive and significant coefficient on *diversification*, conditional on bank controls and year fixed effects. Including county*year fixed effects that account for unobservable time-varying county-level factors, including demand effects, leads only to a small change in the coefficient size in column (2).[28] IV regressions without and with county*year fixed effects in columns (3) and (4) confirm this finding: higher diversification leads to higher growth in banks' small business lending.

Columns (5)–(7) yield similar results for alternative dependent variables. Column (5) uses the log of the loan amount as dependent variable; column (6) bank b's share out of total small business lending in a county; and column (7) the growth in the number of originations (rather than total amounts). Across all specifications, diversification has an economically and statistically significant positive impact on lending. The impact of diversification on small business lending remains positive and significant when controlling for banks' assets side diversification, deposit market power, or branch density (see Table OA7, column 5).

Taken together, these patterns suggest that an increase in banks' geographic diversification leads to a causal increase in banks' liquidity creation and small business lending – arising from more stable funding and cheaper funding costs.

5.3 Real effects

A large literature has established that credit supply shocks affect firm formation and growth, especially for small firms and firms that cannot substitute bank funding with financing from alternative sources. This section analyses whether increased liquidity creation, and especially small business lending, by diversified banks has real effects. I use data on firm growth from the Business Dynamic Statistics. I

[28]The minor change in coefficient size despite a substantial increase in the R^2 suggests that the correlation between diversification and observable or unobservable time-varying county characteristics is low, reducing potential concerns about self-selection and omitted variable bias (Altonji et al., 2005; Oster, 2019).

focus on two proxies for bank dependent firms. First, I classify industries as more or less dependent on bank lending. Second, I contrast larger with smaller firms, as the latter are generally more bank-dependent.

I estimate the following regressions at the county-industry-year level, where industry denotes the 2-digit NAICS industry level,

$$\begin{aligned}\Delta\ \mathit{firms}_{c,i,t} = \rho_1\ \mathit{div.\ exposure}_{c,t} + \rho_2\ \mathit{bank\ dependence}_i \\ + \rho_3\ \mathit{div.\ exposure}_{c,t} \times \mathit{bank\ dependence}_i + \theta_{c,i} + \tau_t + \varepsilon_{c,i,t},\end{aligned} \tag{6}$$

as well as at the county-firm size-year level:

$$\begin{aligned}\Delta\ \mathit{firms}_{c,s,t} = \rho_4\ \mathit{div.\ exposure}_{c,t} + \rho_5\ \mathit{small}_s \\ + \rho_6\ \mathit{div.\ exposure}_{c,t} \times \mathit{small}_s + \theta_{c,s} + \tau_t + \varepsilon_{c,s,t}.\end{aligned} \tag{7}$$

The dependent variable is the log difference in the number of firms in county c between year t and $t-1$.[29] The variable *div. exposure* is county c's exposure to diversified banks, measured via each banks' deposit market share in each county interacted with its diversification value. In particular, $\mathit{div.\ exposure}_{c,t} = \sum_b \frac{\mathit{deposits}_{b,c,t}}{\mathit{deposits}_{c,t}} \times diversification_{b,t}$, where $\mathit{deposits}_{b,c}$ and $\mathit{deposits}_c$ denote bank b's deposits in county c and total county deposits in year t. *Bank dependence* measures industry i's bank dependence in the 2007 Survey of Business Owners (SBO). The firm-level micro survey contains firms' sources of business start-up and expansion capital, as well as their two-digit NAICS industry codes. For each industry I compute the share of firms that report using bank loans to start or expand their business.[30] Finally, the dummy *small* takes on a value for firms with 19 or fewer employees (the smallest available breakdown). Standard errors are clustered at the county level.

A potential concern to identification is that unobservable county-level characteristics could be correlated with diversification exposure and affect firm growth. These could include, for example, changes in income, unemployment, or migration.

[29] I obtain similar results for the log difference in employment (unreported). However, the number of firms likely better captures changes among small firms compared to employment, as employment dynamics can be dominated by a few large companies.

[30] The share of bank dependent firms ranges from 9.4% in Educational Services (NAICS code 61) to 55.6% in Management of Companies and Enterprises (NAICS code 55). Other industries with high bank dependence are Manufacturing, Wholesale Trade, and Accommodation and Food Services. Figure OA3 provides a detailed breakdown by industry.

To absorb such unobservable shocks, I include county*year fixed effects. Note that these fixed effects absorb the coefficient on *div. exposure*.

Table 10 reports results. It first examines the effect of diversification on firms in more or less bank-dependent sectors. The intuition is that the effect of diversification-induced changes in lending should have a larger impact on sectors more dependent on banks. Column (1) shows that firm growth is higher in bank-dependent industries in counties with higher diversification exposure, conditional on county*NAICS and year fixed effects. The estimated coefficients are significant at the 1% level. This results is robust to the inclusion of county*time fixed effects in column (2). To further address the concern that local economic conditions could affect job creation in more or less bank-dependent industries differentially, column (3) focuses on tradable industries, which are not subject to local demand. It reports similar results.[31] In terms of magnitude, for a given level of county exposure to diversified banks, industries with the lowest bank dependence see 1.7 percentage point lower growth in the number of firms compared to those with the highest dependence.

Columns (4) and (5) report results for the size breakdown, building on the established finding that smaller firms are more bank-dependent than larger firms. Column (4) shows that firm growth is relatively higher among smaller firms in counties where diversified banks have a larger footprint. The coefficient on the interaction term is significant at the 1% level. Again, including county*time fixed effects does not materially affect this results in column (5).

These results suggest that the positive effects of greater geographic diversification on liquidity creation and bank lending benefit the real economy.

6 Conclusion

This paper has shown that greater geographic diversification of banks' deposit base increases the dispersion in deposit growth rates *across branches* of the same bank, but reduces banks' volatility in deposit growth rates *over time*. Subsequently, banks' funding cost declines. These patterns are consistent with diversification improving

[31] I rely on the classification of 4 digit industries intro tradable and non-tradable by Mian and Sufi (2014), aggregated to the 2 digit level.

funding stability and lowering bank risk. By enhancing funding stability, diversification allows banks to engage in more liquidity creation and small business lending, thereby stimulating economic activity.

