Geographical Expansion In US Banking: A Structural Evaluation ⋆

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Abstract. We study the effects of idiosyncratic risk, geographical diversification and concentration in the US banking market, using a rich yet tractable structural model of deposit-taking and lending across multiple markets. Despite its complexity, the model lends itself to a transparent calibration strategy use micro-level data on deposits and spreads. We quantify the effects of the industrial structure of the banking industry on deposit spreads and decompose them into components arising markups, size, and risk. We find that both risk premia and markups are significant contributors to spreads, especially in smaller, poorer counties. The model also shows significant diversification benefits from the wave of geographical expansion over the last couple of decades, more than offsetting the negative impact of consolidation on competition and markups.

Keywords: Bank expansion, risk diversification, market concentration, credit supply.

JEL Codes: D43, E44, G21.

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1. Introduction

The structure of the US banking industry has undergone a major transformation over the past few decades. Regulatory changes are widely regarded as a key factor behind these trends. The Riegle-Neal Act (1994), in particular, removed restrictions on branch-network expansion for US banks and allowed Bank Holding Companies (BHCs) to acquire banks in any state. The next two decades saw a wave of geographical expansion and consolidation in the banking industry. Understanding the effects of these changes requires thinking through multiple, intertwined economic mechanisms. On the one hand, this may lead to a rise in market concentration through bank consolidation, thus reducing competition in the banking sector. On the other hand, by opening branches in different regions, a bank can reduce the deposit and credit risk associated with its branch portfolio, since these risks may not be perfectly correlated across regions.

In this paper, we use a structural approach to quantify the effects of US banks' geographical expansion and consolidation. We formulate a general equilibrium model of deposit-taking and lending by banks operating in a number of counties under oligopolistic competition. Risks are not perfectly correlated across counties and a bank can benefit from having branches in different locations. We show how the rich spatial heterogeneity in the model can be disciplined using detailed bank- and county-level data. We then use the calibrated model to quantify the effects of county-level idiosyncratic risks and markups on spreads, lending, and welfare.

As motivation for our analysis and approach, we present some reduced-form empirical evidence on banks' geographical expansion and its implications. We confirm that, since the 1990s, banks have significantly increased the number of counties in which they operate. This has been especially the case for larger banks, which now operate in almost 5 times as many counties as they did prior to the wave of expansion. We then construct measures of banks' exposures to fluctuations in deposits and lending, as well as on loan performance. We find that larger banks, and banks that are more geographically diversified, are less exposed to these risks. On the other hand, we show that larger banks are more leveraged and less dependent on deposits as a source of financing. In addition, we find that bank concentration has increased since the 1990s, both at the county and national levels. Because of these opposite forces, the net benefits of banks' geographical expansion and consolidation on overall riskiness and financial stability are not clear.

Our structural model is a one-period general equilibrium model of heterogeneous banks that operate in an exogenous number of heterogeneous counties. A representative household values both consumption and deposit services, and provides funds to banks in the form of deposits, wholesale funding, and equity. Aggregate deposit services are assumed to take a nested CES form. Deposits at different banks within a county are aggregated into a county-level composite, which is then accumulated to generate the economy-wide aggregate. In the baseline version, the only source of idiosyncratic risk is a county-level shifter which moderates the household's preferences for deposit services. Combined with curvature in the lending technology, this feature gives rise to a motive for diversification. Banks compete by choosing interest rates on their deposits, which are assumed to be set before observing idiosyncratic shocks. The optimal rates, or more precisely, the spread relative to an illiquid asset, is given by a markup times a marginal cost term. In our oligopolistic setting, the former is a function of the substitution elasticities and an appropriately defined market share. The higher a bank's market share, the larger is its markup implying that more concentrated markets will tend to have higher markups. The marginal cost term includes a risk premium, which depends on how the shocks in a particular market covaries with those in the other markets in which the bank operates. A larger (i.e. more positive) covariance makes it less attractive for the bank to raise more resources from that market, i.e. to offer lower spreads. Diversification reduces the risk premium and through that, marginal costs and ultimately, deposit spreads.

Despite its complexity, the model lends itself to a transparent calibration strategy using detailed micro-level data on deposits and spreads. Data on bank-county level deposits are taken from the FDIC's Summary of Deposits (SOD) for the period 1990-2019, while data for bank-county level deposit rates are taken from RateWatch's 6-month CDs for the period 2011-2019. Regarding bank-level variables, we use data from Call Reports for 1990-2019. Our merged panel data consists of approximately $3,000$ counties and $6,200$ banks. We use the calibrated model to quantify the variation in spreads − both in the cross-section and over time − due to markups, marginal costs and risk premia. The model also provides a simple and intuitive way to link changes in spreads into variations in aggregate lending and welfare.

We find that risk premia have a significant effect on spreads, especially for smaller, less diversified banks. Since these banks operate in smaller, poorer counties, these effects are more pronounced in those markets. Smaller counties also exhibit higher levels of concentration, which implies higher markups. Over the last two decades, geographical expansion and the associated diversification benefits have exerted a downward pressure on spreads. Our model suggests that this force has more than offset the upward pressure on spreads due to the rise in concentration. In the cross-section, smaller, poorer counties have experienced the largest declines in risk premia.

Related literature

This paper contributes to several strands of the literature. First, it is related to the growing body of work that documents and analyzes various forms of bank risk diversification, such as alternative sources of funding, exposure to noninterest income, liquidity management, loan quality, and organizational complexity.[1] A paper closely related to ours is that by Aguirregabiria et al. (2016), which provides an empirical analysis on the trade-offs of geographical risk diversification in terms of the variability of deposits. A key contribution of our work is to provide an analysis on how risk matters. In particular, we use our structural general-equilibrium model to analyze how geographical risk affects banks' decisions (both in terms of prices and quantities), and how banks' behavior, in turn, shapes local outcomes.

Second, the paper is related to the literature on oligopolistic competition in macroeconomics and trade. Close studies in this area are Atkeson and Burstein (2008); Hottman, Redding, and Weinstein (2016); Rossi-Hansberg, Sarte, and Trachter (2020); and Berger, Herkenhoff, and Mongey (2022). We extend the framework developed by Atkeson and Burstein (2008) to better depict the IO of the US banking sector. In particular, we allow banks to operate in multiple markets, and assume rich heterogeneity on their marginal revenues and marginal costs that is directly linked to micro-level data.

Third, our paper is related to the literature on banks' market power. Work by Drechsler, Savov, and Schnabl (2017) and Wang, Whited, Wu, and Xiao (2020) analyze how market power affects the transmission of monetary policy through deposit and lending channels. Banks' market power can also have implications for credit supply and financial stability (Black and Strahan (2002); Corbae and D'Erasmo (2021); Carlson, Correia, and Luck (2022)), and for adverse selection in lending markets (Crawford, Pavanini, and Schivardi (2018)). Our contribution to this literature is to quantify how banks' market power interacts with the risk diversification benefits of consolidation.

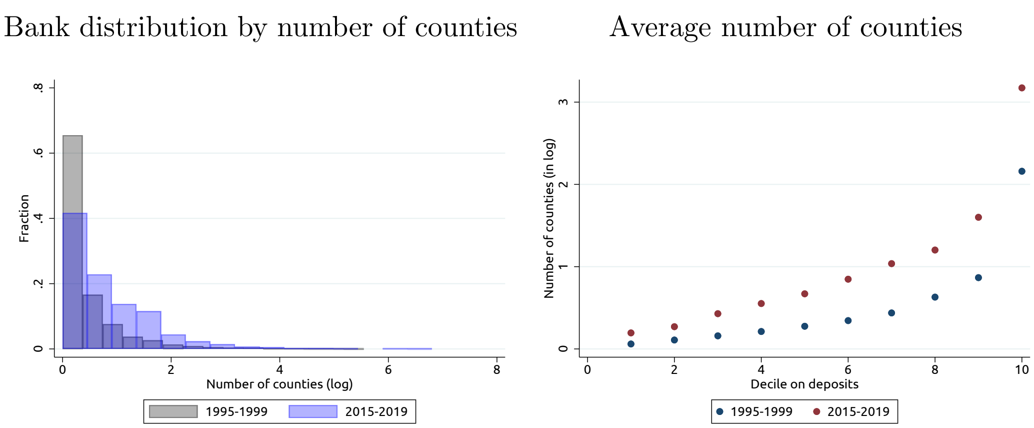
[1] See, for example, Stiroh (2006); Laeven and Levine (2007); Baele, De Jonghe, and Vander Vennet (2007); Cetorelli and Goldberg (2012); Goetz, Laeven, and Levine (2016) Gilje, Loutskina, and Strahan (2016); Correa and Goldberg (2020); and Granja, Leuz, and Rajan (2022).

2. Empirical Evidence

We start our empirical analysis by providing evidence on the wave of banks' geographical expansion that occurred since the 1990s. The left panel of Figure 1 shows the distribution of the number of counties in which banks operated at during 1995-1999 (gray bars) and 2015-2019 (blue bars). The distribution has shifted to the right, meaning that more banks are now operating in more counties. In fact, the average number of counties per bank doubled over the past 20 years.

