Geographical Diversification In Banking: A Structural Evaluation ⋆

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Abstract. We study the effects of diversification and competition in banking, using a rich yet tractable spatial model of deposit-taking. Market-specific risk in deposit demand increases the effective cost for banks, making geographical diversification valuable. Despite its complexity, the model lends itself to a transparent calibration strategy using micro data on deposits flows and rates. The calibrated model points to significant benefits – through reduced risk premia in deposit spreads – from the geographical expansion and consolidation in the banking industry over the last three decades. This is especially true for the smallest/poorest markets. Markups, on the other hand, have changed only modestly. The model also implies that these changes have made the banking system more exposed to aggregate shocks (e.g. to loan returns). Finally, we evaluate the equilibrium effects of replacing all 'local' banks with larger ones. The model predicts that this will significantly lower spreads in some markets, but leave markups more or less unchanged.

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 Interstate Banking and Branching Efficiency Act (1994), for example, removed many restrictions on branch-network expansion for US banks and allowed Bank Holding Companies (BHCs) to acquire banks in any state. Subsequently, the banking industry witnessed a wave of geographical expansion and consolidation. Understanding the effects of these changes requires thinking through multiple, intertwined economic mechanisms: from changes in market concentration and competition to reduced deposit and credit risks through increased diversification.

In this paper, we use a structural approach to quantify idiosyncratic risk, diversification, and consolidation in the US banking sector. We formulate a general equilibrium model of deposit-taking and lending by heterogeneous banks operating in a number of markets (US counties in our empirical implementation) as oligopolists. Deposit supply is subject to shocks that are imperfectly correlated across counties, so that operating in different locations yields diversification benefits. 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 recover the effects of risk premia and markups on deposit spreads and, through that, on aggregate deposit flows and lending.

We begin with some reduced-form evidence as motivation for our analysis. We confirm that, since the 1990s, banks have significantly increased the number of counties in which they operate. In the appendix, we also document reduced-form evidence suggestive of diversification benefits – larger banks tend to be less exposes to fluctuations in deposit flows. On the competition front, we find that national-level market concentration (measured by HHI) in deposit markets has increased since the 1990s, while changes in county-level concentration are mixed. These patterns, while interesting, are hard to interpret without a theoretical framework, thus limiting the analysis of their net impact on deposit markets.

Our model is a one-shot general equilibrium setting with heterogeneous banks operating in an exogenous set of heterogeneous counties. Each county is an oligopolistic market served by a finite number of banks. The representative household in the economy values consumption and deposit services. The latter are assumed to take a nested CES form with deposits at different banks within a county aggregated into county-level composites, which are then accumulated to generate the economy-wide deposit bundle. The only sources of risk are county-level shocks that shift the household's preferences for deposit services. Curvature in banks' payoff functions (arising, for example, from diminishing returns in lending or from curvature in utility) 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. We analyze two cases: in the first, banks are assumed to engage in 'uniform pricing', where each bank sets a single rate across all the markets. This formulation is motivated by earlier work documenting that banks often set similar rates across markets (Radecki, 1998; Heitfield and Prager, 2004; Granja and Paixao, 2021; Begenau and Stafford, 2022). In the second version, banks engage in 'local pricing', i.e. set interest rates separately for each county they operate in. We provide suggestive evidence that reality likely lies somewhere in between these two benchmark cases. As we will show, our main takeaways hold under both assumptions, even if the magnitudes differ somewhat.

The optimal deposit rates – more precisely, the spread relative to an asset which does not provide liquidity – is given by a markup times a 'marginal cost' term. In our oligopolistic setting, the markup is a function of the substitution elasticities and market share, appropriately defined. Intuitively, oligopolist banks internalize their effects on the total amount of deposits in the market. The higher a bank's market share, the larger is this effect and, therefore, higher is its markup. The relevant notion of market differs under the two pricing assumptions – under uniform pricing, markups are based on the bank's average market share across all its markets, while under local pricing, the markup is market-specific and depends on the bank's share in that market. The marginal cost term includes a risk premium component, a novel feature of our framework. This depends on the risk associated with deposit flows. Under uniform pricing, there is a single risk premium at the bank-level, which is increasing in the variability of total bank-level deposits. This is in turn a function of on the covariance matrix of preference shocks in markets that the bank operates. All else equal, the less diversified a bank, i.e. the more positively correlated its shocks are, the higher this variability and thus the larger the spread charged by the bank. Diversification reduces this risk premium and, therefore, marginal costs and deposit spreads. The local pricing case features a bank- and county-specific risk premium, but the intuition is similar – the more positively a county's deposit demand shock covaries with those of other counties the bank operates in, the higher the risk premium (and therefore, higher the spread) charged by the bank in that county.

Despite its richness, the model lends itself to a transparent calibration strategy using detailed micro-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. We use two sources of data for deposit rates – the first one is branch-level rates on CDs and money markets from RateWatch. The second comes from bank financial statements on Call Reports for 1990-2019. We show how these series allow us to recover all the key parameters, including those governing idiosyncratic risk, the degree of curvature and costs. We use the calibrated model to quantify the effect of risk premia and markups on spreads, both in the cross-section and over time.

The results show a significant risk premium component in deposit spreads. As one would expect, smaller, less diversified banks face larger deposit flow risks and consequently charge higher spreads. For the smallest banks, risk premia increase spreads by about 0.40 log points (or almost 50%). The spreads of the largest banks, on the other hand, contain a much lower compensation for risk, with risk premia pushing up spreads by around 0.15 log points. Smaller banks also tend to have somewhat lower average market shares – and therefore, lower markups – than their mid-sized and larger counterparts, although the differences are small.

Across counties, risk premia drive up spreads by as much as a third in the smallest/poorest counties. For the median county, the risk-related increase in spreads is almost 25%. Markups exert the largest effect in smaller/poorer counties, pushing up spreads by around 0.30 log points. Combined, the risk and markup channels increase spreads by over 0.60 log points for the smallest/poorest counties.

Next, we analyze changes in the effects of risk premia and markups on spreads over the last couple of decades (specifically, between 1993 and 2019). First, we find that the geographical expansion and associated diversification benefits have exerted a significant downward pressure on deposit spreads. These changes are most pronounced for the smallest/poorest counties, where the decrease in marginal costs achieved through lower risk premia imply a reduction of spreads of up to 12%. In the aggregate, the reduction in risk premia lowered the cost of deposit services by about 3.4%. Changes in markups are more modest. Under the uniform pricing assumption, the model shows markups declining by about 2.5% in the smallest counties and remain more or less unchanged in the largest counties.

In other words, the changes in the structure of the banking industry over the last 3 decades have benefited the smallest/poorest counties in two ways – diversification-induced reductions in risk premia and, to a lesser extent, lower markups. Under the assumption of local pricing, the decline in markups for the smallest counties is attenuated, i.e. markups have remained more or less flat over the last two decades across the board. Note that this is despite the rise in reduced-form measures of concentration at the national level. This underscores the need for a structural model like ours to draw meaningful lessons about competition.

We also quantify the role of the extensive margin (i.e. entry/exit of banks) in these changes. We find the declines in county-level spreads stemming from risk premia were driven mainly by changes in the extensive margin, especially for smaller counties.

Finally, we leverage the tractability of the model to perform counterfactual experiments. Our first experiment aims at providing a more complete picture of the effects of risk. Specifically, we shut down risk premia entirely and recompute the equilibrium holding other parameters fixed at their baseline values. Consistent with our previous analysis, we find large reductions in deposit spreads, especially in the smallest counties. These effects are only mildly offset by a rise in markups. Our second experiment explores the role of 'local' banks (defined to mean banks operating in less than two counties). In each market, we replace these banks with the largest bank operating in that county. The model predicts a reduction in marginal costs (through lower risk premia), which is only partially offset by a rise in markups. Once again, smaller counties experience the largest benefits from this restructuring. Our final experiment studies how the changes in the structure of the industry might have impacted financial stability. Specifically, we analyze the effect of an economy-wide negative shock to the return to lending. Deposit spreads increase across the board, but more so for smaller counties than for larger ones. More interestingly, the effects are larger at the end of our sample (in 2019) compared with two decades ago (1993). In other words, even as diversification and/or increased competition have benefited depositors, the system might have become more vulnerable to other shocks.

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 diversification – broadly defined – in the banking sector.[1] Our focus on deposit flow risk is also shared by Aguirregabiria et al. (2016) and Corbae and D'Erasmo (2022), who analyze geographical expansion, taking as given an exogenous deposit flow process at each location. We differ from these papers in our explicit modeling of the market for deposits, while taking location choices as given. This allows us to capture the interplay of risk and diversification with competition and markups. These interactions also distinguish our work from that of Oberfield et al. (2024), who endogenize location choice in a spatial model of banking with monopolistic competition and no risk. Our substantive findings

[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).

thus help paint a more complete picture of the effects of geographical expansion. Methodologically, our main contribution is a rich yet tractable general equilibrium framework designed to study the macroeconomic effects of these forces.

Second, our approach to modeling competition is closely related to models widely used in the macroeconomics and trade literature. Key references include Atkeson and Burstein (2008); Hottman, Redding, and Weinstein (2016); Rossi-Hansberg, Sarte, and Trachter (2020); and Berger, Herkenhoff, and Mongey (2022). We extend and adapt this well-known framework to the banking context, where oligopolist 'firms' compete in multiple markets subject to idiosyncratic risk.

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. Implications of bank market power for credit supply and financial stability have been studied by (Black and Strahan, 2002; Corbae and D'Erasmo, 2021; Carlson et al., 2022; Herkenhoff and Morelli, 2024), and for adverse selection in lending markets (Crawford et al., 2018). We contribute to this literature by quantifying the aggregate effects of bank market power on the deposit side, both in the cross-section and the time series.

2. Motivating Facts

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 depicts 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. By 2019, the largest banks in the sample (deciles 9 and 10) operated in 5 times as many counties as they did before the Riegle-Neal Act. The right panel shows that these changes are not contained to a subset of counties or regions. In fact, we observe a larger number of active banks in both smaller and larger counties.