The main contribution of this paper is to propose and test a novel channel through which diversification benefits banks and the real economy. Previous work has predominately focused on how diversification on the asset side reduces bank exposure to idiosyncratic shocks to economic output and thus credit risk, and how it thereby improves banks' access to financing and lowers bank funding costs and risk (Goetz et al., 2016; Doerr and Schaz, 2021; Levine et al., 2021; Gelman et al., 2023). This paper is the first to show that the funding stability channel plays an important role in assessing the benefits of geographic diversification.

My paper also highlights an additional role of banks' branch network. Branches allow lenders to mitigate contracting frictions (Gilje et al., 2016), especially in small business lending (Agarwal and Hauswald, 2010). The decline in the number of branches, in part driven by the rise of IT, may hence be detrimental to small and informationally opaque firms (Nguyen, 2019; Jiménez et al., 2022; Amberg and Becker, 2024). My findings show that a diversified branch network helps banks reduce their funding liquidity risk, with positive effects on lending and economic activity, especially for smaller firms.

Overall, these findings have implications for the discussion on ongoing structural changes in the banking sector. The steady decline in the number of branches could imply greater funding liquidity risks among banks – with implications for financial stability – and local branch closures could harm small businesses. At the same time, as long as bank consolidation goes hand in hand with geographic expansion, greater diversification can offset at least some of the these negative effects.

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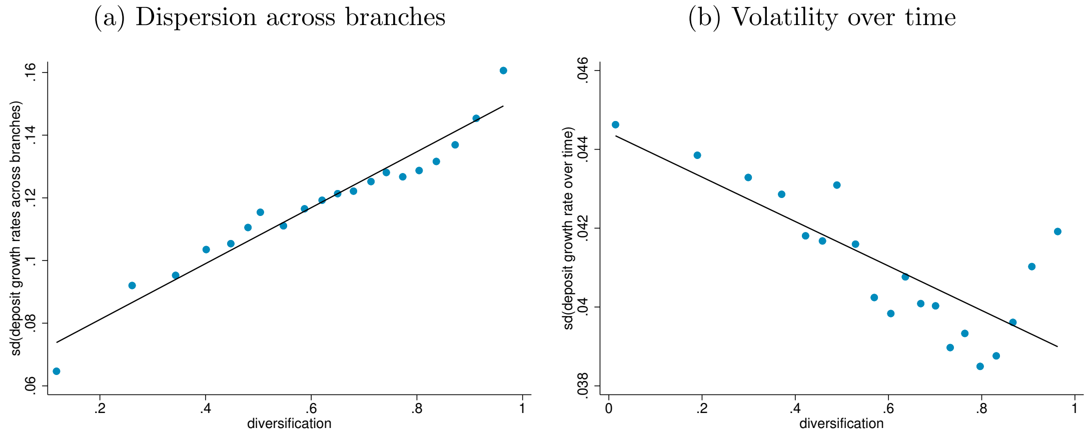
A Figures and tables

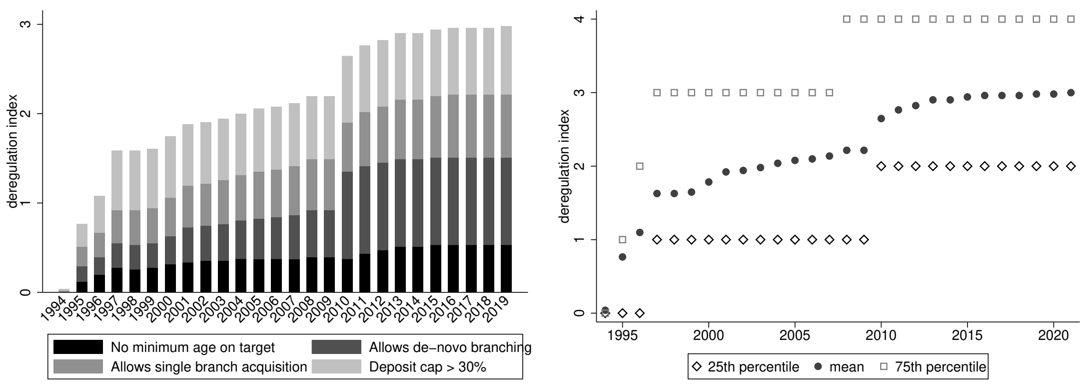
Figure 1: **Diversification and funding stability**



Panel (a) provides a binned scatter plot at the bank-year level. The vertical axis shows the standard deviation in deposit growth rates across branches. The horizontal axis shows banks' geographic diversification of deposits across counties, as defined in Equation (1). Panel (b) provides a binned scatter plot at the bank-year level. The vertical axis shows the standard deviation in each banks' deposit growth rate over time. The horizontal axis shows banks' geographic diversification of deposits across counties, as defined in Equation (1).

Figure 2: **Banking deregulation index**

(a) Components over time (b) Variation across states



Panel (a) shows the evolution of the four components of state-level deregulation index over the sample period. Panel (b) shows the 25th percentile, mean, and 75th percentile of the deregulation index across states in each year.

Table 1: **Summary statistics**

Variable	Obs	Mean	Std. Dev.	Min	Max	P50
diversification	112304	.615	.22	0	.999	.637
sd(Δ deposits)	112304	.118	.099	0	.704	.093
$\overline{\text{sd}(\Delta\text{deposits})}$	112291	.041	.033	.003	.271	.032
$\overline{\text{sd}(\Delta\text{time dep})}$	112264	.051	.047	.003	.383	.036
$\overline{\text{sd}(\Delta\text{sav dep})}$	112224	.077	.067	.006	.475	.056
LC/assets	91260	.073	.135	-.335	.402	.079
Δ CI	109964	.072	.25	-.89	1.727	.061
Δ RE	71212	.11	.165	-.605	1.75	.088
Δ sec	110986	.044	.268	-1.356	1.652	.027
CD rate	66141	1.539	1.311	.001	5.65	1.105
MM rate	66141	.742	.761	.003	5.58	.45
log(assets)	112304	12.412	1.264	8.663	21.573	12.225
deposit ratio	112304	.928	.079	.014	1	.951
non-interest income	112304	.13	.089	0	.651	.112
securities/assets	112304	.221	.135	0	.686	.203
return on assets	112304	.002	.002	-.01	.008	.002
equity ratio	112304	.103	.029	.056	.339	.097

This table reports summary statistics for variables at the bank-year level.