The right panel of Figure 1 depicts how this geographical expansion varied by bank size. In particular, the figure shows the relation between a bank's size (as proxied by deciles on deposits) and the average number of counties in which it operates. The figure provides two main facts. First, larger banks operate in a larger number of counties. Second, banks' geographical expansion has been mainly driven by medium and large banks. During 2015-2019, the largest banks in the sample (deciles 9 and 10) operated in 5 times as many counties as they did during 1995-1999.

Figure 1. Banks' Geographical Expansion



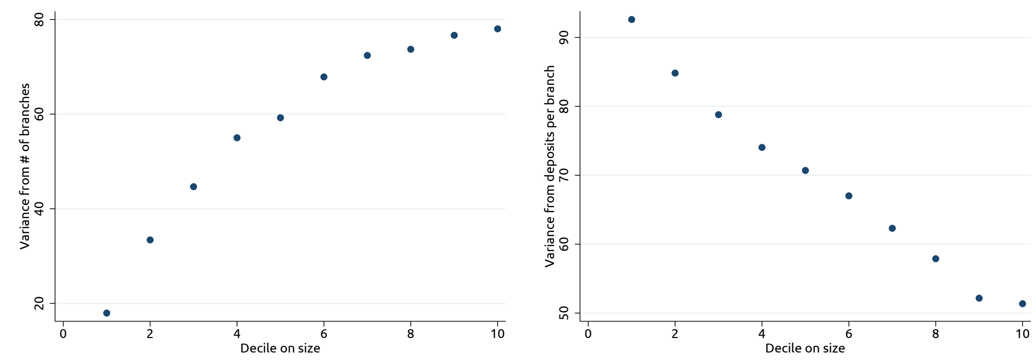
Notes: Own elaboration based on Summary of Deposits (SOD), FDIC.

How has this trend of geographical expansion changed banks' risks? To answer this question, we construct measures of a bank's exposures to fluctuations in deposits and loans, as well as exposure to loan performance. We then analyze how these measures relate to a bank's size and to the number of counties in which it operates.

We start by performing a variance decomposition exercise where we decompose bank-level deposits between number of branches (extensive margin) and deposits per branch (intensive margin)—see Appendix A.1 for details. Both sources of growth are relevant: The variation in the number of branches and in deposits per branch explains on average, 48% and 66% of a bank's total deposit variance (see Appendix Table A.1). Figure 2 shows that the relative importance of each component varies with bank size. In particular, the fraction of deposit variance explained by the extensive margin is increasing in bank size, while the opposite happens with the intensive margin.[2] Overall, these results suggest that county-level shocks to deposits are relatively more relevant for smaller banks.

FIGURE 2. Deposits variance decomposition by bank size

(A) Number of branches (B) Deposits per branch



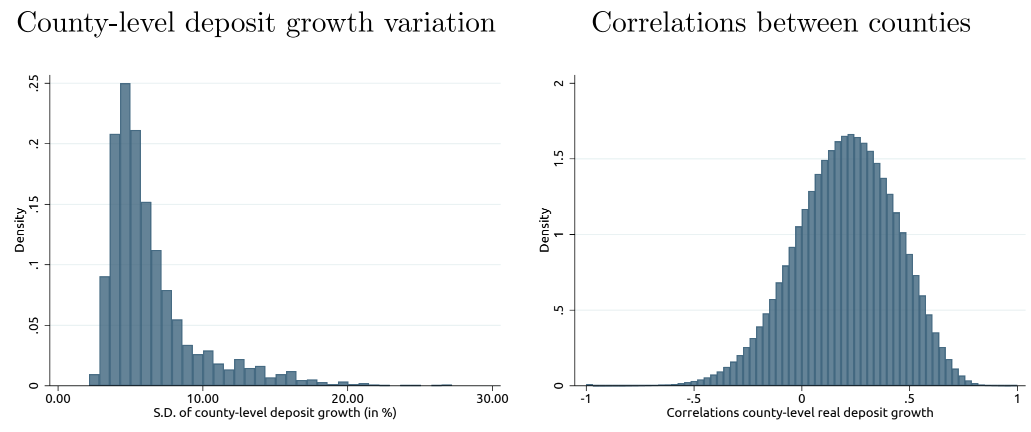
The previous analysis highlights that endogenous branching choices constitute a relevant source of variation for banks' deposits, especially for larger banks. As such, constructing measures of banks' exposures to fluctuations in deposits is challenging because branching may produce time-varying exposures across regions. In particular, this means that we cannot directly interpret second-order moments on deposit growth (e.g., variance) from bank-level time-series. To overcome this challenge, our approach is to assume a stationary covariance matrix of total deposit growth at the county-level, and exploit variation in the time dimension using weights based on banks' deposit shares by county.

Panel (A) of Figure 3 presents a histogram of the dispersion across time of county-level real deposit growth, $\sigma_i(\Delta \ln D_{it})$, where $\Delta \ln D_{it}$ is the log change in total deposits in county i for year t. The figure shows that $\Delta \ln D_{it}$ is volatile, and that there is nontrivial heterogeneity across counties.[3] Panel (B) shows the correlations across counties on deposit growth, $\rho(\Delta \ln D_{it}, \Delta \ln D_{kt})$. The large mass of correlations away from unity highlights the presence

[2] Although not shown, the covariance between the extensive and intensive margins is negative. It is around -10% for small banks and -30% for large banks.

[3] Appendix Figure A.1 recasts this data by showing a map of $\sigma_i(\Delta \ln D_{it})$ across US counties.

Figure 3. County-level deposit growth



Notes: Own elaboration based on Summary of Deposits (SOD), FDIC.

of imperfectly correlated county-level shocks to deposit growth. Combined, these two facts suggest that there is scope for geographical diversification on county-level deposit growth.

We now analyze how this county-level heterogeneity affects bank-level risk. Let ω_{ij}^{τ} be a bank j's relative weight on county i at time τ, defined as

$$\omega_{ij}^{\tau} = \frac{D_{ij}^{\tau}}{\sum_i D_{ij}^{\tau}},$$

where D_{ij}^{τ} is the total stock of deposits that bank j has on county i at time τ. For a given weight ω_{ij}^{τ}, we can then use $\Delta \ln D_{it}$ to construct bank j's weighted deposit change at time t as

$$\Delta \ln D_{jt}^{\tau} = \sum_i \omega_{ij}^{\tau}(\Delta \ln D_{it}).$$

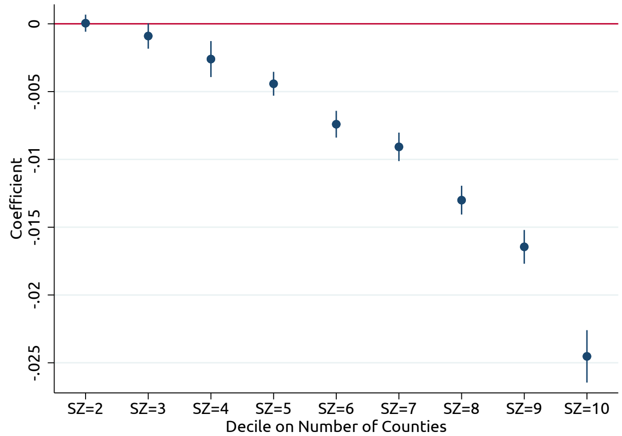
We then compute the time-series standard deviation as

$$\sigma_j^{\tau} = \sqrt{\frac{1}{T}\sum_t \left(\Delta \ln D_{jt}^{\tau} - \overline{\Delta \ln D_{jt}^{\tau}}\right)^2}. \tag{1}$$

The analysis in Figure 3 indicates that bank-level variations across σ_j^{τ} can be linked not only to bank-level differences in branching (i.e., $\{\omega_{ij}^{\tau}\}$), but also to the geographical heterogeneity in the deposit growth process.

We make use of the panel of exposures $\{\sigma_j^{\tau}\}$ to study how deposit risk relates to different banks' characteristics. To this end, we regress σ_j^{τ} onto decile dummies on the number of counties the bank operates ($\{\mathbf{1}_{k,\tau}\}_{k=2}^{10}$), bank fixed effects ($\alpha_j$), and time fixed effects (α_τ). The

Figure 4. Banks' Exposure to Deposit Fluctuation Risk, by Size



Notes: Own elaboration based on Summary of Deposits (SOD), FDIC.

specification is as follows:

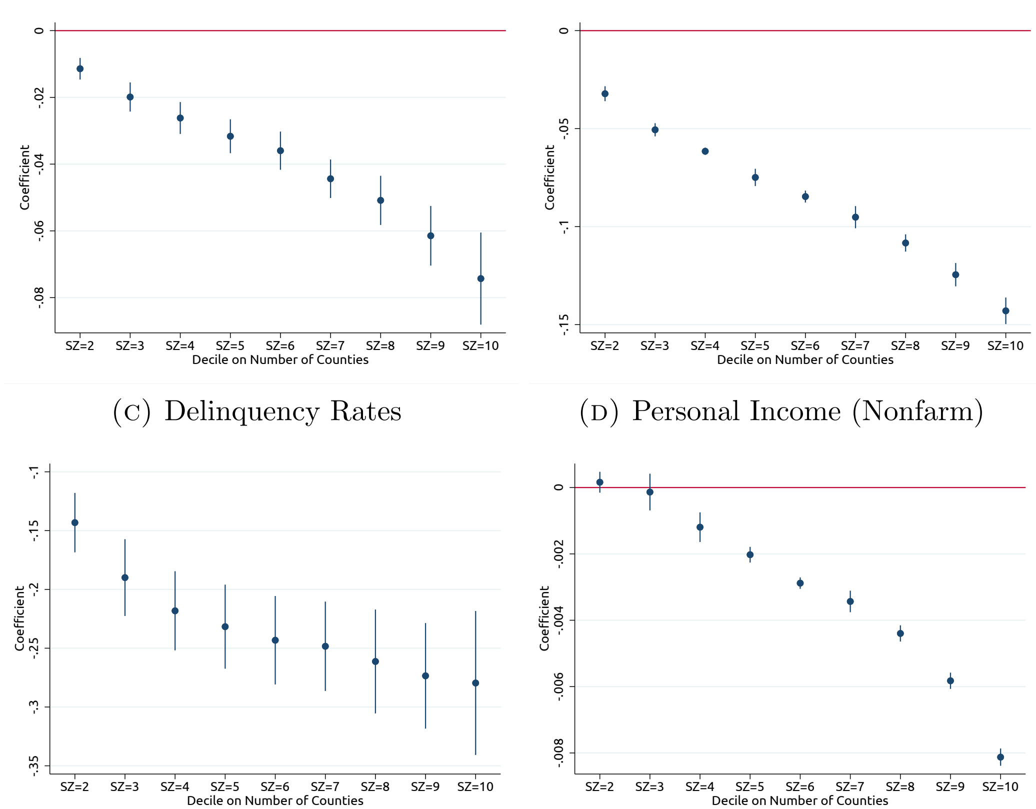
$$\sigma_j^\tau = \beta_1 + \sum_{k=2}^{10} \beta_k \times \mathbf{1}_{k,\tau} + \alpha_j + \alpha_\tau + \epsilon_{j,\tau}.$$

Figure 4 presents the estimates for the β_k parameters. The figure shows that exposure to deposit fluctuation risk falls monotonically with the number of counties a bank operates at.[4] Although not shown, similar results hold when considering deciles on bank size (as proxied by deposits).

We then perform a similar analysis for banks' exposure to risk on lending growth and loan performance. In terms of lending growth, we use county-level data on originations of small business loans and mortgages. Panels (A) and (B) of Figure 5 show that larger banks are less exposed to variations on originations of these loans types. Regarding loan performance, we use data on county-level delinquency rates on mortgage loans. The results in panel (C) suggest that larger banks are less exposed to delinquency rates, although point estimates have

[4]Since the panel dataset on deposits is not balanced (due to banks exiting and M&A activity), we exclude banks with less than 10 years of observations to have a more accurate computation of the variances across the time dimension. Results are very similar quantitatively if we exclude banks with less than 5 or 15 years of observations. Furthermore, if the panel is balanced, the computation from equation (1) is equivalent to calculating the variance-covariance matrix of county-level deposit growth (Σ), and then computing $(\sigma_j^\tau)^2 = \omega_\tau \omega_\tau' \Sigma$, where ω_j^τ is a column vector of weights ω_{ij}^τ. While this alternative method is not affected by banks' exit, it is much more demanding in terms of computation time. Thus, we calculated exposures for 1995 and 2015 and found that results are qualitatively aligned to our baseline ones. Results are available upon request.

Figure 5. Banks' Exposure to Lending Risk and Performance, by Bank Size



(A) Small Business Loans

(B) Mortgages

(C) Delinquency Rates

(D) Personal Income (Nonfarm)

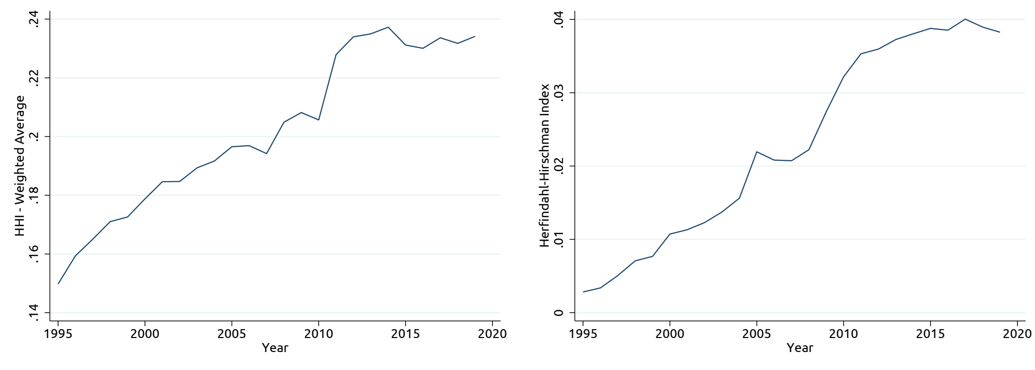
Notes: Own elaborations based on Community Reinvestment Act (CRA), Home Mortgage Disclosure Act (HMDA), Consumer Financial Protection Bureau (CFPB), and BEA.

large confidence intervals due to small sample size. For this reason, in panel (D), we consider county-level nonfarm personal income as a proxy for delinquency rates. The figure shows that larger banks are less exposed to variations in this proxy.

So far, we have shown that banks' geographical expansion might bring diversification benefits, both for deposits and lending. These benefits, in turn, may end up benefiting non-financial sectors, in terms of a more stable credit supply, higher deposits rates, and lower loans spreads. For the period of analysis, however, there has been an increase in banks' concentration, which may have had important effects on banks' market power and markups. Figure 6 illustrates this point by showing Herfindahl-Hirschman indices (HHI) for bank deposit markets. The figure shows that concentration has been increasing steadily during the 1995-2020 period, both at the county and national levels. The increase in concentration may, in turn, affect the riskiness

FIGURE 6. Concentration on Bank Deposit-taking

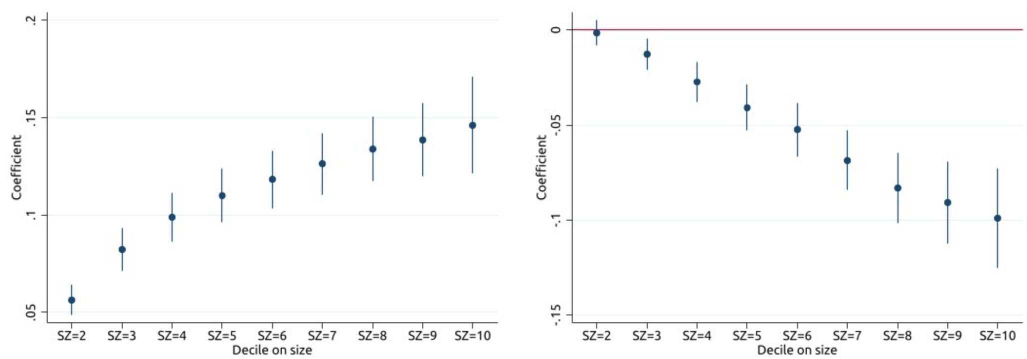
(A) County-level Index (B) National-level Index



Notes: Own elaborations based on Summary of Deposits (SOD), FDIC

FIGURE 7. Leverage and Wholesale Funding, by Bank Size

(A) Liabilities / Assets (B) Deposits / Liabilities



Notes: Own elaborations based on Call Reports.

and stability of the financial sector, since larger banks have a larger leverage and rely less on deposits as a source of funding (as shown in Figure 7).

Because of these opposing forces, the effects of banks' geographical expansion and consolidation on the credit supply, spreads, and financial stability are not obvious. In the next section, we formulate a spatial general-equilibrium model with heterogeneous banks to quantify the aggregate implications.

3. MODEL

In this section, we layout an equilibrium model of heterogeneous and oligopolistic banks operating in a continuum of markets (counties). The economy is populated by a representative household and heterogeneous banks. The household supplies funds to banks both in the form of equity, deposits and wholesale funding. Deposits are special in the sense that they provide liquidity services. Banks invest (or equivalently lend) out these funds using a technology that is subject to diminishing returns (at the bank level). For simplicity, we will model these as intra-period transactions, which allows us to work with effectively a static setting.

There is a continuum of heterogeneous counties, each with a discrete number of operating banks. Motivated by the data, we allow for sparsity at the bank-county level, in the sense that not all banks operate on all counties. We assume banks behave oligopolistically in (county-level) deposit markets and compete by setting interest rates on deposits at the county level. Bank profits are paid to household.

Despite its complexity, we derive analytical expressions for a number of objects of interest which lead to a simple and transparent empirical strategy—which we exploit heavily in the quantitative analysis of Section 4.

3.1. *Representative Household's Problem*

The households starts each period endowed with $\bar{W}$ units of consumption goods.[5] An (exogenous) amount E_j units is assumed invested in equity of bank j. The rest of the endowment can be invested either as deposits or wholesale funding to banks, H_j.