Figure 1. Banks Geographical Expansion

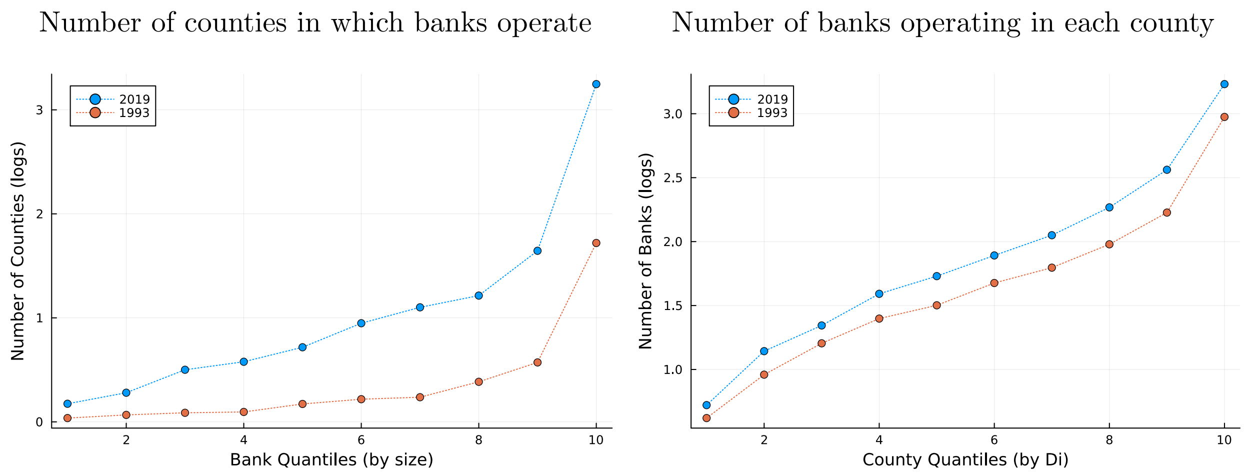


Figure 2. Share of deposits in banks that operate in ≥ 10 counties

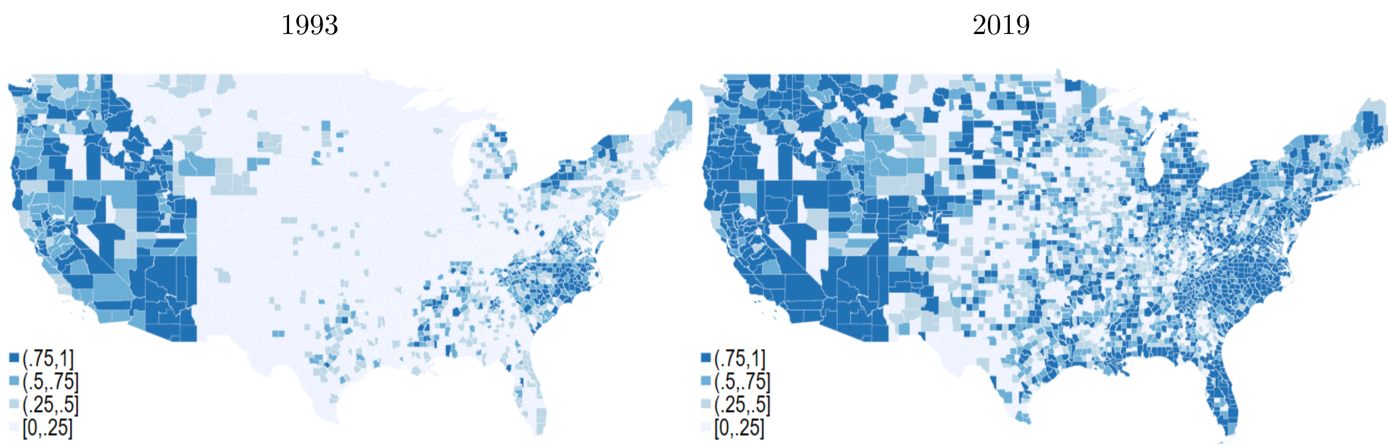


Figure 2 provides a county-level measure of diversification. For each county, it shows the share of county-level deposits that are in banks that operate in at least 10 other counties. There has been a widespread increase in the number of locations in which banks operate. In the 1990s, this diversification measure was small since many banks operated locally. In many regions of the mid-west for instance, the share of diversified deposits was 0. In 2019, on the other hand, we observe a much larger share across all counties and regions.

To illustrate the potential gains of diversification simply based on observables, in Appendix B.1 we provide suggestive empirical evidence on the relation between bank-level deposit risk and the number of counties a bank operates at. We construct a panel of bank-level exposures to deposit risks that controls for the effects of endogenous branching, and then study how these exposures relate to banks' characteristics. In effect, we find that exposure to deposit fluctuation risk falls monotonically with the number of counties a bank operates at. Similar results hold when considering exposures to fluctuations in originations of small business loans and mortgages, as well as delinquencies. Although not shown, results also hold when considering deciles on bank size (as proxied by deposits).

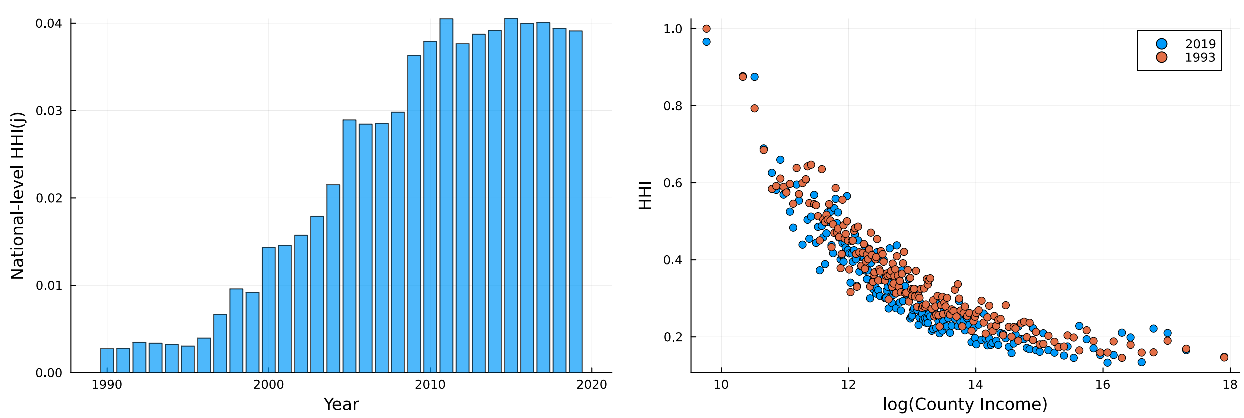
So far, we have argued that banks' geographical expansion might bring diversification benefits, both for deposits and lending. These benefits, in turn, may end up benefiting non-financial sectors, in terms of a more stable credit supply, higher deposits rates, and lower loans spreads. For the period of analysis, however, there has been an increase in banks' concentration at the national level, which may have had important effects on banks' market power.

Figure 3 illustrates this point by showing Herfindahl-Hirschman indices (HHI) for bank deposit markets, both at the national (left panel) and county levels (right panel). The figure shows that concentration at the national level has been increasing steadily during the 1990-2020 period. At the county-level, the effects are mixed. Since many banks set their rates at the national level, the increase in concentration may have led to larger markups in the market for deposits. Moreover, the higher concentration may affect the riskiness and stability of the financial sector, since larger banks have a larger leverage and rely less on deposits as a source of funding.

Because of these opposing forces, the net 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.

Figure 3. Concentration in Deposit Markets

National-level Herfindahl Index: $\sum_j \left(\frac{Dj}{\sum_j Dj}\right)^2$ County-level Herfindahl Index: $\sum_{j\in i} \left(\frac{Dij}{\sum_{j\in i} Dij}\right)^2$



3. The 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 a large number of heterogeneous banks. The household uses its endowment to supply funds to banks in the form of equity, deposits and wholesale funding. Deposits are special in the sense that they provide liquidity services which yield direct utility to the household. Banks invest (or equivalently lend out) the funds at their disposal. For simplicity, we model all these as intra-period transactions which allows us to work with effectively a static setting.

There is a continuum of heterogeneous deposit markets (counties), each with a finite number of operating banks. Not all banks operate in all markets, the source of idiosyncratic risk. Banks act as oligopolists in deposit markets and compete by setting interest rates on deposits. We analyze separately two polar cases for banks' rate setting behavior. First, we consider a scenario in which banks set deposit rates at the county level ('local pricing'). Second, we consider a version of 'uniform pricing' in which each bank sets a single deposit rate across all the counties in which it operates. This formulation is motivated by an empirical literature documenting that banks often set similar rates across multiple markets (Radecki, 1998; Heitfield and Prager, 2004; Granja and Paixao, 2021; Begenau and Stafford, 2022). Of course, reality lies somewhere in between these two extreme cases. For instance, a bank may set the same rate across all branches of a given state, but different rates across states.[2]

We derive analytical expressions for a number of objects of interest, notably spreads, risk premia and markups. We exploit these heavily in the quantitative analysis of Section 4, leading to a simple and transparent empirical strategy.

3.1. *Representative Household's Problem*

The representative household is endowed with $\bar{W}$ units of consumption goods. They can then invest these funds in three different assets: bank equity (denoted by E) deposits (described in more detail below), or wholesale funding to banks (denoted H).

The household's value from the liquidity services is a function of a composite of individual deposits across counties and banks. Let D_{ij} denote the household's deposits with bank j in county i. We use a nested CES specification for aggregating deposits – the first level aggregates

[2]Data on deposit rates at the county-level suggests that banks set more than just one rate, but a bank fixed effect explains an overwhelming fraction of the variation in deposit rates.