Table 2: **Gravity equation**

VARIABLES	(1) logit dep share	(2) OLS dep share	(3) OLS dep share	(4) OLS dep share	(5) OLS dep share	(6) OLS dep share
log(distance)	-0.773***	-0.114***	-0.113***	-0.115***	-0.121***	-0.139***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(pop ratio)	0.267***	0.012***	0.012***	0.014***	0.014***	0.015***
	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	546,391	546,391	546,391	546,391	546,391	545,793
R-squared		0.629	0.630	0.647	0.661	0.740
Year FE	-	-	✓	✓	✓	✓
Home State FE	-	-	-	✓	✓	-
Host State FE	-	-	-	-	✓	-
Home State*Host County FE	-	-	-	-	-	✓

This table shows results for Equation (3) at the bank-county-year level. The dependent variable is the deposit share of bank b in county c (out of total bank deposits). *log(distance)* denotes log of one plus the distance between the bank headquarters county and bank branch county. *log(population ratio)* is the log ratio of host (bank branch) to home (bank HQ) county population. Column (1) runs a fractional logit model. Columns (2)–(5) run OLS specifications and add various fixed effects. Standard errors are robust. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: **Diversification and dispersion in branch deposit growth**

VARIABLES	(1) sd(Δ deposits)	(2) sd(Δ deposits)	(3) sd(Δ deposits)	(4) 2SLS sd(Δ deposits)	(5) 2SLS sd(Δ deposits)	(6) 2SLS sd(Δ deposits)
diversification	0.077***	0.072***	0.077***	0.095***	0.085***	0.204***
	(0.003)	(0.002)	(0.006)	(0.007)	(0.007)	(0.023)
Observations	113,073	113,050	112,304	113,073	113,050	112,304
R-squared	0.041	0.071	0.394			
Controls	-	✓	✓	-	✓	✓
Bank FE	-	-	✓	-	-	✓
Year FE	-	-	✓	-	-	✓
F stat				1586	1593	727.3

This table reports results for Equation (2) at the bank-year level. The dependent variable is the standard deviation in deposit growth rates across branches. *Diversification* is banks' geographic diversification of deposits across counties, as defined in Equation (1). Columns (4)–(6) instrument *diversification* with the IV based on the gravity-deregulation model (see Equation (3)). Standard errors are clustered at the bank level. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: **Diversification and volatility of bank deposit growth**

VARIABLES	(1) sd(Δdeposits)	(2) sd(Δdeposits)	(3) sd(Δdeposits)	(4) 2SLS sd(Δdeposits)	(5) 2SLS sd(Δsav dep)	(6) 2SLS sd(Δtime dep)
diversification	-0.010***	-0.009***	-0.013***	-0.022***	-0.032***	-0.028***
	(0.001)	(0.001)	(0.002)	(0.007)	(0.011)	(0.009)
Observations	117,821	117,800	117,176	117,176	117,054	117,119
R-squared	0.004	0.022	0.345			
Controls	-	✓	✓	✓	✓	✓
Bank FE	-	-	✓	✓	✓	✓
Year FE	-	-	✓	✓	✓	✓
F stat				756.6	751.9	754.8

This table reports results for Equation (2) at the bank-year level. The dependent variable is the standard deviation in deposit growth rates over time in columns (1)–(4). It is the standard deviation in growth rates of demand and time deposits over time in columns (5) and (6). *Diversification* is banks' geographic diversification of deposits across counties, as defined in Equation (1). Columns (4)–(6) instrument *diversification* with the IV based on the gravity-deregulation model (see Equation (3)). Standard errors are clustered at the bank level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 5: **Asset diversification, deposit market power, and bank branch density**

	(1)	(2)	(3)	(4)	(5)	(6)
	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
VARIABLES	sd(Δ deposits)	sd(Δdeposits)	sd(Δ deposits)	sd(Δdeposits)	sd(Δ deposits)	sd(Δdeposits)
diversification	0.150***	-0.049***	0.150***	-0.049***	0.150***	-0.051***
	(0.030)	(0.013)	(0.030)	(0.013)	(0.030)	(0.013)
diversification (HMDA/CRA)	0.010***	0.003**	0.010***	0.003**	0.010***	0.003**
	(0.003)	(0.001)	(0.003)	(0.001)	(0.003)	(0.001)
DMP			0.001	-0.007	0.001	-0.007
			(0.018)	(0.006)	(0.018)	(0.006)
branch density					-0.000	-0.000
					(0.000)	(0.000)
Observations	52,868	53,798	52,868	53,798	52,868	53,798
Controls	✓	✓	✓	✓	✓	✓
Bank FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
F stat	451.3	439.5	453	441.1	452.7	439.6

This table reports results for Equation (2) at the bank-year level, where the dependent variable is the standard deviation in deposit growth rates across branches in columns (1), (3), and (5); and the standard deviation in deposit growth rates over time in columns (2), (4), and (6). *Diversification* is banks' geographic diversification of deposits across counties, as defined in Equation (1), instrumented with the IV based on the gravity-deregulation model (see Equation (3)). *Diversification (HMDA/CRA)* is banks' geographic diversification of mortgage and small business loans across counties. *DMP* is banks' deposit market power, as defined in Drechsler et al. (2017). *Branch density* is banks' bank branch density (total branches/total deposits), as defined in Benmelech et al. (2023). Standard errors are clustered at the bank level. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: **Diversification and dispersion in branch deposit growth – rate setters vs non-rate setter**