Let D_{ij} denote the household's deposits with bank j in county i. We assume that the household's value from the liquidity services is a function of a composite of individual deposits. We use a nested CES specification for aggregating deposits – the first level aggregates deposits of different banks in a given county i to a county-level D_i. The second level then combines these into an economy-wide composite D. Formally:

$$D = \left(\int_0^1 \phi_i D_i^{\frac{\theta-1}{\theta}} di \right)^{\frac{\theta}{\theta-1}} \quad \text{and} \quad D_i = \left(\sum_{j=1}^{J_i} \psi_{ij} D_{ij}^{\frac{\eta-1}{\eta}} \right)^{\frac{\eta}{\eta-1}}. \tag{2}$$

The parameter $\theta > 1$ denotes the elasticity of substitution across county-level deposits, while $\eta > 1$ captures the substituability across services provided by banks within a county. We assume $\eta > \theta$, meaning that deposits within a county are more substitutable than deposits across counties.[6] The variable ϕ_i denotes the household's preference for deposits in county i

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[5]Given the analysis is effectively static, we suppress the time subscript.

[6]This is standard in the literature on oligopolistic competition in macroeconomics and trade (see, e.g., Atkeson and Burstein (2008)).

and will be the only source of randomness in this version of the model. The term ψ_{ij} captures the relative preference for deposits in bank j within county i.

The household derives utility from consumption and deposit services according to a function $u(C, D)$. The household's problem is given by

$$\max_{C,\{D_{ij}\}} u(C, D) \tag{3}$$
$$\text{s.t. } C = \left(\overline{W} - E - \int_0^1 \sum_{j=1}^{J_i} D_{ij} di\right) R + \int_0^1 \sum_{j=1}^{J_i} R_{ij}^D D_{ij} di + \Pi.$$

Optimization yields the following demand function for deposits of bank j in county i

$$\frac{R - R_{ij}^D}{R - R_i^D} = \psi_{ij} \left(\frac{D_{ij}}{D_i}\right)^{-\frac{1}{\eta}}, \tag{4}$$

where R_{ij}^D is the interest rate offered by the bank. The bank-level spread $R - R_{ij}^D$ and the county-level one $R - R_i^D$ are linked through:

$$R - R_i^D = \left(\sum_{j=1}^{J_i} \psi_{ij}^{\eta} \left(R - R_{ij}^D\right)^{1-\eta}\right)^{\frac{1}{1-\eta}}. \tag{5}$$

$$\tag{6}$$

Analogously, demand for the composite deposit aggregate D_i is

$$\frac{R - R_i^D}{R - R^D} = \phi_i \left(\frac{D_i}{D}\right)^{-\frac{1}{\theta}}, \tag{7}$$

where

$$R - R^D = \left(\int_0^1 \phi_i^{\theta} \left(R - R_i^D\right)^{1-\theta} di\right)^{\frac{1}{1-\theta}}. \tag{8}$$

3.2. *Banks' Problem*

Bank j makes loans (L_j) using funds from equity, total deposits and wholesale funding. We assume the lending technology exhibits diminishing returns, so that the return on an additional loan unit is $R + z - \frac{\omega_L}{2} L_j$. The bank competes for deposits by choosing an interest rate R_{ij}^D for each county i it operates in. The total cost for a bank to provide a unit of deposit is given by $R_{ij}^D + k_{ij}$, where k_{ij} captures the non-interest expense associated with deposits. Wholesale funding (H_j) is available through a competitive economy-wide market. We assume that the household's supply for wholesale funding is perfectly elastic (hence, banks have to pay R on H_j), and that the marginal cost for bank j of raising an additional unit of funding from this market is given by $R + \frac{v_j}{2} H_j$. Banks are heterogeneous in their non-interest costs (k_{ij}), and in their cost of accessing wholesale funding (v_j).

Finally, we assume that the county-level demand shifters (ϕ_i) is stochastic and unknown at the time banks set their interest rates. These shocks are drawn from a joint distribution G (which we estimate using micro-level data) after the banks choose their interest rates on deposits. The timeline of events is as follows. First, banks choose deposit rates R^D_{ij} (or equivalently, spreads) and wholesale funding H_j. Second, the ϕ_i shocks are realized, and the household chooses C and $\{D_{ij}\}$. Third, banks make loans.

Under these assumptions, the problem of bank j is given by

$$\Pi_j = \max_{\{R^D_{ij}\}, H_j} \mathbb{E}\left\{ \left(R + z - \frac{\omega_L}{2} L_j\right) \times L_j - \left(R + \frac{v_j}{2} H_j\right) \times H_j - \int_0^1 \mathcal{D}_{ij}(\cdot)\left(R^D_{ij} + k_{ij}\right) d\Lambda_j(i) \right\}$$

$$\text{s.t. } L_j = \int_0^1 \mathcal{D}_{ij}(\cdot) d\Lambda_j(i) + H_j + E_j, \tag{9}$$

where, for any function $y(\phi)$, $\mathbb{E}(y) = \int y(\phi) dG(\phi)$, $\Lambda_j(\cdot)$ denotes the (exogenous) measure of counties in which bank j operates, and $\mathcal{D}_{ij}(\cdot)$ denotes the demand for deposits faced by bank j in county i as given by equations (4) and (7), which depends on the interest rate charged by the bank. Banks compete oligopolistically at the county level. That is, when choosing R^D_{ij}, they internalize its effects on R^D_i and D_i, but they take as given the aggregates R^D and D.

The optimality conditions on wholesale funding and spreads imply

$$H_j = \frac{z - \omega_L \left(\mathbb{E} \int_0^1 \mathcal{D}_{ij} d\Lambda_j(i) + E_j\right)}{\omega_L + v_j}, \tag{10}$$

and

$$R - R^D_{ij} = \underbrace{\frac{\eta(1 - s_{ij}) + \theta s_{ij}}{\eta(1 - s_{ij}) + \theta s_{ij} - 1}}_{=\text{MKP}_{ij}} \underbrace{\left\{ (k_{ij} - z) + \omega_L \left[H_j + E_j + \frac{\mathbb{E}\left[\mathcal{D}'_{ij} \int_0^1 \mathcal{D}_{ij} d\Lambda_j(k)\right]}{\mathbb{E}\mathcal{D}'_{ij}} \right] \right\}}_{=\text{MC}_{ij}}, \tag{11}$$

where s_{ij} is the effective market share of bank j in county i, which is defined as:

$$s_{ij} \equiv \frac{R - R^D_{ij}}{R - R^D_i} \frac{D_{ij}}{D_i} = \psi_{ij} \left(\frac{D_{ij}}{D_i}\right)^{\frac{\eta - 1}{\eta}} \in (0, 1) \tag{12}$$

Using the demand functions (4)-(7), the last term of equation (11) can be written as:

$$\frac{\mathbb{E}\left[\mathcal{D}'_{ij} \int_0^1 \mathcal{D}_{kj} d\Lambda_j(k)\right]}{\mathbb{E}\left[\mathcal{D}'_{ij}\right]} = D \int_0^1 \mathbb{E}[\phi^\theta_k] \left(\frac{R - R^D_k}{R - R^D_{kj}}\right)^\eta \psi^\eta_{kj} \left(\frac{R - R^D_k}{R - R^D}\right)^{-\theta} \frac{\mathbb{E}\left[\phi^\theta_i \phi^\theta_k\right]}{\mathbb{E}\left[\phi^\theta_i\right] \mathbb{E}[\phi^\theta_k]} d\Lambda_j(k). \tag{13}$$

3.3. *Decomposition of Spreads: Markups and Marginal Costs*

Equation (11) shows that spreads can be decomposed into a markup and marginal cost component. The structure of the markup is identical to that of Atkeson and Burstein (2008), and it is a function of a bank's market share and the within- and across-county elasticities. If the bank has a market share approaching to zero, it only perceives the within-county elasticity η and chooses a constant markup $\frac{\eta}{\eta-1}$. As s_{ij} increases, the bank needs to internalize the effects of its own choices on the county-level aggregates. For the limit case in which s_{ij} approaches one, the bank only cares about the across-county elasticity θ and charges a constant markup $\frac{\theta}{\theta-1}$.

Under the assumption that (i) $\eta > \theta > 1$ and (ii) there is a finite number of banks in each county ($s_{ij} \in (0,1)$), markups are increasing on s_{ij} and banks do not necessarily pass through changes in their costs one-for-one into spreads. In this case, for instance, an increase in the marginal cost for bank j operating in county i, relative to other banks operating in that county, leads to a decrease in its market share and to a decrease in its markup.