D_{ij} of different banks in a given county i to construct a county-level D_i. The second level then combines these into an economy-wide composite D. Formally:

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

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 at different banks within the same county are more substitutable than those across counties.[3] The variable ϕ_i denotes the household's relative preference for deposits in county i and will be the only source of randomness in the model. It is meant to capture factors that may affect county-level demand for deposits (including, for instance, income, wealth, or economic conditions). In our empirical strategy, described in Section 4, these preference shifters will be pinned down by the data. Analogously, the term ψ_{ij} captures the relative preference for deposits in bank j within a given county.[4]

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

$$\max_{C,\{D_{ij}\}} \quad u(C, D) \tag{2}$$
$$\text{s.t. } C = \left(\overline{W} - E - \int_0^1 \sum_{j=1}^{J_i} D_{ij} di \right) R + \int_0^1 \sum_{j=1}^{J_i} R_{ij}^D D_{ij} di + \Pi.$$

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

$$\frac{R - R_{ij}^D}{R - R_i^D} = \psi_{ij} \left(\frac{D_{ij}}{D_i} \right)^{-\frac{1}{\eta}}, \tag{3}$$

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:

$$R - R_i^D = \left(\sum_{j=1}^{J_i} \psi_{ij}^{\eta} \left(R - R_{ij}^D \right)^{1-\eta} \right)^{\frac{1}{1-\eta}}. \tag{4}$$

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

[4]These preferences can be micro-founded in a discrete choice problem over bank deposits if the non-monetary value of each bank deposit is drawn from a correlated Gumbel in which θ and η govern the similarity of draws across and within markets, respectively (see Verboven (1996); Berger et al. (2022)). We provide details in Appendix C.1.

Analogously, demand for the composite deposit aggregate D_i is

$$\frac{R - R_i^D}{R - R^D} = \phi_i \left(\frac{D_i}{D}\right)^{-\frac{1}{\theta}}, \tag{5}$$

where

$$R - R^D = \left(\int_0^1 \phi_i^\theta \left(R - R_i^D\right)^{1-\theta} di\right)^{\frac{1}{1-\theta}}. \tag{6}$$

3.2. *Banks' Problem under Local Pricing*

Bank j makes loans (L_j) using total funds from equity, deposits and wholesale funding. We assume the lending technology exhibits diminishing returns, so that the return on an additional loan unit is $R + z - \frac{\chi_j}{2} L_j$. This curvature is the source of a distaste for risk or equivalently, a motive for diversification. The bank competes for deposits by choosing an interest rate it offers on deposits. Under local pricing, it chooses 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 $R_{ij}^D + \kappa_{ij}$, where κ_{ij} captures the non-interest expense associated with deposits. Wholesale funding (H_j) is available through a competitive economy-wide market. The household's supply for wholesale funding is assumed to be perfectly elastic (hence, banks have to pay R on H_j). Banks are also subject to issuance costs of $\frac{\nu_j}{2} H_j^2$, so the marginal cost for bank j of raising an additional unit of funding from this market is given by $R + \frac{\nu_j}{2} H_j$. Banks are heterogeneous in their non-interest costs (κ_{ij}), and in their cost of accessing wholesale funding (ν_j).

The timing of events is as follows. First, banks choose deposit rates R_{ij}^D (or equivalently, spreads $R - R_{ij}^D$) and wholesale funding H_j. The county-level demand shifters (ϕ_i) are unknown at the time banks set their interest rates, but banks' known their joint distribution, G. 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

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

$$\text{s.t. } L_j = \int_0^1 \mathcal{D}_{ij}(\cdot) d\Lambda_j(i) + H_j + E_j, \tag{7}$$

where $\Lambda_j(\cdot)$ denotes the (exogenous) measure indexing 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 (3) and (5).[5] These are functions of interest rates offered by the bank (as well as those of its competitors).

Banks compete oligopolistically at the county level. That is, when choosing R_{ij}^D, they internalize its effects on R_i^D and D_i, but they take as given the aggregates R^D and D. The optimality conditions with respect to wholesale funding and spreads imply:

$$H_j = \frac{z - \chi_j \left(\mathbb{E} \int_0^1 \mathcal{D}_{ij} d\Lambda_j(i) + E_j \right)}{\chi_j + \nu_j}, \tag{8}$$

and

$$R - R_{ij}^D = \underbrace{\frac{\eta(1 - s_{ij}) + \theta s_{ij}}{\eta(1 - s_{ij}) + \theta s_{ij} - 1}}_{MKP_{ij}} \underbrace{\left[\kappa_{ij} - z + \chi_j \left(\mathbb{E}(L_j) + \mathbb{C}ov \left(\frac{\mathcal{D}'_{ij}}{\mathbb{E}(\mathcal{D}'_{ij})}, \int_0^1 \mathcal{D}_{ij} d\Lambda_j(k) \right) \right) \right]}_{MC_{ij}}, \tag{9}$$

where s_{ij} denotes the bank's effective market share in county i:

$$s_{ij} \equiv \frac{R - R_{ij}^D}{R - R_i^D} \frac{D_{ij}}{D_i} = \psi_{ij} \left(\frac{D_{ij}}{D_i} \right)^{\frac{\eta - 1}{\eta}} \in (0, 1). \tag{10}$$

Equation (9) decomposes spreads into a markup and marginal cost component. The markup term, MKP_{ij}, is identical to that of Atkeson and Burstein (2008), and is a function of the bank's market share s_{ij} and the within- and across-county elasticities. As s_{ij} approaches zero, the elasticity of the deposit demand curve faced by the bank approaches the within-county elasticity parameter η and therefore, the optimal markup becomes $\frac{\eta}{\eta - 1}$. As s_{ij} increases, the bank internalizes the effects of its own choices on the county-level aggregates which changes the effective demand elasticity. Specifically, the elasticity of deposit demand is a weighted average of the within-county and across-county elasticity parameters (η and θ respectively). As s_{ij} approaches one, the across-county elasticity θ becomes the relevant one and the markup converges to $\frac{\theta}{\theta - 1}$. Given the assumption that $\eta > \theta > 1$, markups are increasing in s_{ij}.

The marginal cost term, MC_{ij}, comprises of the net cost of raising deposits ($\kappa_{ij} - z$), an adjustment for the diminishing returns in lending, and a risk component that depends on how correlated a bank's county-level deposits are. Intuitively, a county where marginal deposit inflow tends to be high during times of high bank-level deposits (i.e., for the bank as a whole) is a less attractive source of funds because it generates deposit inflows when the marginal return on funds is lower. Thus, it receives a less attractive deposit rate (or higher spread).

[5] That is, $\Lambda_j(i) = 1$ if bank j operates in county i and $\Lambda_j(i) = 0$ otherwise. For a bank j that operates in a finite set of counties $\mathcal{M}_j$, then $\int_0^1 d\Lambda_j(i) = \int_{\mathcal{M}_j} di$.

Using the CES structure and the demand functions in Equations (3)-(5), we can rewrite the covariance term in Equation (9) as follows:

$$\mathbb{C}ov\left(\frac{\mathcal{D}'_{ij}}{\mathbb{E}(\mathcal{D}'_{ij})}, \int_0^1 \mathcal{D}_{ij} d\Lambda_j(k)\right) = \int_0^1 \mathbb{E}\left(D_{kj}\right) \frac{Cov\left(\phi_i^\theta \phi_k^\theta\right)}{\mathbb{E}\left[\phi_i^\theta\right]\mathbb{E}\left[\phi_k^\theta\right]} d\Lambda_j(k)$$

Using this expression, we can then express banks' marginal cost, MC_{ij}, more succinctly as follows:

$$MC_{ij} = \kappa_{ij} - z + \chi_j \mathbb{E}\left(L_j\right)\left(1 + RP_{ij}\right), \tag{11}$$

where

$$RP_{ij} \equiv w_j^D \int_{k\in\mathcal{M}_j} w_{kj}^D \frac{\rho_{ik}\sigma_i\sigma_k}{\mu_i\mu_k} dk. \tag{12}$$

denotes the county-level risk premium and $\mathcal{M}_j$ denotes the set of counties in which bank j operates. The parameters $\mu_i \equiv \mathbb{E}[\phi_i^\theta]$, $\sigma_i \equiv \mathbb{V}^{1/2}(\phi_i^\theta)$, and $\rho_{ik} \equiv \text{corr}(\phi_i^\theta, \phi_k^\theta)$ are the relevant first- and second moments of the county-level shocks. These are weighted by coefficients $w_j^D \equiv \frac{\int_{k\in\mathcal{M}_j} \mathbb{E}\left(D_{kj}\right) \mathrm{d}_k}{\mathbb{E}(L_j)}$ and $w_{kj}^D \equiv \frac{\mathbb{E}\left(D_{kj}\right)\Lambda_j(k)}{\int_{k\in\mathcal{M}_j} \mathbb{E}\left(D_{kj}\right)\mathrm{d}_k}$, which denote, respectively, the share of bank j's total loans that are expected to be come from deposits and the fraction of the bank's deposits that are expected to come from county k.

Equation (12) shows that risk premia affect banks' marginal costs and their spreads on deposits. That is, the spread offered by bank j in county i depends on the correlation $\{\rho_{ik}\}$ of that county's deposit shocks with those of the other counties the bank operates in. The higher the correlation, *ceteris paribus*, the higher is the risk premium and the spread (or equivalently, the lower is the deposit rate R_{ij}^D). Intuitively, a county whose deposit demand tends to be high during times of high total deposit demand from the bank's perspective is subject to a higher deposit spread. This expression also highlights how geographical expansion affects spreads. To the extent that a bank raises deposits from imperfectly correlated locations ($\rho_{ik} < 1$), it has lower risk exposures and therefore, a lower marginal cost.

In summary, we explicit the key elements affecting deposit spreads by plugging in the expression for marginal cost into (9), thus obtaining the following expression for local-pricing optimal bank spreads:

$$R - R_{ij}^D = \left(\frac{\eta(1-s_{ij}) + \theta s_{ij}}{\eta(1-s_{ij}) + \theta s_{ij} - 1}\right)\left(\kappa_{ij} - z + \chi_j \mathbb{E}\left(L_j\right)\left(1 + RP_{ij}\right)\right). \tag{13}$$

In our quantitative analysis, we use Equation (13) to decompose a bank's deposit spreads from observable data and directly quantify how changes in a bank's geographical footprint affects deposit spreads.