VARIABLES	(1) sd(Δ deposits)	(2) sd(Δ deposits non-RS)	(3) sd(Δ deposits RS)	(4) 2SLS sd(Δ deposits non-RS)	(5) 2SLS sd(Δ deposits RS)
diversification	0.076***	0.084***	0.072***	0.267***	0.169***
	(0.008)	(0.012)	(0.015)	(0.039)	(0.046)
Observations	83,279	46,697	30,031	46,697	30,031
R-squared	0.458	0.396	0.476		
Controls	✓	✓	✓	✓	✓
Bank FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
F stat				361.2	237.8

This table reports results for Equation (2) at the bank-year level. The dependent variable is the standard deviation in deposit growth rates across all branches in column (1), across all branches that are not rate setters in columns (2) and (4), and across all branches that are rate setters in columns (3) and (5). *Diversification* is banks' geographic diversification of deposits across counties, as defined in Equation (1). Columns (4)–(5) instrument *diversification* with the IV based on the gravity-deregulation model (see Equation (3)). Standard errors are clustered at the bank level. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: **Diversification and funding costs**

VARIABLES	(1) MM rate	(2) MM rate	(3) 2SLS MM rate	(4) CD rate	(5) CD rate	(6) 2SLS CD rate
diversification	-0.231***	-0.208***	-0.187	-0.137***	-0.101***	-0.146**
	(0.059)	(0.066)	(0.148)	(0.042)	(0.037)	(0.072)
Observations	432,176	369,040	369,040	432,176	369,040	369,040
R-squared	0.716	0.864		0.904	0.968	
Controls	✓	✓	✓	✓	✓	✓
Bank FE	✓	✓	✓	✓	✓	✓
Year FE	✓	-	-	✓	-	-
Branch FE	-	✓	✓	-	✓	✓
County*Year FE	-	✓	✓	-	✓	✓
F stat			402.3			402.3

This table reports results for Equation (4) at the branch-year level. The dependent variable is the average deposit rate on demand deposits in columns (1)–(3) and on time deposits in columns (4)–(6). *Diversification* is banks' average geographic diversification of deposits across counties, as defined in Equation (1). Columns (3) and (6) instrument *diversification* with the IV based on the gravity-deregulation model (see Equation (3)). Standard errors are clustered at the bank level. *** p<0.01, ** p<0.05, * p<0.1.

Table 8: **Diversification and liquidity creation**

VARIABLES	(1) 2SLS LC/assets	(2) 2SLS Δ CI	(3) 2SLS Δ RE	(4) 2SLS Δ sec
diversification	0.053***	0.277***	0.172***	-0.050
	(0.009)	(0.044)	(0.040)	(0.045)
Observations	95,507	114,685	74,563	115,725
Controls	✓	✓	✓	✓
Bank FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
F stat	598.2	759.9	425.1	768.7

This table reports results for Equation (2) at the bank-year level. The dependent variable is the Berger and Bouwman (2009) measure of liquidity creation in column (1); and the growth in total C&I lending, real estate lending, and securities in columns (2), (3), and (4). *Diversification* is banks' geographic diversification of deposits across counties, as defined in Equation (1), instrumented with the IV based on the gravity-deregulation model (see Equation (3)). Standard errors are clustered at the bank level. *** p<0.01, ** p<0.05, * p<0.1.

Table 9: **Diversification and small business lending**

VARIABLES	(1) Δ amt	(2) Δ amt	(3) 2SLS Δ amt	(4) 2SLS Δ amt	(5) 2SLS log(amt)	(6) 2SLS share	(7) 2SLS Δ nr
diversification	0.780***	0.793***	1.017***	1.040***	0.636**	0.038***	0.379**
	(0.192)	(0.195)	(0.206)	(0.210)	(0.322)	(0.004)	(0.185)
Observations	502,232	501,162	502,232	501,162	500,822	501,162	501,162
R-squared	0.012	0.097					
Controls	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	-	✓	-	-	-	-
County*Year FE	-	✓	-	✓	✓	✓	✓
F stat			166.1	154.4	154.1	154.4	154.4

This table reports results for Equation (5) at the bank-county-year level. The dependent variable is the growth rate in total small business lending in columns (1)–(4); the log of the total loan amount in column (5); bank b's share of total small business lending in a county in column (6); and the growth rate in the number of small business loans in column (7). *Diversification* is banks' geographic diversification of deposits across counties, as defined in Equation (1). Columns (3)–(7) instrument diversification with the IV based on the gravity-deregulation model (see Equation (3)). The analysis excludes all counties in which a bank operates branches. Standard errors are clustered at the bank level. *** p<0.01, ** p<0.05, * p<0.1.

Table 10: **Real effects**

VARIABLES	(1) Δ firms	(2) Δ firms	(3) tradable Δ firms	(4) Δ firms	(5) Δ firms
div exposure	-0.017***			-0.002	
	(0.002)			(0.002)	
div exposure × bank dependence	0.063***	0.058***	0.038***		
	(0.008)	(0.009)	(0.010)		
div exposure × small				0.008***	0.009***
				(0.002)	(0.002)
Observations	1,085,781	1,085,594	861,235	224,279	223,797
R-squared	0.035	0.112	0.127	0.083	0.341
County*NAICS FE	✓	✓	✓	-	-
County*Size FE	-	-	-	✓	✓
Year FE	✓	CY	CY	✓	CY