In addition to markups, our model proposes a theory for a bank's marginal costs as a function of its size, geographical diversification, and exposure to risk. After replacing with Equation (13) and the definition of loans L_j, we can express MC_{ij} as:

$$MC_{ij} = k_{ij} - z + \omega_L \mathbb{E}\left(L_j\right) \underbrace{\left(1 + d_j \int_{k \in M_j} \omega_{kj}^D \frac{\rho_{ik}\sigma_i\sigma_k}{\mu_i\mu_k} dk\right)}_{\equiv RP_{ij}}, \tag{14}$$

where $d_j \equiv \frac{\int_{k\in M_j} \mathbb{E}\left(D_{kj}\right)\Lambda_j(k)}{\mathbb{E}(L_j)}$ is the share of total deposits for bank j, $\omega_{kj}^D \equiv \frac{\mathbb{E}\left(D_{kj}\right)\Lambda_j(k)}{\int_{k\in M_j}\mathbb{E}\left(D_{kj}\right)\Lambda_j(k)}$, $\Lambda_j(k)$ is the measure of bank j in county k, σ_k is the volatility of the ϕ_k shock, and ρ_{ik} is the correlation between the demand-shifter shocks of county i and k. The equation shows that we can decompose a bank's marginal cost in two channels. The first one, $\mathbb{E}(L_j)$, is a size channel and it is a direct outcome from the decreasing returns to scale assumption on banks' lending activity. The second one is a risk premium channel (RP_{ij}). It originates from banks operating in risky and correlated locations. We can approximate this risk premium term as

$$\ln RP_{ij} \approx \quad d_j \int_{k \in M_j} \omega_{kj}^D \frac{\rho_{ik}\sigma_i\sigma_k}{\mu_i\mu_k} dk. \tag{15}$$

For a given $\mathbb{E}\left(L_j\right)$, a bank that finances its lending based on deposits from imperfectly correlated locations ($\rho_{ik} < 1$) can decrease its overall exposure to risk and achieve a lower marginal cost.

An important feature of our model is that it allows us to decompose a bank's marginal cost with observables that can be directly linked to the data. In other words, we can use Equation (14) to directly quantify how changes in a bank's geographical allocation affect its marginal costs, without the need to repetitively solve for the equilibrium of the model. In particular, we can study cross-sectional patters and time-variation in RP_{ij}. As we explain next, this feature of the model can be extended to other measures of interest.

3.4. *A "Sufficient Statistic" Approach*

An important feature of our framework is that, up to a first-order, we can link our model with observables to directly quantify the effects of changes in the geographical location of banks, without the need of repeatedly solving the model.

Suppose that our goal is to analyze the effects of a change in the distribution of banks across counties. Assume that, for those banks that were already operating in a given county, we observe the vector of changes in their deposit rates: $\{\Delta \ln\left(R - R_{ij}^D\right)\}_{\forall\{i,j\}}$ (intensive margin changes). Assume that we also observe changes across the extensive margin, as captured by $\{\Delta\left(\psi_{ij}\right)\}_{\forall\{i,j\}}$. With only these observables, we can then use our model to directly analyze the effects of these changes on banks' deposits and loans, and county-level deposits and rates. In particular:

$$\Delta\ln\left(R - R_i^D\right) = \frac{1}{1-\eta}\left\{\sum_{j=1}^{J_i} s_{ij}\left[(1-\eta)\,\Delta\ln\left(R - R_{ij}^D\right) + \frac{1}{\psi_{ij}^{\eta}}\Delta\psi_{ij}^{\eta}\right] + \sum_{j'}\frac{\psi_{ij'}^{\eta}\left(R - R_{ij'}^D\right)^{1-\eta}}{\left(R - R_i^D\right)^{1-\eta}}\right\},$$

$$\Delta\ln\left(R - R^D\right) = \sum_i s_i \cdot \Delta\ln\left(R - R_i^D\right),$$

$$\Delta\ln D_{ij} = -\eta\Delta\ln\left(R - R_{ij}^D\right) + (\eta-\theta)\,\Delta\ln\left(R - R_i^D\right) + \left(\theta - \frac{1}{\gamma}\right)\Delta\ln\left(R - R^D\right) + \frac{\Delta\psi_{ij}^{\eta}}{\psi_{ij}^{\eta}},$$

$$\Delta\ln D_i = \left(\theta - \frac{1}{\gamma}\right)\Delta\ln\left(R - R^D\right) - \theta\Delta\ln\left(R - R_i^D\right),$$

$$\Delta\ln L_j = \sum_i \frac{D_{ij}\Lambda_{ij}}{\sum_i D_{ij}\Lambda_{ij}}\Delta\ln D_{ij} + \frac{D_{C1}\Lambda_{C1}}{\sum_i D_{i1}\Lambda_{i1}},$$

with $s_i \equiv \frac{\phi_i^{\theta}\left(R - R_i^D\right)^{1-\theta}\Lambda_i}{\sum_i \phi_i^{\theta}\left(R - R_i^D\right)^{1-\theta}\Lambda_i}$ and $s_{ij} \equiv \frac{\psi_{ij}^{\eta}\left(R - R_{ij}^D\right)^{1-\eta}}{\sum_{j=1}^{J_i}\psi_{ij}^{\eta}\left(R - R_{ij}^D\right)^{1-\eta}}$.

This first-order approximation of our model provides us with a "sufficient statistic" type of approach to quantify the effects of changes in the geography of banks on aggregate spreads, deposits, and loans. Combined with Equation (14), we can then use this approach to decompose the effects into those driven by the size component and those explained by the diversification component of banks' marginal costs. Lastly, given an utility function U for the representative household, we can also use this approximation to perform welfare analysis just by using the changes in spreads observed in the data.

$$\Delta U\left(\{D_i\},\{L_j\}\right) = \frac{d\ln U}{d\ln D}\sum_i \frac{d\ln D}{d\ln D_i}\Delta\ln D_i + \frac{d\ln U}{d\ln C}\sum_j \frac{d\ln C}{d\ln L_j}\Delta\ln L_j. \tag{16}$$

4. Quantitative Analysis

In this section we provide a quantitative analysis of the model. First, we describe our calibration procedure, describing the data sources and how we use them. Despite the complexity of the model, we have a transparent calibration strategy that exploits rich micro-level data. Then, we provide details on the solution algorithm. This is an iterative algorithm on allocations (rates and quantities) given parameters. Finally, we explore model counterfactuals that provide important insights on the benefits of banks' risk diversification through consolidation.

4.1. *Data Sources and Model Calibration*

Annual data on bank-county level deposits are taken from the FDIC's Summary of Deposits (SOD) for the period 1990-2019, while data for bank-county level deposit rates are taken from RateWatch's savings accounts and 6-month CDs for the period 2011-2019.[7] We merge these two datasets by county and banks' IDs (RSSD ID), for the period 2011-2019. In turn, R is taken to be the yield of 5-year treasuries. Regarding bank-level variables, we use data from Call Reports for the period 1990-2019. We compute E_j as total assets minus total liabilities, and H_j as total liabilities minus total deposits.[8] We also use the average return on loans (interest on loans / total loans) to calibrate ω_L and z, as detailed below.

Since Ratewatch does not cover the universe of bank-county pairs, we need to impute missing observations.[9] To this end, we run a simple panel regression on the merged dataset:

$$R_{ijt} = \alpha_0 + \alpha_i + \alpha_t + \mathbf{\Gamma}'_B \mathbf{X}^B_{jt} + \mathbf{\Gamma}'_C \mathbf{X}^C_{it} + \beta_F \mathbf{1}^F_{ij} + \epsilon_{ijt},$$

where α_i are county FE, α_t are year FE, and $\mathbf{X}^B_{jt}$ and $\mathbf{X}^C_{it}$ are a battery of bank- and county-level characteristics, respectively, and $\mathbf{1}^F_{ij} = 1$ if bank j has follower branches in county i. [10]

---

[7] We compute a weighted average of these rates, with weights given by each bank's relative deposit type volume on its balance sheet.

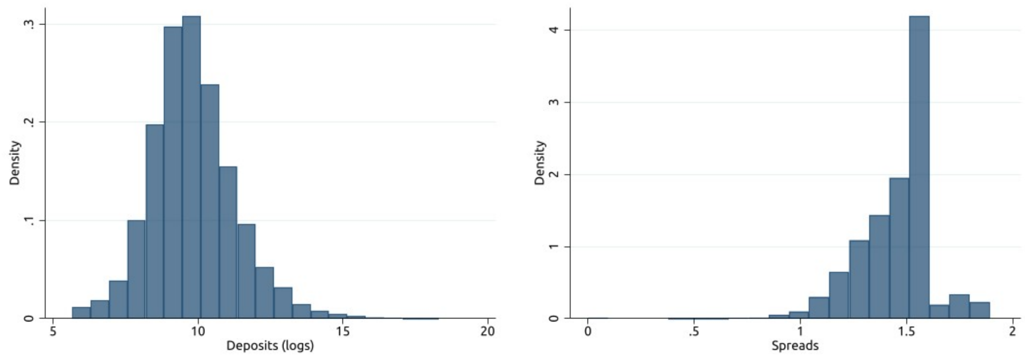
[8] E_j, H_j, and D_{ij} are detrended by the growth rate of total assets to adjust for a time-trend.

[9] Ratewatch covers, on average, 67% of total deposits included in the SOD dataset. Note that we consider both, rate setters and followers in the sample from Ratewatch.

[10] Bank-level characteristics include average return on loans, average deposit rate, net income over total assets, net worth over total assets, total liabilities over total assets, deposits over total liabilities, securities over total

Figure 8. Heterogeneity in the Data

(A) Distribution of D_{ij} (B) Distribution of $R - R^D_{ij}$



Notes: Own elaborations based on Ratewatch and Summary of Deposits (FDIC)

The R^2 of the panel regression is $\approx 70\%$. Once we impute missing bank-county pairs, we get approximately $3,000$ counties and $6,200$ banks. Figure 8 shows the distribution of D_{ij} (left panel) and of R^D_{ij} (right panel) in the dataset, picturing a rich heterogeneity on both variables. In turn, Figure 9 depicts the relation between deposits and spreads, and between lending and average return on loans. Panel (A) of the figure shows that counties with higher deposits are associated with higher spreads. Panel (B) shows that banks with higher lending are associated with lower average returns.