3.3. *Banks' Problem under Uniform Pricing*

We now turn to the analysis of banks' optimal rate setting problem under uniform pricing. As mentioned earlier, for this version, we assume bank j sets a single rate across all markets in which it operates, i.e. $R_{ij}^D = R_j^D \ \forall i$. The problem of bank j can be written as follows:

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

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

Equation (14) characterizes the optimal bank deposit spread (detailed derivations are relegated to the appendix):

$$R - R_j^D = \left(\frac{\eta(1-s_j) + \theta s_j}{\eta(1-s_j) + \theta s_j - 1}\right)\left(\kappa_j - z + \chi_j \mathbb{E}(L_j)(1 + RP_j)\right). \tag{14}$$

We denote the marginal cost under uniform pricing as $MC_j \equiv \kappa_j - z + \chi_j \mathbb{E}(L_j)\left(1 + RP_j\right)$. The risk premium RP_j term, in turn, is given by

$$RP_j = w_j^D \int_{k \in \mathcal{M}_j} \tilde{w}_{kj}^D \left(\int_{i \in \mathcal{M}_j} w_{ij}^D \frac{\rho_{i,k}\sigma_i\sigma_k}{\mu_i \mu_k} di\right) dk, \tag{15}$$

and the relevant bank-level variables are defined as:

$$s_j \equiv \frac{\sum_i \mathbb{E}\left(D_{ij}\right)\Lambda_{ij} s_{ij}}{\sum_i \mathbb{E}\left(D_{ij}\right)\Lambda_{ij}} \quad \kappa_j \equiv \frac{\mathbb{E}\left(\sum_i \mathcal{D}_{ij}' \Lambda_{ij}\kappa_{ij}\right)}{\mathbb{E}\left(\sum_i \mathcal{D}_{ij}'\Lambda_{ij}\right)}$$

$$w_{ij}^D \equiv \frac{\mathbb{E}\left[D_{ij}\right]\Lambda_{ij}}{\sum_i \mathbb{E}\left[D_{ij}\right]\Lambda_{ij}} \quad \tilde{w}_{ij}^D \equiv \frac{\mathbb{E}\left[D_{ij}\right](\eta(1-s_{ij}) + \theta s_{ij})\Lambda_{ij}}{\sum_i \mathbb{E}\left[D_{ij}\right](\eta(1-s_{ij}) + \theta s_{ij})\Lambda_{ij}},$$

Equation (14) is similar in structure to (13), the optimal spread under local pricing. There are, however, two differences. Under local pricing, markups vary by county and are increasing in the county-level market share s_{ij}. Under uniform pricing, markups are determined by a weighted average of market shares across all the markets in which the bank operates at, s_j. Second, the (bank-level) risk premium under uniform pricing is only a function of the volatility of the bank's total deposits. Under local pricing, the risk premium is county-specific and depends on the covariance of that county's risk with other counties in the bank's portfolio.

4. Mapping the Model to the Data

In this section, we describe the data and our calibration procedure. The model, despite its richness, lends itself to a transparent calibration strategy using micro-level data.

4.1. *Data Sources*

Annual data on deposits at the branch-level is taken from the FDIC's Summary of Deposits (SOD) for the period 1990-2019. This is an annual survey of branch office deposits as of June 30 for all FDIC-insured institutions. The dataset covers all US states, encompassing over 86,000 branches as of 2019. The dataset contains a unique identifier for a branch (UNINUMBR) and a bank (IDRSSD). We use data from Call Reports for bank-level variables such as loans, deposits, total assets, and liabilities. In particular, we compute E_j as total assets minus total liabilities, and H_j as total liabilities minus total deposits.

We use two sources for deposit rates. The first one are Call Reports, which contain detailed bank-level data for the universe of banks at quarterly frequency since 1990. Because Call Reports do not provide pricing data, we compute bank-level deposit rates as the ratio between a bank's interest expenses on savings and time deposits and its corresponding deposits.

The second source is Ratewatch. The vendor provides branch-level deposit rates gathered through surveys across different types of deposits, including savings accounts and time deposits. The data are at a weekly frequency and cover the 2011-2019 period. The survey is quite comprehensive, with responding branches covering around 80% of total domestic deposits. Since RateWatch provides rates at the product level, we compute a weighted average deposit rates across deposit products (certificate of deposits and saving accounts) using as weights bank-level balances for each deposit type from Call Reports.[6] Lastly, based on our view of a county as the relevant market, we collapse the RateWatch interest rate data to the year-county-bank level using branch-level deposits as weights.[7]

We use the 5-Year High Quality Market (HQM) Corporate Bond Spot Rate as our measure of the market rate R.[8] We then compute interest rate spreads, $R - R_{ij}^D$ and $R - R_j^D$ as the difference between the market and deposit rates.

The data from Call Reports and RateWatch map naturally to our two pricing specifications. For our baseline analysis, we adopt the uniform pricing specification and use deposit rates based on Call Reports data. This data has better coverage, both across banks (the Call Reports cover

[6] Deposit products considered from Ratewatch are 12, 24, and 60-month CDs (12MCD10K, 24MCD10K, and 60MCD10K), as well as money markets (MM25K). Bank-level weights for time deposits are deposit balances with less than 1 year of remaining maturity, with 1-3 years, and more than 3, respectively. Rates on money markets are weighted using savings accounts balances.

[7] In Appendix D.2, we also show that all our results are robust to an alternative definition of a local market to be at the MSA level, instead of at the county level.

[8] This rate is available at FRED, under the HQMCB5YR identifier.

the universe of US domestic banks) and over time (the data are available at least since 1990, while the RateWatch data starts only in 2011). The latter feature allows us to make comparisons before and after the Riegle-Neal Act of 1994 and use a longer sample us to compute the variance-covariance matrix for the county-level ϕ_i shocks using a larger sample period of 30 years.

In line with previous studies, we find evidence suggestive of uniform pricing practices. In particular, a bank-year fixed effect accounts for more than 90% of the observed variation in deposit spreads at the bank-county-year level.[9] There is, however, a small amount of unexplained dispersion which suggests some local pricing behavior. Later in this section, we exploit this dispersion to estimate the within-county demand elasticity, η.

Table 1 shows some descriptive statistics for deposits (SOD) and spreads (Call Reports) in 2019. The table shows data consists of a sizable number of observations both at the bank-county and bank levels. Also, as expected, the distribution of deposits has a very large dispersion (10-14 times the mean) and is significantly right-tailed, both for bank-county and bank-level data. In turn, the distribution of bank-level spreads has a milder yet significant dispersion (roughly 33% of the mean), and a very mild left skewness.

Table 1. Descriptive Statistics on Deposits and Spreads for 2019

	Deposits (in millions of USD)		Spreads (in %)
	Bank-county level	Bank-level	Bank-level
Mean	100.4	484.1	1.48
Median	14.8	28.1	1.50
10^{th} percentile	2.7	6.6	0.80
90^{th} percentile	115.7	249.8	2.11
Standard deviation	1080.6	6821.5	0.49
Skewness	47.2	33.5	-0.25
Observations	24579	5099	5099

Notes: This table shows descriptive statistics on deposits and spreads for 2019. Deposits are based on data from Summary of Deposits. Spreads are based on data from Call Reports and FRED.

[9]To rule out a high explanatory power being driven by local banks with few locations, we only focus on banks operating in more than 100 counties. Of course, we cannot rule out the possibility that banks are engaged in local pricing but find it optimal to set very similar rates across the markets in which they operate.

4.2. *Model Calibration*

We describe next our calibration strategy, which involves two steps. We first estimate the elasticities of substitution within- and across- counties (η and θ). Using those elasticities, we then use our model to map observables to parameters and to recover county-level shocks.

Elasticities of Substitution

We use an instrumental variable (IV) strategy to estimate the within-county elasticity of substitution η. Our instrument is a weighted average of changes in local wages across all the locations in which a bank operates. The main idea is that a bank's cost of providing deposit services, κ_{ij}, is affected by changes in the average wage rate faced by the bank, but these changes do not alter the relative preference parameters ψ_{ij}. For each bank, we construct a Bartik-type instrument by weighting wage changes in a county with the share of that county in the bank's total deposits in a base year t_0 (which is set to 2011). For bank j operating in counties $k \in \mathcal{M}_j$, our instrument is given by $\sum_{k\in\mathcal{M}_j} \Delta \ln \text{Wage}_{kt} \times \frac{D_{kj0}}{D_{j0}}$. Wage changes are computed from MSA-level wages reported by the U.S. Bureau of Labor Statistics (BLS). We restrict attention to banks that operate in at least 20 counties to further reduce the potential for our instrument to be correlated with demand shifters.

Equation (16) and (17) describe our two-stage regression. In the first stage, we regress bank-county level changes in deposit spreads on our Bartik instrument. In the second stage, we regress bank-county level deposit changes onto the instrumented changes in spreads. We include county-bank fixed effects to control for any time-invariant common characteristics at the bank-county pair, and county-time FE to control for any common variation in the county of reference. Our coefficient of interest is β^D, which can be directly mapped into the within-county elasticity of substitution (i.e., $\eta = -\beta^D$).

$$\Delta \ln R^D_{ijt} = \gamma^R_{ij} + \alpha^R_{it} + \beta^R \left[\sum_{k\in\mathcal{M}_j} \Delta \ln \text{Wage}_{kt} \times \frac{D_{kj0}}{D_{j0}} \right] + \epsilon^R_{ijt} \tag{16}$$

$$\Delta \ln D_{ijt} = \gamma^D_{ij} + \alpha^D_{it} + \beta^D \widehat{\Delta \ln R^D_{ijt}} + \epsilon^D_{ijt}. \tag{17}$$

The results are shown in Table 2. Based on our preferred specification in column (2) – which includes bank-county and county-time fixed effects – we get $\eta \approx 4.5$. Column (1) shows estimates for a specification without county-time fixed effects. The point estimate is smaller, consistent with the insight in Berger et al. (2022). Even if the instrument is uncorrelated with bank-specific demand shifters, it could still influence equilibrium deposits through its effects on county-level variables.[10] The county-time fixed effect allows us to account for all those interactions and indirect effects, and recover the true structural elasticity η.