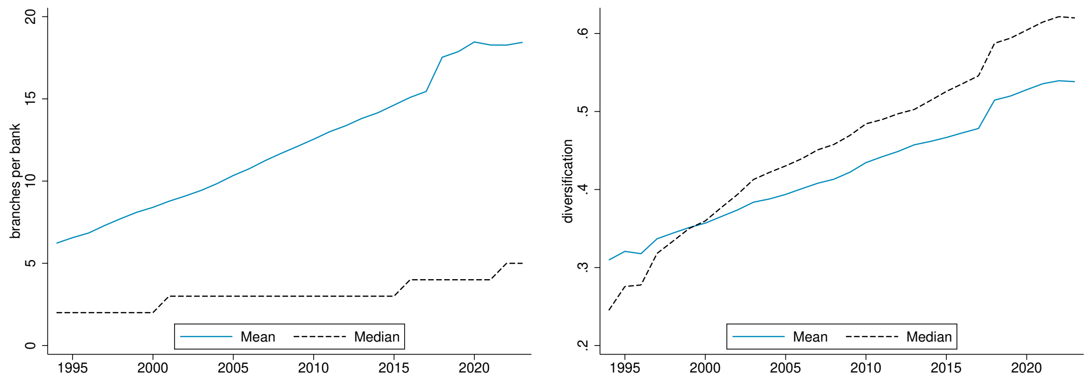
This table reports results for Equations (6) and (7) at the county-sector-year and county-firm-size year level, respectively. The dependent variable is the log difference in the number of firms. The variable *div exposure* is a county's exposure to diversified banks, measured via each banks' deposit market share in each county interacted with its diversification value. *Bank dependence* measures each industry's bank dependence from the 2007 Survey of Business Owners. The dummy *small* takes on a value for firms with 19 or fewer employees. CY denotes county*year fixed effects. Standard errors are clustered at the county level. *** p<0.01, ** p<0.05, * p<0.1.

B Online Appendix

Figure OA1: **Branches per bank and diversification over time**

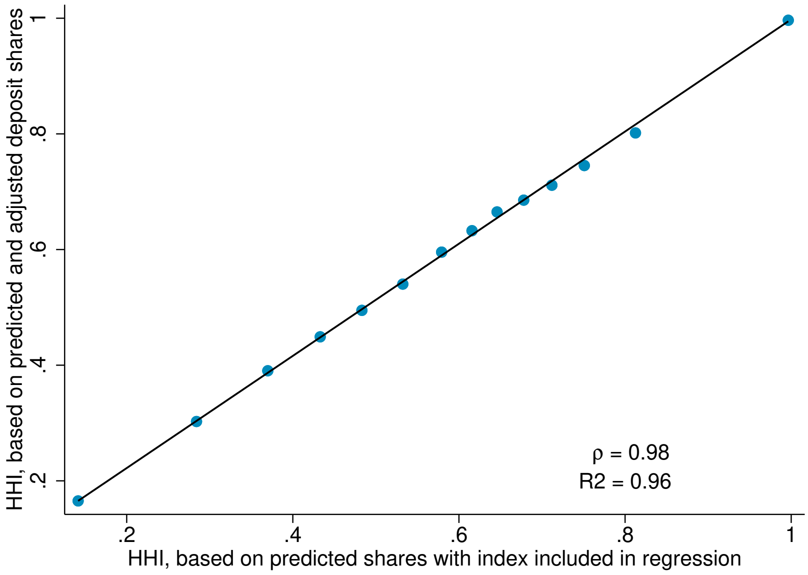
(a) Branches per bank

(b) Diversification



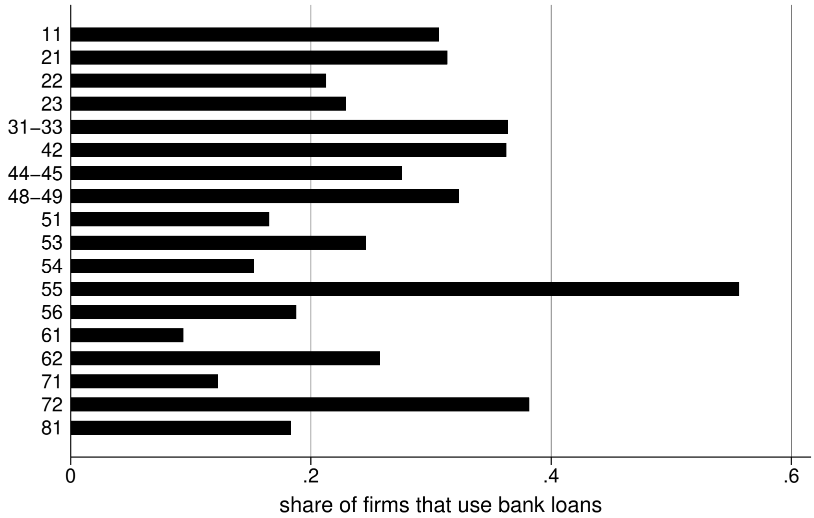
Panel (a) shows the average and median number of branches per bank for the universe of banks and branches in the FDIC SOD data. Panel (b) shows the average and median value of diversification (as defined in Equation (1)) for the universe of banks and branches in the FDIC SOD data.

Figure OA2: **HHI – different zero-stage specifications**



This figure shows the HHI computed from predicted deposit shares obtained from Equation (3). The y-axis shows the HHI obtained from first predicting deposit shares with a fractional logit model and then adjusting them with the state-level deregulation index. The x-axis shows the HHI obtained from predicting deposit shares with a fractional logit model that directly includes the state-level deregulation index in the regression.

Figure OA3: **Industry bank dependence**



This figure shows the share of firms in each sector that use bank loans to start or expand operations. Source: Survey of Business Owners.

Table OA1: **Gravity equation – robustness**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	gravity	baseline	pre 2008	post 2008	top 4	top 10	top 100	dist < 100 m
VARIABLES	dep share	dep share	dep share	dep share	dep share	dep share	dep share	dep share
log(distance)	-0.773***	-0.801***	-0.750***	-0.852***	-0.851***	-0.897***	-0.910***	-0.785***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.001)
log(pop ratio)	0.267***							
	(0.002)							
Observations	546,391	546,391	252,956	293,435	94,875	135,687	254,888	355,801
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
County*Year FE	-	-	-	-	-	-	-	-
Pseudo R2	0.385	0.376	0.334	0.414	0.464	0.495	0.464	0.286

This table shows results for Equation (3) at the bank-county-year level. The dependent variable is the deposit share of bank b in county c (out of total bank deposits). *log(distance)* denotes log of one plus the distance between the bank headquarters county and bank branch county. *log(population ratio)* is the log ratio of host (bank branch) to home (bank HQ) county population. All columns run a fractional logit model. Standard errors are robust. Columns (3) and (4) restrict the sample to the years before and after 2008, respectively. Columns (5), (6), and (7) restrict the sample to the largest 4, 10, and 100 banks in each year in terms of total BHC deposits. Column (8) restricts the sample to branches within a 100 mile radius of the headquarters county. *** p<0.01, ** p<0.05, * p<0.1.