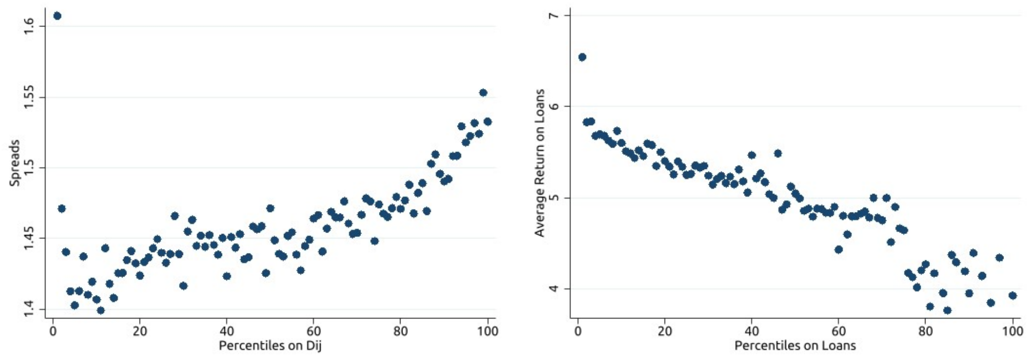
We now describe our calibration strategy. In the model, banks first choose prices $\left\{R - R^D_{ij}\right\}$ subject to risk coming from $\{\phi_i\}$. Upon the realization of that uncertainty, banks absorb $\{D_{ij}\}$ as determined by households. In the data, we observe, on a yearly basis, $\{D_{ij}\}$ and the spreads chosen by banks for each county $\left\{R - R^D_{ij}\right\}$. Our calibration consists of using those observables not only to pin down the model parameters, but also to recover the model-implied county-level shocks, $\{\phi_i\}$.

In what follows, we first preset the values for η, θ, and γ. Next, we use household's optimality conditions to back out $\{\psi_{ij}\}$ and $\{\phi_i\}$. Without loss of generality, we assume the following

assets, real estate loans over total assets, commercial and industrial loans over total assets, and the (log) number of counties that the bank operates. County-level characteristics (in logs) include income per capita, deposits per capita, relative deposits, relative total personal income, relative employment, relative polutation, share of nonfarm over total personal income, and the number of banks operating in a county.

Figure 9. Relation Between Rates and Deposits

(A) Spreads and Deposits (B) Loan Returns and Deposits



Notes: Own elaborations based on Ratewatch, Summary of Deposits (FDIC), and Call Reports.

normalizations: $\bar{\psi}_i = \sum_j \psi_{ij}$ and $\bar{\phi} = \frac{1}{I}\sum_i \phi_i$. Combining the definition for D_i and county-wide demand function, we get

$$\psi_{ij} = \left(R - R^D_{ij}\right) D_{ij}^{\frac{1}{\eta}} \left(\frac{1}{\bar{\psi}_i}\sum_j \left(R - R^D_{ij}\right) D_{ij}^{\frac{1}{\eta}}\right)^{-1}.$$

We can directly compute $\{\psi_{ij}\}$ using data on spreads and deposits for a particular year. Then, using the set of equations (2) and (5), we can compute $\left\{R - R^D_i\right\}$, $\{D_i\}$, and $\{s_{ij}\}$.

The next step is to solve for $\{\phi_i\}$. Combining the definition for D and the economy-wide demand function, we obtain

$$\phi_i = \left(R - R^D_i\right) D_i^{\frac{1}{\theta}} \left(\frac{1}{\bar{\phi} I}\sum_i \left(R - R^D_i\right) D_i^{\frac{1}{\theta}}\right)^{-1}.$$

Again, using the set of equations (2) and (5) we compute $R - R^D$ and D.

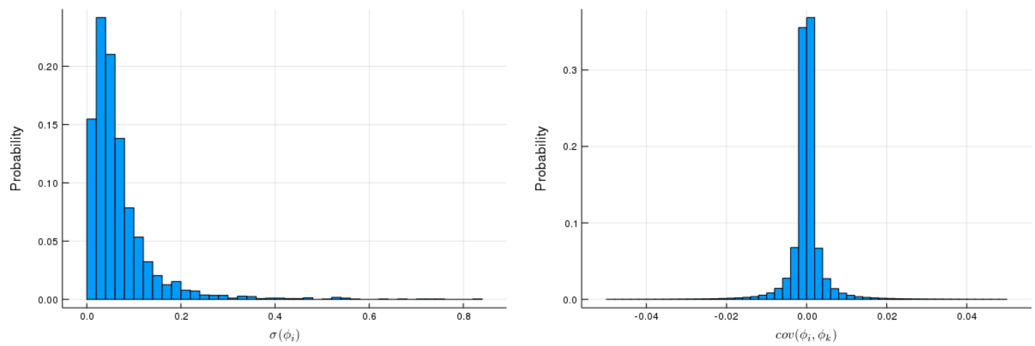
Consider ϕ to be a multivariate random variable (i.e., a vector indexed by counties). From the previous steps, we obtained a panel for ϕ_{it}, since we can repeat the procedure for each year between 2011-2019. We use this panel to calculate $\mathbb{E}[\phi_i^\theta]$ and $\mathbb{E}[\phi_i^\theta \phi_k^\theta]$ along the time dimension, for any pair $\{i, k\}$. Given that, we compute

$$\frac{\mathbb{E}\left[\mathcal{D}'_{ij}\sum_{k=1}^{I}\mathcal{D}_{kj}\Lambda_{kj}\right]}{\mathbb{E}\left[\mathcal{D}'_{ij}\right]} = D\sum_{k=1}^{I}\left(\frac{R - R^D_k}{R - R^D_{kj}}\right)^{\eta}\psi_{kj}^{\eta}\left(\frac{R - R^D_k}{R - R^D}\right)^{-\theta}\frac{\mathbb{E}\left[\phi_i^\theta\phi_k^\theta\right]}{\mathbb{E}\left[\phi_i^\theta\right]}\Lambda_{kj}, \tag{17}$$

$$\mathbb{E}\sum_{i=1}^{I}\mathcal{D}_{ij}\Lambda_{ij} = D\sum_{i=1}^{I}\psi_{ij}^{\eta}\left(\frac{R - R^D_i}{R - R^D_{ij}}\right)^{\eta}\left(\frac{R - R^D}{R - R^D_i}\right)^{\theta}\mathbb{E}\left[\phi_i^\theta\right]\Lambda_{ij}. \tag{18}$$

FIGURE 10. Degree of Uncertainty

(A) Histogram of $\sigma(\phi_i)$ (B) Histogram of $\mathrm{Cov}(\phi_i, \phi_k)$



Using H_j, E_j, and $\{D_{ij}\}$ from the data, we can obtain L_j for each bank. Also, in the model, average interest income is given by

$$R_j^L = R + z - \frac{\omega_L}{2} L_j,$$

so that we can estimate z and ω_L based on a panel regression. We can then obtain k_{ij} and ν_j from optimality conditions (11) and (10), respectively. Finally, if we assume the household has quasilinear preferences, $U(C, D) = C + \xi \frac{D^{1-\gamma}}{1-\gamma}$, and assuming a standard value for γ, we can use the household's optimality conditions to obtain ξ.

In the model, diversification benefits will depend on the degree of uncertainty arising from $\{\phi_i\}$. This uncertainty depends on both, the volatility of the ϕ_i process $(\sigma(\phi_i))$ and its covariance across counties. Figure 10 provides insights on these moments, based on the calibration exercise. Panel (A) of the figure shows that the volatility of ϕ_i is nontrivial, on average being around 0.10, which is 10% of the unconditional mean of ϕ_i. Panel (B), in turn, shows that the $\mathrm{Cov}(\phi_i, \phi_k)$ is centered around 0, with both positive and negative signs.

4.2. *Disentangling the Effects: Risk Premia vs Markups*

We now make use of our calibrated model to quantify the relevance of markups and the risk premium on deposit spreads.

We first aggregate our measure of risk premia at the bank- and county-level to study how risk premium correlates with observables. Consider a bank that operates in a finite number of counties M_j. Based on equation (14), we can directly obtain $\ln RP_{ij}$ from the data as

$$\ln RP_{ij} \approx d_j \sum_k \omega_{kj}^D \frac{\rho_{ik}\sigma_i\sigma_k}{\mu_i\mu_k},$$

where $\omega_{ij}^D \equiv \frac{\mathbb{E}(D_{ij})\Lambda_i}{\sum_{i=1}^{M_j}\mathbb{E}(D_{ij})\Lambda_i}$, $d_j \equiv \frac{\sum_{k=1}^{M_j}\mathbb{E}(D_{ij})\Lambda_i}{\mathbb{E}(L_j)}$, and Λ_i is the discretized version of our continuous $\Lambda(i)$ measure. We can aggregate this measure at the bank- and county-level as follows:

$$\text{At the Bank-level: } RP_j \equiv \sum_i \omega_{ij}^D \cdot \left(d_j \sum_k \omega_{kj}^D \frac{\rho_{ik}\sigma_i\sigma_k}{\mu_i\mu_k} \right)$$

$$\text{At the County-level: } RP_i \equiv \sum_j s_{ij} \cdot \left(d_j \sum_k \omega_{kj}^D \frac{\rho_{ik}\sigma_i\sigma_k}{\mu_i\mu_k} \right),$$

where s_{ij} is the effective market share of bank j in county i —defined in Equation (12). We use an analogous procedure to aggregate markups.