TABLE 2. Estimation of within-county elasticity η

$\Delta \ln D_{ijt}$		
	(1)	(2)
$\Delta \widehat{\ln R_{ijt}}$	-3.73	-4.81
	(1.14)	(1.65)
Bank-county FE	Yes	Yes
Time FE	Yes	-
County-time FE	No	Yes
Observations	23,937	23,041
1st stage F-stat	18.55	12.10

We calibrate the other elasticity parameter θ by targeting average markups. To this end, we first construct a reduced-form estimate for a bank's marginal costs. We follow Berger et al. (2009) and Corbae and D'Erasmo (2021) and run the following regressions for noninterest expenses (NIE) and noninterest income (NII):

$$\begin{aligned}\ln\ NIE_{jt} =& \alpha_j + \alpha_t + \beta_0 \log\ \ell_{jt} + \beta_1 (\log\ \ell_{jt})^2 + \epsilon_{jt},\\ \ln\ NII_{jt} =& \gamma_j + \gamma_t + \rho_0 \log\ \ell_{jt} + \rho_1 (\log\ \ell_{jt})^2 + \epsilon_{jt},\end{aligned}$$

where ℓ_{jt} denotes total assets, α_j are bank FE, and α_t are time FE. Data on these variables comes from Call Reports for the period 2010-2019. Since θ has a significant influence on markups only for banks with large market shares, we restrict attention to banks with above-median total assets in 2019. Our estimate for marginal costs is then given by:

$$\widehat{MC}_j = \frac{\partial NIE_{jt}}{\partial \ell_{jt}} - \frac{\partial NII_{jt}}{\partial \ell_{jt}}.$$

Next, we combine this with with the data on bank-level spreads to derive an estimate of markups $\widehat{MKP}_j = (R - R_j^D)/\widehat{MC}_j$. For the median bank in this set, the markup is estimated to be approximately 1.3. Recall that markups in the model are given by $\frac{\theta s_j + \eta(1-s_j)}{\theta s_j + \eta(1-s_j) - 1}$. This

[10]In addition to the correlation between wage growth and deposit demand, there could also be effects on the county-level price index because the bank is large and therefore influences the price index directly, or because other banks in the county change their prices in response.

points to the following estimate:

$$\theta = \frac{\widehat{MKP}_j - \eta\,(1 - s_j)\left(\widehat{MKP}_j - 1\right)}{s_j\left(\widehat{MKP}_j - 1\right)}.$$

The market share s_j for the median bank is about 0.15. Given our calibration of $\eta = 4.5$, this yields $\theta \approx 3$. In Appendix D.4, we demonstrate the robustness of our main findings to using a lower value for θ.

Other parameters

Given the elasticities η and θ, the optimality conditions of the model can be used to recover the rest of the parameters and the county-level shocks, ϕ_i. First, we use the household optimality conditions to back out $\{\psi_{ij}\}$. We allow these to vary in an arbitrary way by year. Combining the definition for D_i in (1) with bank-county level demand function (3) and the county-level ideal price index (4), we obtain the bank-county level demand shifters:

$$\psi_{ij} = \frac{\hat{\psi}_{ijt}}{\left(\sum_j \hat{\psi}_{ijt}^{\eta}\right)^{\frac{1}{\eta}}}, \qquad \text{where} \tag{18}$$

$$\hat{\psi}_{ij} = \left(R - R_{ijt}^{D}\right) D_{ijt}^{\frac{1}{\eta}} \left(\sum_j \left(R - R_{ijt}^{D}\right) D_{ijt}^{\frac{1}{\eta}}\right)^{-1}. \tag{19}$$

Equation (18) imposes a normalization (specifically, $\sum_j \psi_{ijt}^{\eta} = 1$).[11] Once we have the $\{\psi_{ijt}\}$ for a given year, we can use equations (1), (4), and (10) to directly compute $\{D_{it}\}$, $\left\{R - R_{it}^{D}\right\}$, and $\{s_{ijt}\}$, respectively, for that year.

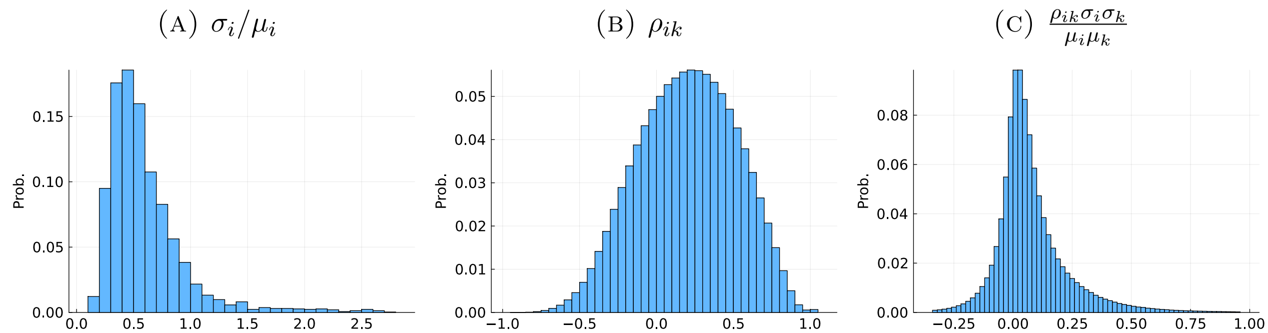
The next step is to recover the realized shocks $\{\phi_{it}\}$ (again up to a normalization constant). Combining the definition for D in Equation (1) with the economy-wide demand function in (5) and the economy-wide ideal price index in (6), we get

$$\phi_{it} = \frac{\hat{\phi}_{it}}{\left(\sum_j \hat{\phi}_{it}^{\theta}\Lambda_i\right)^{\frac{1}{\theta}}}, \qquad \text{where} \tag{20}$$

$$\hat{\phi}_{it} = \left(R - R_{it}^{D}\right) D_{it}^{\frac{1}{\theta}} \left(\sum_i \left(R - R_{it}^{D}\right) D_{it}^{\frac{1}{\theta}}\Lambda_i\right)^{-1}. \tag{21}$$

[11] This normalization implies that, in the special case in which there is no dispersion in R_{ijt}, the county-level composite spread equals the bank-county level ones. That is, $R_{it} = R_{ijt}$, where R_{it} is defined in Equation (4).

FIGURE 4. Estimated county-level moments



As before, the first expression reflects a normalization ($\sum_i \phi_{it}^{\theta}\Lambda_i = 1$).[12] Given a panel of observed shocks $\{\phi_{it}\}_{\forall i}^{t=1:N}$, we can estimate $\{\rho_{ik}, \sigma_i, \mu_i\}$. Figure 4 depicts these moments. The top panel shows that the coefficient of variation, σ_i/μ_i, is about 50%, indicating a non-trivial amount of risk. The distribution of the pairwise correlation ρ_{ik} highlights the potential for diversification.

The last step of the calibration consists of recovering the remaining parameters that characterize marginal costs: $\{\kappa_{ij}, z\}$ and $\{\chi_j\}$. In our formulation, χ_j indexes diminishing returns in lending. However, we prefer to interpret χ_j as capturing curvature in payoffs more generally. For example, it can also be micro-founded with an alternative specification where banks are risk-averse. In line with this broader interpretation, we use the model's optimal pricing equation and observed spreads to recover χ_j.

In principle, with rich enough data, one could estimate χ_j for each bank separately. However, in practice, data limitations require the use of some structure.[13] We make the following assumption: χ_j is inversely proportional to bank size (expected total assets). This assumption reduces the exercise to estimating a single parameter $\chi \equiv \chi_j \mathbb{E}(L_j)$. It also implies that any variation across banks in the effect of risk on spreads comes from the riskiness of their portfolio (more precisely, the RP_{ijt} term) rather than curvature heterogeneity.

Rearranging the optimal pricing equation (13), we obtain the following regression specification:

$$\frac{R - R_{ijt}^{D}}{MKP_{ijt}} = \kappa_{ij} - z + \chi\left(1 + RP_{ijt}\right) + \epsilon_{ijt}. \tag{22}$$

[12]We detrend $\{\hat{\phi}_{it}\}_{t=1990}^{2019}$ to ensure that our estimates of the covariance matrix are not distorted by county-level trends. Using a common (i.e. aggregate) trend produces very similar results.

[13]Although we have more than 16,000 banks in our dataset, many of those banks are active only for part of the sample. This limits our ability to precisely estimate χ_j for each bank.

TABLE 3. Estimation of χ

	(1)	(2)
$RP_{ij,t}$	0.008	0.010
	(0.0003)	(0.0003)
Observations	160,214	158,558
Bank-county FE	Yes	Yes
Year FE	Yes	-
Year-Bank FE	No	Yes

We estimate (22) using a panel of bank-county-year data. We add bank-county fixed effects (which capture unobserved county-bank characteristics i.e., the $\kappa_{ij} - z$ term) and bank-year fixed effects to control for unobserved time variation. Table 3 shows the results. We find similar point estimates under uniform pricing. Given χ, we then use equation (22) to back out $\kappa_{ij} - z$.

5. Results: Effects of Risk Premia and Markups

We use our calibrated model to quantify the effects of markups and risk premia on deposit spreads.[14] To this end and for the uniform-pricing case, we use a first-order approximation of Equation (14):

$$\begin{aligned}\ln\left(R - R_j^D\right) &\approx \ln MKP_j + \ln MC^* + \frac{1}{MC^*}(MC_j - MC^*) \\ &= \underbrace{\ln MKP_j}_{\text{Effect of Markups}} + \ln MC^* + \underbrace{\frac{\chi}{MC^*} RP_j}_{\text{Effect of Risk Premia}} + \frac{1}{MC^*}(\kappa_j - z + \chi) - 1, \qquad (23)\end{aligned}$$

where $MC_j \equiv \kappa_j - z + \chi + \chi\ RP_j$ denotes the bank-level marginal cost and MC^* the point of approximation. We use an analogous decomposition for the local-pricing case, based on Equation (13).