Table OA2: **Diversification and dispersion in branch deposit growth – online deposits**

VARIABLES	(1) sd(Δ deposits non-HQ)	(2) 2SLS sd(Δ deposits non-HQ)	(3) sd(Δ deposits)	(4) sd(Δ deposits)	(5) 2SLS sd(Δ deposits)	(6) 2SLS sd(Δ deposits)
diversification	0.038***	0.387***	0.077***	0.051***	0.204***	0.204***
	(0.009)	(0.037)	(0.006)	(0.007)	(0.023)	(0.027)
cyber/HQ deposit share				-0.050***		-0.002
				(0.005)		(0.010)
Observations	95,891	95,891	112,304	112,304	112,304	112,304
R-squared	0.339		0.394	0.396		
Controls	✓	✓	✓	✓	✓	✓
Bank FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
F stat		570.3			727.3	691.3

This table reports results for Equation (2) at the bank-year level. The dependent variable is the standard deviation in deposit growth rates across branches. In columns (1) and (2) it is computed for branches that are not classified as cyber branch or the headquarters branch. In columns (3)–(6) it is computed across all branches. *Diversification* is banks' geographic diversification of deposits across counties, as defined in Equation (1). *Cyber/HQ deposit share* is each banks' share of deposits held in cyber branches or the headquarters branch in a given year. Columns (2), (5), and (6) instrument *diversification* with the IV based on the gravity-deregulation model (see Equation (3)). Standard errors are clustered at the bank level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table OA3: **Diversification and funding stability – macro volatility**

VARIABLES	(1) sd(Δdeposits)	(2) sd(Δdeposits)	(3) sd(Δdeposits)	(4) 2SLS sd(Δdeposits)	(5) 2SLS sd(Δdeposits)	(6) 2SLS sd(Δdeposits)
diversification	-0.013***	-0.013***	-0.013***	-0.021***	-0.020***	-0.017***
	(0.002)	(0.002)	(0.002)	(0.007)	(0.007)	(0.007)
VIX high (0/1)	-0.021***			-0.019***		
	(0.004)			(0.004)		
div × VIX high	-0.005***			-0.002		
	(0.001)			(0.004)		
EBP high (0/1)		-0.013***			-0.011***	
		(0.003)			(0.004)	
div × EBP high		-0.003***			-0.001	
		(0.001)			(0.003)	
Δ GDP low (0/1)			-0.011***			-0.013***
			(0.003)			(0.003)
div × Δ GDP low			-0.004***			-0.006***
			(0.001)			(0.002)
Observations	117,176	117,176	117,176	117,176	117,176	117,176
R-squared	0.340	0.340	0.338			
Controls	✓	✓	✓	✓	✓	✓
Bank FE	✓	✓	✓	✓	✓	✓
F stat 1				381.2	381.9	382.2
F stat 2				660	758.8	761.8

This table reports results for Equation (2) at the bank-year level. The dependent variable is the standard deviation in deposit growth rates over time. *Diversification* is banks' average geographic diversification of deposits across counties, as defined in Equation (1). Columns (4)–(6) instrument *diversification* with the IV based on the gravity-deregulation model (see Equation (3)). *VIX*, *EBP*, and *Δ GDP* denote the CBOE Volatility Index (obtained from FRED), the Excess Bond Premium (obtained from Gilchrist and Zakrajšek (2012)) and real GDP growth (obtained from FRED). Each variable is coded into a dummy. For the VIX and EBP the dummy takes on a value of one if the observation lies in the top quartile of the distribution, for GDP it takes on a value of one if it lies in the bottom quartile. Standard errors are clustered at the bank level. *** p<0.01, ** p<0.05, * p<0.1.

Table OA4: **Diversification and funding stability – robustness**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
			HQ*Y FE	HQ*Y FE	HQ*Y FE	HQ*Y FE	HQ*Y FE	HQ*Y FE
	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
VARIABLES	sd(CD rates)	sd(MM rates)	sd(Δ deposits)	sd(Δsav dep)	LC/assets	Δ CI	Δ RE	Δ sec
diversification	-0.133	0.036	0.209***	-0.032***	0.054***	0.269***	0.164***	0.029
	(0.171)	(0.221)	(0.023)	(0.011)	(0.009)	(0.045)	(0.040)	(0.046)
Observations	9,710	9,710	112,301	117,051	95,506	114,682	74,513	115,722
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Bank FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
F stat	73.22	73.22	771.9	791.5	624.2	771.4	432.1	780.3

This table reports results for Equation (2) at the bank-year level. The dependent variable is the standard deviation in demand deposit rates or time deposit rates across branches in columns (1) and (2). It is the standard deviation in deposit growth rates across branches or over time in columns (3) and (4). Columns (5)–(8) use measures of liquidity creation as in Table 8. *Diversification* is banks' geographic diversification of deposits across counties, as defined in Equation (1), and instrumented with the IV based on the gravity-deregulation model (see Equation (3)). Columns (3)–(8) include fixed effects at the bank headquarters state × year level. Standard errors are clustered at the bank level. *** p<0.01, ** p<0.05, * p<0.1.