Figure 11 shows the bank-level measure of risk premium by bank size (left panel) and by the number of counties a bank operates at (right panel). In both cases, there is a clear negative correlation: Risk premium is significantly higher for smaller banks and for banks that operate in a small number of counties.

Figure 11. Bank-level Risk Premia by Bank Characteristics

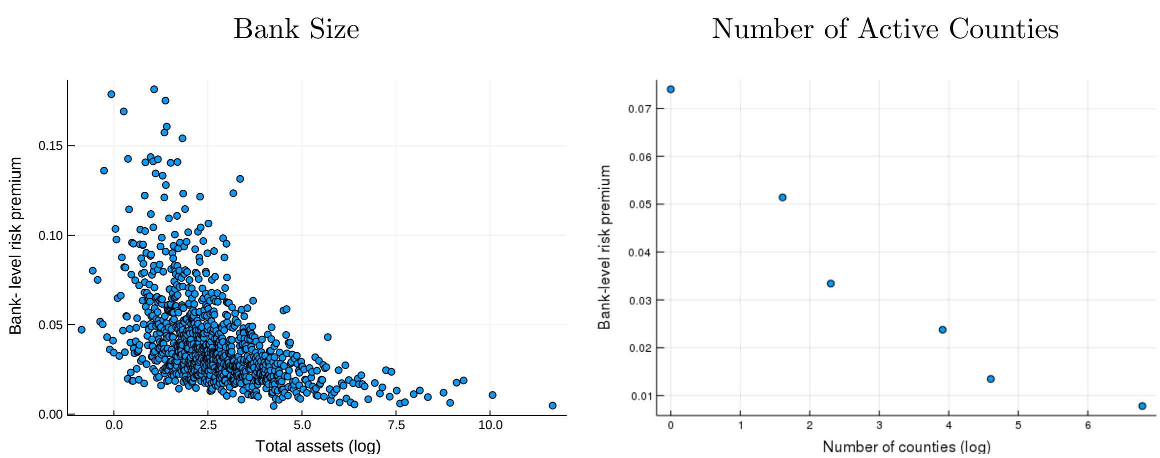
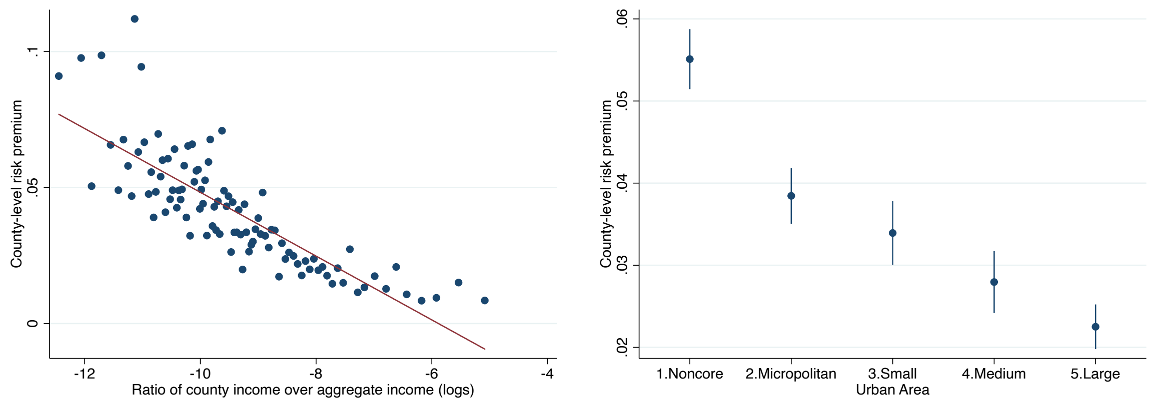


Figure 12 shows the county-level risk premium by county size (left panel) and by the degree of urbanization (right panel). Risk premium is significantly higher in smaller counties and in rural areas. We also find that the average risk premium is higher in counties with lower per capita income (see appendix).

Figure 12. County-level Risk Premia by County Characteristics

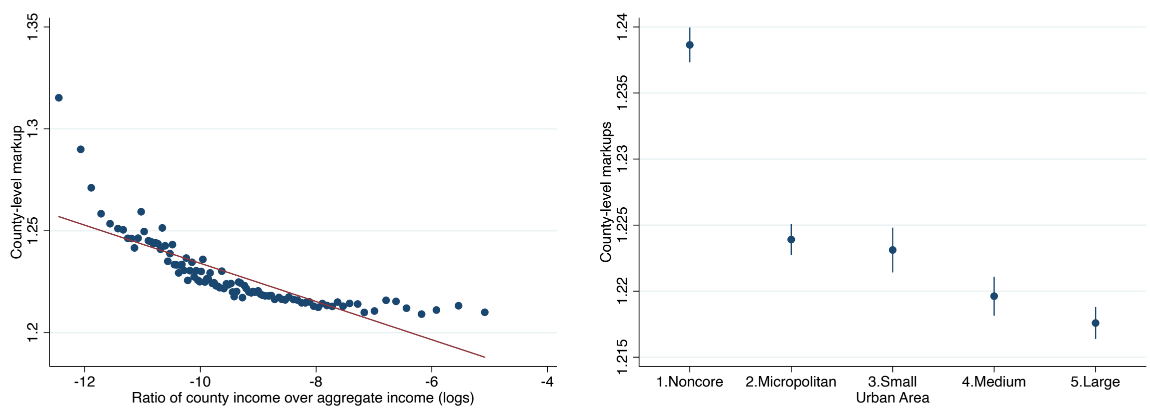
County Relative Size | Urban vs Rural



We now turn our attention to markups. Figure 13 shows the county-level markups by county size (left panel) and by the degree of urbanization (right panel). As expected, markups are higher for smaller counties and rural areas, since bank concentration is higher.

Figure 13. County-level Markups by County Characteristics

County Relative Size | Urban vs Rural



Next, we consider two counterfactuals aimed at capturing the intensive margin effects of diversification and markups, and its variation over time. In the first counterfactual, we measure a bank's diversification benefits by comparing the observed $\ln RP_{ij}$ with a counterfactual in which counties are perfectly correlated. That is,

$$\Delta \ln RP_{ij}^{IM} \equiv \quad d_j \int_{k \in M_j} \omega_{kj}^{D} \frac{(\rho_{ik} - 1)\sigma_i \sigma_k}{\mu_i \mu_k} dk. \tag{19}$$

This object captures the reduction in risk premium from banks operating in imperfectly correlated counties.

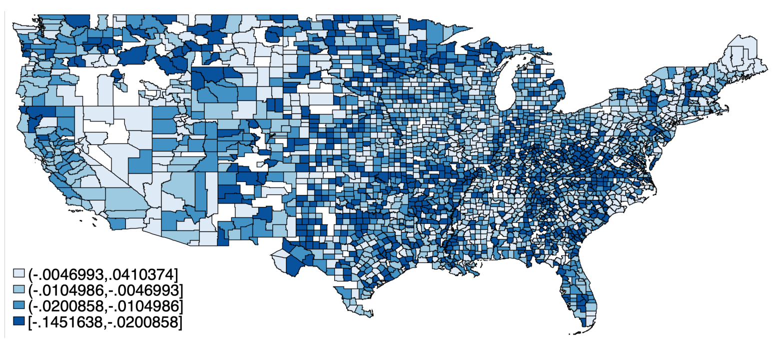
In the second counterfactual, we compare the effects of markups under oligopolistic competition against the monopolistic competition case (i.e., $s_{ij} = 0$). That is, we compute

$$\Delta \ln MKP_{ij} = \ln \left(\frac{\eta(1 - s_{ij}) + \theta s_{ij}}{\eta(1 - s_{ij}) + \theta s_{ij} - 1} \right) - \ln \left(\frac{\eta}{\eta - 1} \right). \tag{20}$$

In both cases, we take as given banks' weights $\left(d_j, \omega^D_{kj}\right)_{\forall k,j}$ and shares $(s_{ij})_{\forall i,j}$, for different time periods.

In Figure 14, we show the effects of diversification on deposit spreads by US counties. The figure depicts changes in the intensive margin effect of RP between the pre and post periods across counties. From the figure, we observe that most counties gained from diversification, but the degree of variation is heterogeneous across counties. The largest rise in diversification benefits is observed in counties in the Southeast region. On the other hand, counties in the Northeast, Midwest, and West regions are the ones that experienced the smaller decrease in rates due to banks' diversification.

Figure 14. Map of variation in diversification benefits



The documented heterogeneity can be linked to county-level characteristics. For instance, in the left panel of Figure 15, we show that smaller counties and rural counties exhibit a larger drop in spreads through a reduction in risk premium. This is also true for counties with lower income per capita (see appendix). Figure 16 depicts the variation in the intensive margin of markups. Interestingly, the change in this intensive margin is small, with no clear patterns across county characteristics.