5.1. *Cross-sectional Patterns*

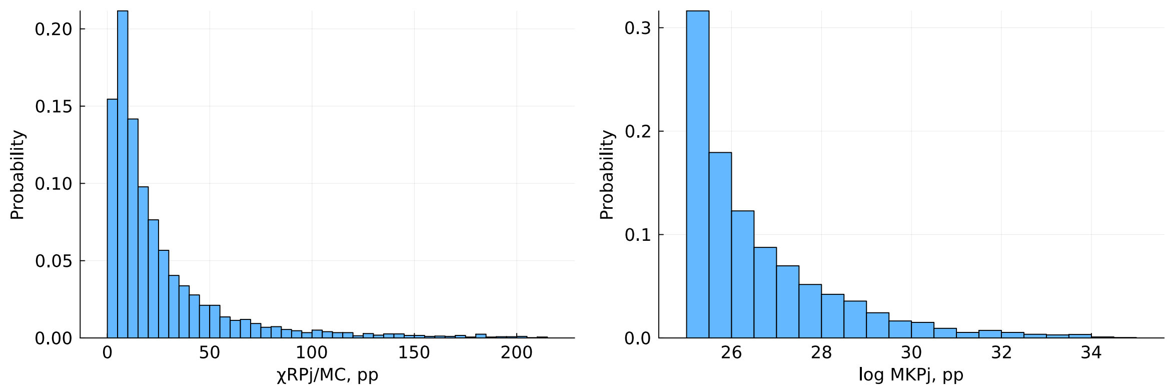
We start by analyzing current cross-sectional patterns in the effects of markups and risk premia on spreads for 2019, the last year in our sample. Figure 5 shows the distributions of $\frac{\chi}{MC^*} RP_j$ and $\ln MKP_j$, i.e. the contributions of risk (left panels) and markups (right panels)

[14]All the results in this section are based on our interpretation of a county as defining the boundaries of the local market. In Appendix D, we also show that our results are robust to alternative definitions of local markets. In particular, we show that all of our results hold if we define a local market as an MSA instead.

Figure 5. Effect on (log) Spreads

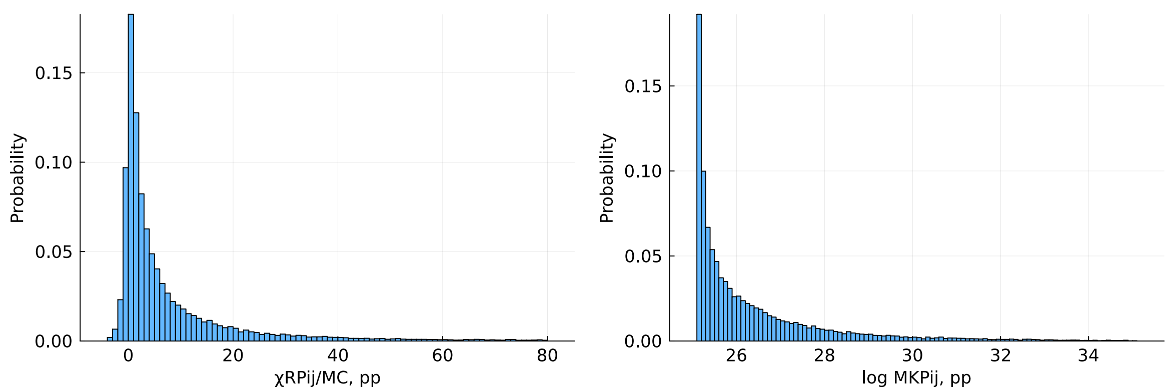
(a) Uniform Pricing (bank level)

Risk Premia | Markups



(b) Local Pricing (bank-county level)

Risk Premia | Markups

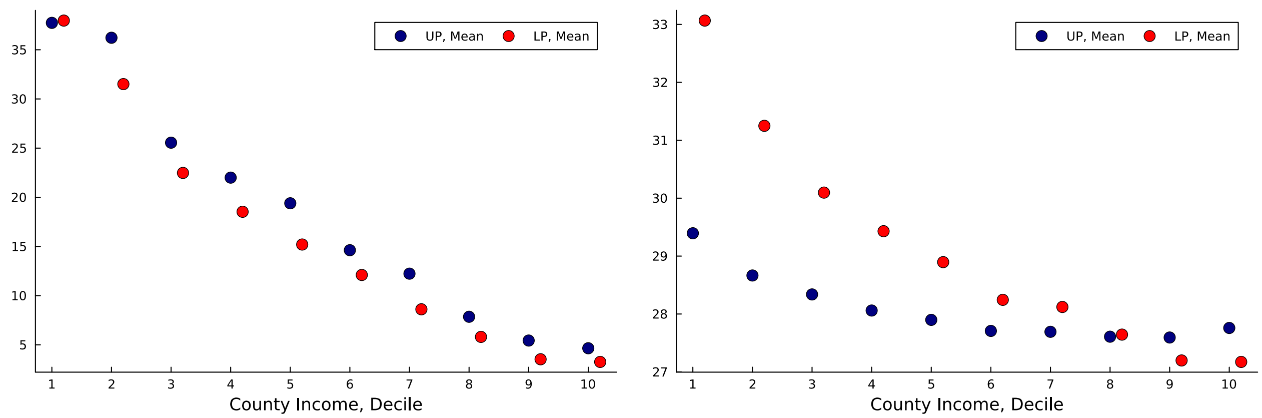


to (log) spreads. The top panel depicts the bank-level distribution for the uniform pricing case while the bottom panel shows the bank-county level case under local pricing (rates are from RateWatch). Both display considerable heterogeneity, whether across banks or bank-county pairs. For the median bank, the risk premium accounts for about 20% of its marginal costs and markups around 25%. At the ij-level, the effects of risk premia are relatively smaller, on average accounts for less than 10% of a bank's marginal costs. This is because banks with low risk premia are typically large banks that operate in many locations and, thus, they shift the bank-county risk distribution to the left. Still, the ij-level distribution exhibits a long right tail, which indicates that risk can account for a sizable share of banks' marginal costs.

Next, we explore how the effects of risk premia and markups covary with county and bank characteristics. The effects of risk premia and markups on county-level spreads are obtained by

Figure 6. Effects on (log) Spreads, by County

(A) Risk Premia (B) Markups, logs



a weighted average of their effects on spreads offered by banks in that county, using the model-consistent market share s_{ij} as weights. For example, under uniform pricing, the contribution of risk to county-level spreads is $\sum_{j\in\mathcal{J}_i} s_{ij}\,\frac{\chi}{MC_i^*}RP_j$ and that of markups is $\sum_{j\in\mathcal{J}_i} s_{ij}\,\ln MKP_j$, respectively, where $\mathcal{J}_i$ denotes the set of banks that operate in county i.[15] The definitions are analogous for the local-pricing case.

Panel (A) of Figure 6 shows the average contribution of risk in counties across different size deciles. Blue (red) dots show the means for each group under uniform (local) pricing. Under both assumptions, we find that the effects of risk on spreads are substantially higher in smaller counties, reflecting the fact that these markets are served by relatively undiversified banks. The magnitudes are economically significant – for the bottom decile, the average effect of risk is about 0.35 log points. Panel (B) depicts the effects of markups, which are also declining with county size. Markups are higher under local pricing (except for the largest two deciles). Combined, the risk and markup forces drive up spreads by over 0.60 log points in smallest/poorest counties.

We now turn to bank-level patterns. Under uniform pricing, we use the effects of markups and risk premia on spreads defined in Equation (23), since they are already at the bank level. For the local-pricing case, we aggregate the bank-county level variables using the deposit shares, i.e. $\sum_{i\in\mathcal{M}_j} w_{ij}^D\,\frac{\chi RP_{ij}}{MC_j^*}$ and $\sum_{i\in\mathcal{M}_j} w_{ij}^D\,\ln MKP_{ij}$ respectively.[16]

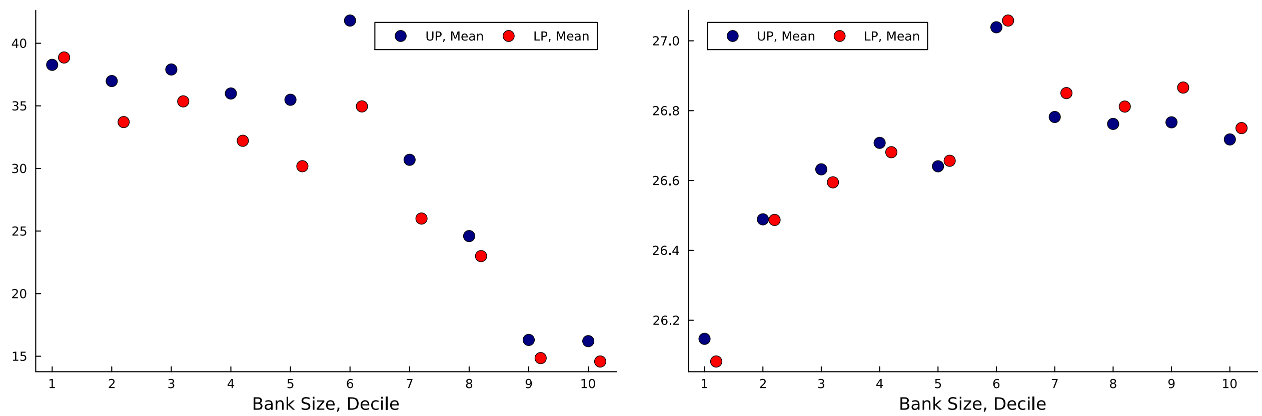
Panel (A) of Figure 7 shows risk premia exert a larger effect on spreads offered by smaller banks, which typically operate in fewer markets. Again, the magnitudes are sizable – for the

[15] For this exercise, we approximate marginal costs around the county average, i.e $MC_i^* = \sum_{j\in\mathcal{J}_i} s_{ij}MC_j$.

[16] In this case, we approximate marginal costs around the bank-level average, $MC_j^* = \sum_{i\in\mathcal{M}_j} \omega_{ij}^D MC_j$.

Figure 7. Effects on (log) Spreads, by Bank

(A) Risk Premia (B) Markups



bottom decile, risk premia push up spreads by almost 0.40 log points. Panel (B) shows the pattern for markups. Larger banks tend to have, on average, a higher market share and thus larger markups, though the differences are quite small. It is worth noting that the graph masks considerable heterogeneity within each decile group.