Table OA5: **Diversification and funding stability – depositor characteristics**

	(1)	(2)	(3)	(4)	(5)	(6)
			2SLS			2SLS
VARIABLES	sd(Δ deposits)	sd(Δ deposits)	sd(Δ deposits)	sd(Δdeposits)	sd(Δdeposits)	sd(Δdeposits)
diversification	0.077***	0.077***	0.209***	-0.013***	-0.013***	-0.021***
	(0.006)	(0.006)	(0.023)	(0.002)	(0.002)	(0.007)
exposure: income pc		0.019***	0.021***		0.003	0.003
		(0.006)	(0.006)		(0.002)	(0.002)
exposure: age 65+		-0.113**	-0.117**		0.006	0.006
		(0.056)	(0.059)		(0.021)	(0.021)
exposure: bachelor+		0.206***	0.187***		0.043***	0.044***
		(0.035)	(0.037)		(0.015)	(0.016)
Observations	112,304	112,112	112,112	117,176	116,981	116,981
R-squared	0.394	0.395		0.345	0.345	
Controls	✓	✓	✓	✓	✓	✓
Bank FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
F stat			723.6			754.8

This table reports results for Equation (2) at the bank-year level. The dependent variable is the standard deviation in demand deposit rates or time deposit rates across branches in columns (1)–(3). It is the standard deviation in deposit growth rates across branches or over time in columns (4)–(6). *Diversification* is banks' geographic diversification of deposits across counties, as defined in Equation (1). It instrumented with the IV based on the gravity-deregulation model (see Equation (3)) in columns (3) and (6). Exposure denotes the exposure of bank b in year t to county characteristics (income per capita, the share of the population of age 65 and above, the share of the population with a bachelor degree or higher), aggregated to the bank level with deposit shares of each bank in each county. Standard errors are clustered at the bank level. *** p<0.01, ** p<0.05, * p<0.1.

Table OA6: **Diversification and funding costs – local deposit market shares**

VARIABLES	(1) MM rate	(2) 2SLS MM rate	(3) CD rate	(4) 2SLS CD rate
diversification	-0.209***	-0.186	-0.101***	-0.147**
	(0.066)	(0.148)	(0.037)	(0.072)
bank deposit market share	-0.057	-0.056	0.116*	0.113*
	(0.108)	(0.108)	(0.065)	(0.065)
Observations	369,040	369,040	369,040	369,040
R-squared	0.864		0.968	
Controls	✓	✓	✓	✓
Bank FE	✓	✓	✓	✓
Year FE	-	-	-	-
Branch FE	✓	✓	✓	✓
County*Year FE	✓	✓	✓	✓
F stat		400.5		400.5

This table reports results for Equation (4) at the branch-year level. The dependent variable is the average deposit rate on demand deposits in columns (1)–(2) and on time deposits in columns (3)–(4). *Diversification* is banks' average geographic diversification of deposits across counties, as defined in Equation (1). *Bank deposit market share* is the share of deposits held in branches of bank b out of total deposits in all branches in county c in each year. Columns (2) and (4) instrument *diversification* with the IV based on the gravity-deregulation model (see Equation (3)). Standard errors are clustered at the bank level. *** p<0.01, ** p<0.05, * p<0.1.

Table OA7: **Diversification and liquidity creation – asset diversification, deposit market power, and branch density**

VARIABLES	(1) 2SLS LC/assets	(2) 2SLS Δ CI	(3) 2SLS Δ RE	(4) 2SLS Δ sec	(5) 2SLS Δ amt
diversification	0.052***	0.171*	0.119	-0.187*	0.845***
	(0.019)	(0.096)	(0.150)	(0.112)	(0.259)
diversification (HMDA/CRA)	0.005**	0.071***	0.088***	0.004	1.083***
	(0.002)	(0.011)	(0.011)	(0.013)	(0.331)
DMP	-0.030**	0.061	0.074	-0.003	0.060
	(0.012)	(0.052)	(0.057)	(0.068)	(0.244)
branch density	0.000	-0.000*	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	40,900	52,272	25,058	52,859	501,162
Controls	✓	✓	✓	✓	✓
Bank FE	✓	✓	✓	✓	-
Year FE	✓	✓	✓	✓	-
County*Year FE	-	-	-	-	✓
F stat	381.4	430.1	167.9	437	155.5

This table reports results for Equation (2) at the bank-year level in column (1)–(4) The dependent variable is the Berger and Bouwman (2009) measure of liquidity creation in column (1); and the growth in total C&I lending, real estate lending, and securities in columns (2), (3), and (4). It reports results for Equation (5) at the bank-county-year level in column (5), where the dependent variable is the growth rate in total small business lending. *Diversification* is banks' geographic diversification of deposits across counties, as defined in Equation (1), instrumented with the IV based on the gravity-deregulation model (see Equation (3)). *Diversification (HMDA/CRA)* is banks' geographic diversification of mortgage and small business loans across counties. *DMP* is banks' deposit market power, as defined in Drechsler et al. (2017). *Branch density* is banks' bank branch density (total branches/total deposits), as defined in Benmelech et al. (2023). Standard errors are clustered at the bank level. *** p<0.01, ** p<0.05, * p<0.1.

Table OA8: **Diversification and liquidity creation**

VARIABLES	(1) 2SLS less 1y loans/assets	(2) 2SLS 1-5 years loans/assets	(3) 2SLS 5+ years loans/assets
diversification	0.094	0.157**	0.450***
	(0.087)	(0.070)	(0.144)
Observations	109,174	108,980	108,752
Controls	✓	✓	✓
Bank FE	✓	✓	✓
Year FE	✓	✓	✓
F stat	731.3	731.5	727.5

This table reports results for Equation (2) at the bank-year level. The dependent variable is the share or loans with maturity of one year or less over total assets in column (1); the share or loans with maturity of one to five years over total assets in column (2); and the share or loans with maturity of five years or longer over total assets in column (3). *Diversification* is banks' geographic diversification of deposits across counties, as defined in Equation (1), instrumented with the IV based on the gravity-deregulation model (see Equation (3)). Standard errors are clustered at the bank level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table OA9: **Diversification, funding stability, and liquidity creation – alternative IV**