FIGURE 15. Variation in diversification benefits by county size and urbanization

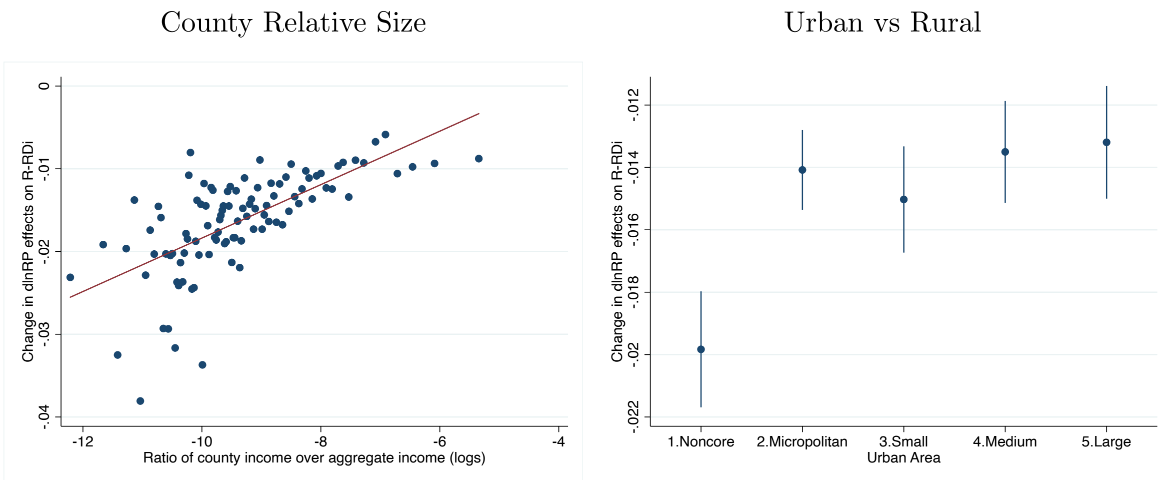
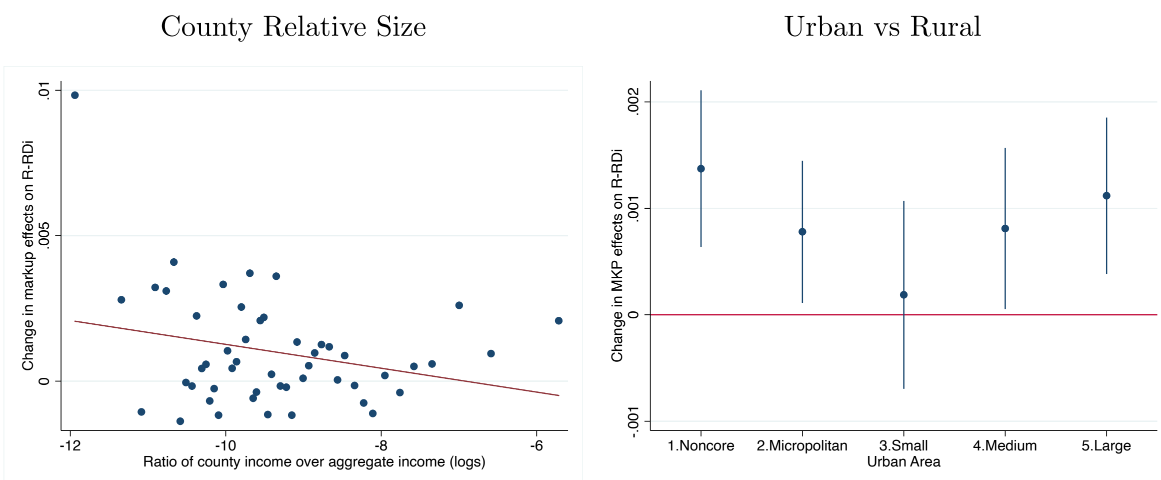


FIGURE 16. Variation in markup effects by county size and urbanization



In Table 1, we consider how these counterfactual exercises translate to aggregate spreads. The overall effect of diversification on MC_{ij} depends on ω_L, so we show results for three cases. In the first column (RP only), we consider the case in which $z = k_{ij}$, so that ω_L does not affect diversification benefits. In the second and third columns, we show results for high and low ω_L, respectively.

The table shows that the magnitudes for both the diversification and markups columns are increasing in time, which is consistent with our empirical stylized facts: (i) banks have expanded geographically across the US, and (ii) banks' concentration has increased at both the county- and national-level. More importantly, for the 2010 decade, we find that the intensive-margin effects of diversification on spreads can be significantly larger than those of markups.

Table 1. Intensive Margins: Variation over Time

	$\Delta \ln(R - R^D)$			
	Diversification			Markups
Period	RP only	ω_L high	ω_L low	
1990s	-1.3%	-2.1%	-0.1%	1.1%
2010s	-2.1%	-15.4%	-0.8%	1.4%

5. Conclusion

In this paper, we provide empirical evidence that is suggestive of diversification benefits. We also build a structural model with rich heterogeneity at the bank and county levels. The model is calibrated using rich micro-level data. The calibrated model shows existence of risk at county level, and that bank diversification matters for spreads, deposits, and lending.

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Appendix A. Empirical Analysis

A.1. *Variance Decomposition on Deposit Growth*

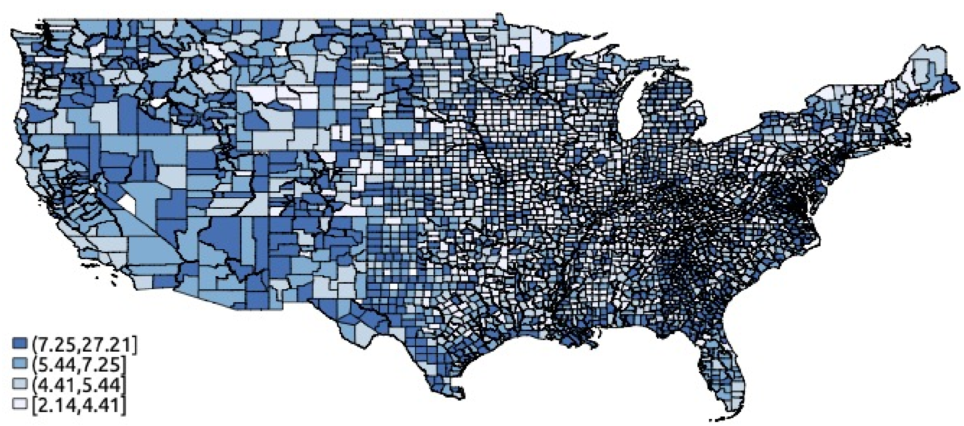
In this section, we evaluate the extensive vs intensive margins of deposit variation for US banks. Each bank has total deposits equal to $N_{jt} \times D_{jt}/N_{jt}$. Taking logs, we can perform the following variance decomposition:

$$Var\left(\ln D_{jt}\right) = Var\left(\ln N_{jt}\right) + Var\left(\ln\left(D_{jt}/N_{jt}\right)\right) + 2Cov\left(N_{jt}, \ln\left(D_{jt}/N_{jt}\right)\right). \tag{A.1}$$

Table A.1. Variance decomposition on deposit growth

	Mean	Median
Number of branches	48%	31%
Deposits per branch	66%	55%

Figure A.1. Dispersion on county-level deposit growth



Notes: Own elaborations based on Ratewatch, Summary of Deposits (FDIC), and Call Reports.

Appendix B. Quantitative Analysis

B.1. *Solution Algorithm*

Next, we develop an iterative algorithm that solves for allocations given model parameters.

(1) Guess spreads $\{R - R_{ij}^D\}^0$.

(2) Compute $R - R_i^D$ and $R - R^D$ based on equations (5) and (8).

(3) Substituting the household's optimality condition,

$$D = \xi^{\frac{1}{\gamma}} \left(R - R^D\right)^{-\frac{1}{\gamma}},$$

into the economy-level CES demand function (7), and taking expectations, compute

$$\mathbb{E}\left[D_i\right] = \left(R - R_i^D\right)^{-\theta} \mathbb{E}\left[\phi_i^\theta\right] \xi^{\frac{1}{\gamma}} \left(R - R^D\right)^{\theta - \frac{1}{\gamma}}.$$

(4) Apply expectations onto county-level CES demand function (4) to compute $\mathbb{E}\left[D_{ij}\right]$

(5) Compute H_j based on optimality condition (10), and $\mathbb{E}\left[L_j\right]$ based on the balance-sheet constraint.

(6) Compute marginal costs based on equation (14).

(7) Compute market shares $s_{ij} = \psi_{ij}^\eta \left(\frac{R - R_{ij}^D}{R - R_i^D}\right)^{1-\eta}$ and markups $MKP_{ij} = \frac{(\eta - \theta)s_{ij} - \eta}{1 + (\eta - \theta)s_{ij} - \eta}$.

(8) Compute new spreads, $\{R - R_{ij}^D\}^1$, using optimality condition (11).

(9) Iterate until convergence $\|\{R - R_{ij}^D\}^1 - \{R - R_{ij}^D\}^0\| \approx 0$