6. Diversification Benefits and Markups Across Time

Next, we use the model to decompose changes in banks' deposit spreads across time. Our goal is to quantify the effects of the observed changes in banks' geographical allocation on county-level markups, marginal costs, and risk premia. To this end, we compute changes in these objects between 1993, the pre-Riegle-Neal Act period ($t = 0$), and 2019 ($t = 1$). For brevity, we only show results under uniform pricing. In Appendix D.1, we show that the patterns are quite similar under the local pricing assumption as well.[17]

Analogous to the cross-sectional analysis in the previous section, we use a first-order approximation of the change in county-level spreads:

$$\Delta \ln(R - R_i^D) \approx \underbrace{\Delta\left(\sum_{j \in \mathcal{J}_{it}} s_{ijt} \ln MKP_{jt}\right)}_{\text{Change in Markups}} + \underbrace{\frac{\chi}{MC_i^*}\Delta\left(\sum_{j \in \mathcal{J}_{it}} s_{ijt} RP_{jt}\right)}_{\text{Change in Risk Premia}} + \underbrace{\frac{1}{MC_i^*}\Delta\left(\sum_{j \in \mathcal{J}_{it}} s_{ijt}(\kappa_{jt} - z)\right)}_{\text{Change in other costs}}, \tag{24}$$

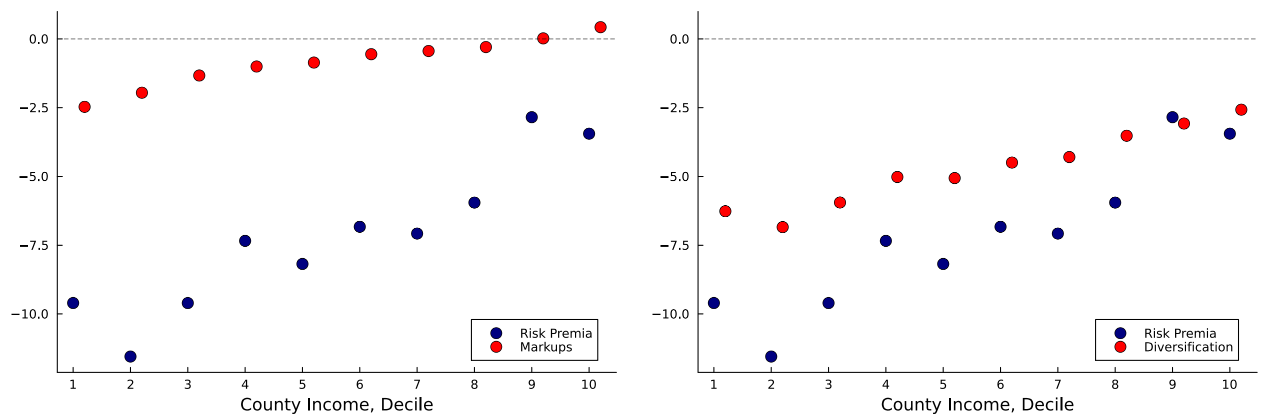
[17]Since the Ratewatch data starts only in 2011, we do not have bank-county-level deposit rates for 1993. Therefore, we use bank-level rates from the Call Reports for the pre- period and bank-county-level rates from Ratewatch for the post- period. We view this as a reasonable approximation since most banks were in fact "local" banks in the early 1990s (as shown in Figures 1 and 2).

where the operator Δ defines changes across periods $t = 1$ and $t = 0$.[18]

Panel (A) of Figure 8 depicts the first two terms on the right hand side of (24) – i.e. changes in markups and risk premia – by county size. The reduction in spreads from lower risk premia are much larger in smaller (poorer) counties and they imply a reduction of deposit spreads of over 10%. For larger counties, on the other hand, the effects on risk premia on marginal costs are smaller since the banks that operated in these counties were already well-diversified in the 1990s. The figure also shows that markups actually *decreased* for smaller counties and implied a 3-5% reduction in deposit spreads.

FIGURE 8. Changes in (log) Spreads, 1993-2019, by County

(A) Markups and Risk Premia (B) Diversification



6.1. *Role of Diversification*

We can further decompose the changes in risk premia into variation in the extent of geographical diversification and other movements in the riskiness of a bank's deposit flows (for instance, the composition of its deposits could have shifted towards less volatile counties). To disentangle these two forces, we construct a measure of diversification. For each bank j and date t we define:

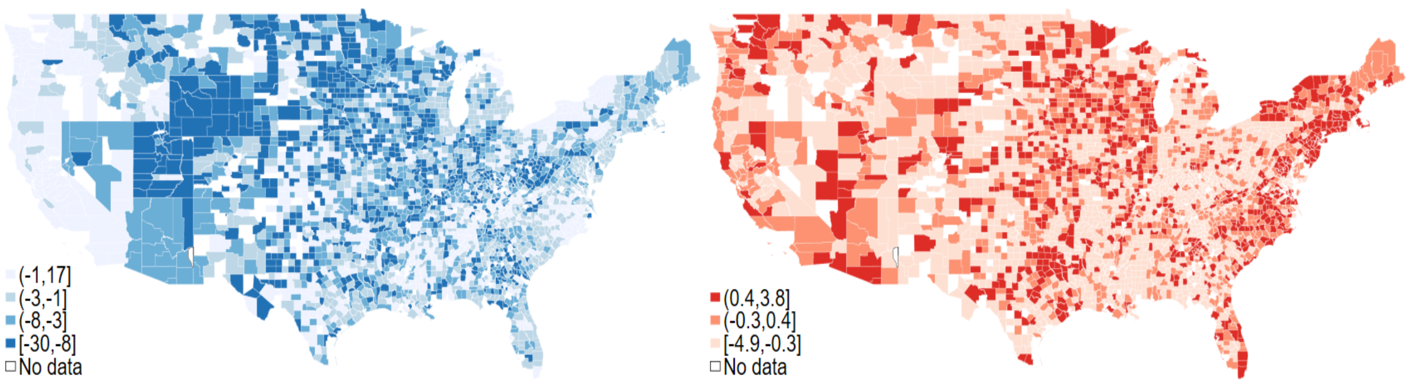
$$Diver_{jt} \equiv RP_{jt} - RP_{jt}\mid_{\rho=1} = RP_{jt} - \left[w^D_{jt} \int_{k \in \mathcal{M}_{jt}} \tilde{w}^D_{kjt} \left(\int_{i \in \mathcal{M}_j} w^D_{ijt} \frac{\sigma_i \sigma_k}{\mu_i \mu_k} di \right) dk \right], \tag{25}$$

where $RP_{jt}\mid_{\rho=1}$ is the (bank-level) risk premium under the assumption that all counties are perfectly correlated (but the other moments and weights remain the same). We can then

[18]Whenever we compare changes across time, we approximate marginal costs around the time-0 county average, i.e $MC^*_i = \sum_{j \in \mathcal{J}_{i0}} s_{ij0} MC_{j0}$.

FIGURE 9. Changes in (log) Spreads, 1993-2019

(A) Risk premia (B) Markups



use (24) to aggregate this measure to the county level using the bank market shares s_{ijt} as weights, so the effect of changes in diversification on (log) spreads in county i is given by $\frac{\chi}{MC_i^*}\Delta\left(\sum_{\mathcal{J}_{it}} s_{ijt} Diver_{jt}\right)$.

Panel (B) of Figure 8 depicts these effects. It compares the total effect of changes in risk premia (in blue) on county-level (log) spreads with the component attributable to diversification (in red). The graph points to a significant role for diversification, with changes in that component accounting for well over half of the declines in risk premia in the smallest counties.

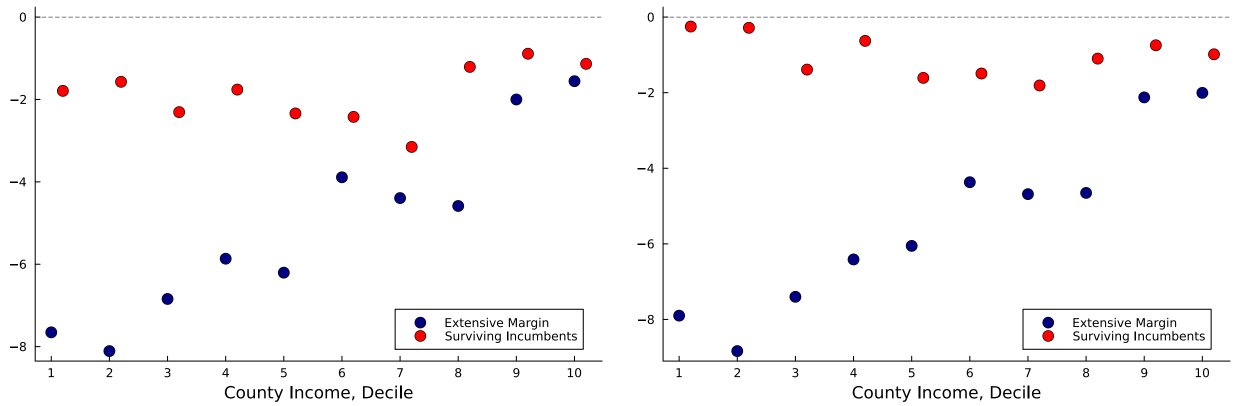
Figure 9 shows a map of the US with a decomposition of changes in spreads. Panel (A) shows changes in deposit spreads due to risk premia. The largest risk-related reductions were observed in Wyoming, South Dakota, West Virginia, Oklahoma, and Nebraska. For larger/richer regions (for instance, California or the North East), reductions in risk premia were modest (in part because those regions were served by diversified banks even before the Riegle-Neal Act). As for markups – shown in Panel (B) – we find much smaller changes with mild increases in the North East region (particularly, in Connecticut, New York, and New Jersey) and in Nevada. Perhaps surprisingly, we find markups declined in a large number of counties, particularly in the Midwest and South regions.

6.2. *Role of entry/exit*

Next, we explore the role of the extensive margin in the observed time variation in risk premium. We do this by allocating county-level changes across surviving incumbents, entrants, and exiting banks. For this, we define a survivor as a bank that operated in county i in both periods (1993 and 2019). An entrant (exiting) bank is one that only operated in county i

FIGURE 10. Decomposition of Changes in Risk Premia

(A) Uniform Pricing (B) Local Pricing



during 2019 (1993). Let $\{\hat{J}_i\}$ be the set of survivors, $\{\tilde{J}_{i0}\}$ the set of exiters, and $\{\tilde{J}_{i1}\}$ the set of entrants. For each period $t \in \{0, 1\}$, let $M_{it} \equiv \sum_{j \in \tilde{J}_{it}} s_{ijt}$ denote the combined market share of banks in county i that operate only in period t.