VARIABLES	(1) 2SLS sd(Δ deposits)	(2) 2SLS sd(Δdeposits)	(3) 2SLS LC/assets	(4) 2SLS Δ CI	(5) 2SLS Δ RE	(6) 2SLS Δ sec
diversification	0.202***	-0.023***	0.132***	0.290***	0.199***	-0.020
	(0.022)	(0.006)	(0.016)	(0.043)	(0.038)	(0.043)
Observations	112,304	117,176	95,507	114,685	74,563	115,725
Controls	✓	✓	✓	✓	✓	✓
Bank FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
F stat	837.3	845.4	699.5	854.5	481.9	863.2

This table reports results for Equation (2) at the bank-year level. *Diversification* is banks' geographic diversification of deposits across counties, as defined in Equation (1). The table replicates the baseline findings, but instruments *diversification* with the IV based on the gravity-deregulation model that includes the deregulation index directly in the gravity Equation (3). Standard errors are clustered at the bank level. *** p<0.01, ** p<0.05, * p<0.1.

Table OA10: **Diversification, funding stability, and liquidity creation – number of branches**

VARIABLES	(1) 2SLS sd(Δ deposits)	(2) 2SLS sd(Δdeposits)	(3) 2SLS LC/assets	(4) 2SLS Δ CI	(5) 2SLS Δ RE	(6) 2SLS Δ sec
diversification	0.207***	-0.024***	0.127***	0.278***	0.168***	-0.055
	(0.023)	(0.007)	(0.016)	(0.045)	(0.041)	(0.045)
nr of branches	0.004***	-0.003***	-0.003***	0.002	-0.005*	-0.011***
	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)	(0.003)
Observations	112,304	117,176	95,507	114,685	74,563	115,725
Controls	✓	✓	✓	✓	✓	✓
Bank FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
F stat	718.4	748.9	612.8	752.6	417.7	762.1

This table reports results for Equation (2) at the bank-year level. *Diversification* is banks' geographic diversification of deposits across counties, as defined in Equation (1), instrumented with the IV based on the gravity-deregulation model (see Equation (3)). All regressions control for the number of branches per bank. For ease of interpretation, the coefficient on the number of branches is multiplied by 100. Standard errors are clustered at the bank level. *** p<0.01, ** p<0.05, * p<0.1.

Table OA11: **List of variables**

Variable name	Definition	Source
diversification$_{b,t}$	Bank deposit diversification, see Equation (1)	FDIC SOD
diversification IV$_{b,t}$	Bank deposit diversification based on gravity-deregulation model, see Equations (1) & (3)	FDIC SOD, Rice and Strahan (2010), NBER distance database, FRED
div. exposure$_{c,t}$	County exposure to diversified banks, $\sum_b \frac{deposits_{b,c,t}}{deposits_{c,t}} \times div_{b,t}$	FDIC SOD
number of branches$_{b,t}$	Total number of total branches	FDIC SOD
asset div.$_{b,t}$	Bank diversification as in Equation (1), but based on loan originations	FIEC (HMDA, CRA)
DMP$_{b,t}$	Deposit market power, $\sum_c \frac{\text{deposits}_{b,c,t}}{\text{deposits}_{b,t}} \times \text{Branch HHI}_{c,t}$	FDIC SOD, Drechsler et al. (2017); Li et al. (2023)
branch density$_{b,t}$	Total deposits over number of branches	FDIC SOD, Benmelech et al. (2023)
deposit share$_{b,c,t}$	Bank b's share out of total deposits in county c	FDIC SOD
distance$_{B,c}$	Distance between bank HQ and branch county (in miles)	NBER county distance database
population ratio$_{c,B,t}$	Total population in branch county over total population in HQ county	FRED (resident population by county)
sd(Δ deposits)$_{b,t}$	Standard deviation in deposit growth rates across branches	FDIC SOD
sd(Δ deposits non-RS)$_{b,t}$	Standard deviation in deposit growth rates across branches that are not rate setters	FDIC SOD, RateWatch
sd(Δ deposits RS)$_{b,t}$	Standard deviation in deposit growth rates across branches that are rate setters	FDIC SOD, RateWatch
sd(Δ deposits non-HQ)$_{b,t}$	Standard deviation in deposit growth rates across branches that are not the HQ branch or designated as 'cyber branches'	FDIC SOD
$\overline{\text{sd}(\Delta\text{deposits})}_{b,t}$	Standard deviation in deposit growth rates over time	Call reports

List of variables (continued)

Variable name	Definition	Source
MM rate$_{br,t}$	Deposit rate on demand deposits	RateWatch
CD rate$_{br,t}$	Deposit rate on time deposits	RateWatch
LC/assets$_{b,t}$	Asset-side liquidity creation measure	Berger and Bouwman (2009)
Δ CI$_{b,t}$	Growth in C&I loans	Call reports
Δ RE$_{b,t}$	Growth in real estate loans	Call reports
Δ sec$_{b,t}$	Growth in securities	Call reports
log(assets)$_{b,t}$	Log of total bank assets	Call reports
deposit ratio$_{b,t}$	Total deposits over total liabilities	Call reports
non-interest income$_{b,t}$	Non-interest over total operating income	Call reports
securities/assets$_{b,t}$	Total securities over total assets	Call reports
return on assets$_{b,t}$	Net income over assets	Call reports
equity ratio$_{b,t}$	Total equities over total assets	Call reports
cyber/HQ deposit share$_{b,t}$	Share of total deposits held in HQ branch or branches designated as 'cyber branch'	FDIC SOD
VIX$_t$	CBOE Volatility Index	FRED series VIXCLS
EBP$_t$	Excess Bond Premium	Gilchrist and Zakrajšek (2012) and FEDS notes
ΔGDP$_t$	Real Gross Domestic Product, % change	FRED series A191RL1A225NBEA
Δ firms$_{c,s/i,t}$	Growth in number of firms in a county and industry/firm size cell	BDS
small$_s$	Dummy for firms with 19 or fewer employees	BDS
bank dependence$_i$	Industry bank dependence	SBO