Using these definitions, we can decompose county-level changes in risk premia as follows:

$$\Delta \sum_{j \in \mathcal{J}_{it}} s_{ijt} RP_{jt} = \underbrace{M_{i1}\Big(\sum_{j \in \{\tilde{J}_{i1}\}} \frac{s_{ij1}}{M_{i1}} RP_{j1} - \sum_{j \in \{\hat{J}_i\}} \frac{s_{ij1}}{1 - M_{i1}} RP_{j1} \Big)}_{\text{Entrants vs. Survivors}} + \underbrace{M_{i0}\Big(\sum_{j \in \{\hat{J}_i\}} \frac{s_{ij0}}{1 - M_{i0}} RP_{j0} - \sum_{j \in \{\tilde{J}_{i0}\}} \frac{s_{ij0}}{M_{i0}} RP_{j0} \Big)}_{\text{Survivors vs. Exiters}}$$
$$+ \underbrace{\sum_{j \in \{\hat{J}_i\}} \left(\frac{s_{ij1}}{1 - M_{i1}} RP_{j1} - \frac{s_{ij0}}{1 - M_{i0}} RP_{j0} \right)}_{\text{Within Survivors Changes}}. \tag{26}$$

The first term on the right-hand side captures changes in county-level risk driven by new entrants. It compares the average risk of banks that entered county i in period $t = 1$ relative to that of the average survivor.[19] We multiply this difference by the market share of entrants, M_{i1} to arrive at a measure of their contribution to changes in the county-level risk premium. The second term repeats this procedure, but for exiters relative to survivors. We define the sum of these two terms as the "extensive margin" while the last term captures changes in risk across surviving incumbents.

The decomposition in Equation (26) can directly mapped into the contribution of these margins to changes in county-level spreads in (24). Figure 10 shows the results for this decomposition by county-size. We observe that the decline in risk premia came mostly through

[19]Note that $\sum_{\{\tilde{J}_{i1}\}} \frac{s_{ij1}}{M_{i1}} = \sum_{\{\hat{J}_i\}} \frac{s_{ij1}}{1-M_{i1}} = 1$.

changes in the extensive margin, particularly for smaller counties. The changes within survivors were generally small and relatively uncorrelated to county size.

Aggregate Effects

Next, we turn into the economy-wide effects. We use a similar first-order approximation to compute changes in the aggregate spread index, $R - R_t^R$:

$$\Delta \ln(R - R^D) \approx \underbrace{\Delta\Big(\sum_i s_{it} \sum_{j \in \mathcal{J}_{it}} s_{ijt} \ln MKP_{jt}\Big)}_{\text{Agg Change in Markups}} + \underbrace{\Delta\Big(\sum_i s_{it} \frac{\chi}{MC_i^*} \sum_{j \in \mathcal{J}_{it}} s_{ijt} RP_{jt}\Big)}_{\text{Agg Change in Risk Premia}} + \underbrace{\Delta\Big(\sum_i s_{it} \frac{1}{MC_i^*} \sum_{j \in \mathcal{J}_{it}} s_{ijt} (\kappa_{jt} - z)\Big)}_{\text{Agg Change in other costs}} . \quad (27)$$

Note that these terms also reflect time variation in county shares, s_{it}. To isolate those effects, we will also consider a version in which the shares s_{it} are held fixed at their 1993 levels, s_{i0}.

Table 4 presents the first two terms on the right hand side of (27), namely the effects of changes in markups and risk premia, along with the contribution of diversification. Panel (A) shows the contribution of each channel to changes in the national deposit spread (log points) as well as for three broad county groups (small, medium, and large) based on counties' total income in 1993. Panel (B) depicts these contributions as shares of total change in spreads.

We find that changes in the industrial structure between 1993 and 2019 induced a modest decrease in the aggregate deposit spread. Changes in risk premium push spreads down by a little less than 4 log points while markup changes contributed to 1 log point increase. This is not surprising, since aggregate changes are mostly driven by large counties, for which we find small changes in both risk and markups. At the county level, however, the net effect of banks' geographical changes can account for a sizable share of spreads. For the "medium" county group, we find a net decrease in deposits spreads between of 9 log points (in pp). This explains more than one-third of the total decrease in deposits spreads during the considered period. Lastly, the table highlights that changes under local pricing are remarkably similar compared to our baseline uniform-pricing case.

Table 4. Changes Across Time: The Role of Diversification and Markups

(A) Contribution to changes in spreads (log points)

	Uniform pricing				Local Pricing			
	Risk Premium		Markup	Net	Risk Premium		Markup	Net
	Total	Diver			Total	Diver		
National Level								
Aggregate	-3.4	-2.3	0.8	-2.6	-3.4	-2.1	0.9	-2.5
Aggregate (fixed shares)	-3.6	-2.8	0.4	-3.1	-3.7	-2.8	0.2	-3.4
By Group of Counties								
Small Counties (<p10)	-9.0	-7.1	-2.7	-11.7	-8.3	-8.5	-0.5	-8.8
Medium Counties	-8.4	-4.8	-0.7	-9.1	-8.5	-5.2	-0.3	-8.8
Large Counties (>p90)	-3.4	-2.5	0.5	-2.9	-3.7	-2.4	0.1	-3.6

(B) Share of total change in spreads

	Uniform pricing				Local Pricing			
	Risk Premium		Markup	Net	Risk Premium		Markup	Net
	Total	Diver			Total	Diver		
National Level								
Aggregate	10.8%	7.4%	-2.6%	8.1%	10.8%	6.5%	-2.9%	7.9%
Aggregate (fixed shares)	11.3%	8.8%	-1.4%	9.9%	11.6%	8.9%	-0.7%	10.9%
By Group of Counties								
Small Counties (<p10)	33.4%	26.2%	10.0%	43.4%	30.6%	31.5%	1.9%	32.5%
Medium Counties	39.7%	22.6%	3.3%	43.0%	40.2%	24.8%	1.4%	41.6%
Large Counties (>p90)	12.3%	8.9%	-1.8%	10.5%	13.1%	8.6%	-0.2%	12.9%

Notes: Panel (A) decomposes changes in log aggregate spreads, $\ln(R - R^D)$, between 1993 and 2019 into a change in markups and risk premia, using (27). The Aggregate (fixed shares) rows show results holding the county-level shares fixed at their 1993 levels. Bottom rows show the results by groups of counties, based on their total income in 1993. Medium counties are those between the 45- and 55- percentiles. Panel (B) expresses these changes as a share of the total change in $\ln(R - R_t^D)$. For the national level, the numbers in Panel (A) are divided by $\Delta \ln(R - R^D)$. For the county groups, the shares are averages of the county-level shares. Since spreads have generally decreased between 1993 and 2019, a positive (negative) value means that the particular channel led to a reduction (increase) in spread.

7. Counterfactual Experiments

In this section, we use the model to perform counterfactuals that provide further insight into the effects of risk and market power. In the first experiment, we recompute the equilibrium assuming $RP_{ij} = 0 \; \forall i, j$. In the second one, we quantify the role of 'local' banks (defined to mean those operating in less than two counties) by replacing them with the largest bank in each county. Finally, we consider the financial stability implications of the changes in the structure of the industry over the last two decades by analyzing equilibrium responses to a negative shock to returns to lending. In all cases, we recompute the equilibrium holding the other parameters fixed, and study the effect on spreads. Appendix C.3 details the solution algorithm.

We begin by specifying functional forms for preferences. We assume a quasi-linear structure:

$$U(C, D) = C + \xi \frac{D^{1-\gamma}}{1-\gamma}. \tag{28}$$

The associated first order condition is given by

$$R - R^D = \frac{U_D}{U_C} = \xi D^{-\gamma}. \tag{29}$$

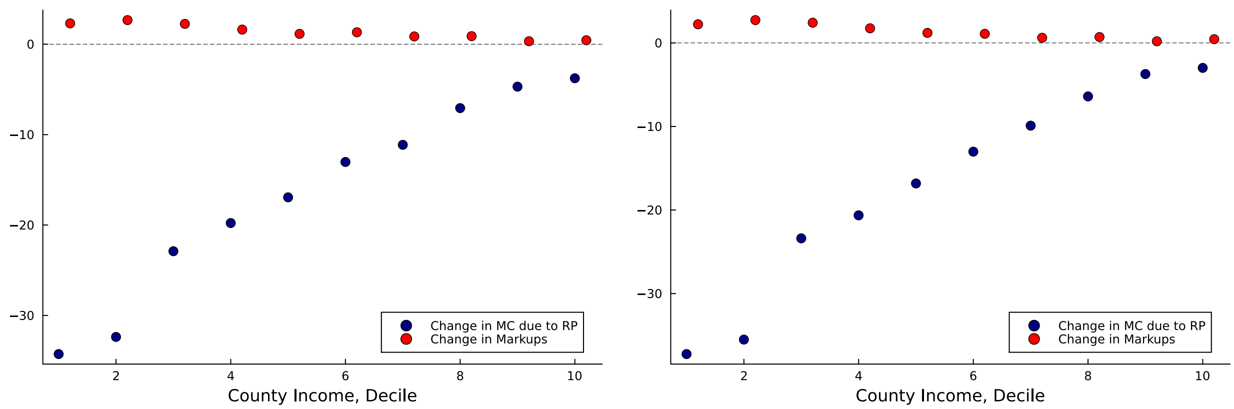
With quasi-linear preferences, aggregate deposits D only depend on the economy-wide spread, $R - R^D$ and parameters (under a more general utility function, they would also depend on aggregate consumption, which would impose an additional fixed point condition on the equilibrium).

7.1. *Effect of Risk*

We begin by examining a counterfactual scenario in which $RP_j = 0$ for all banks. This complements the analysis presented in the preceding sections by offering a comprehensive view of the equilibrium response, rather than merely a decomposition. As depicted in Figure 11, the elimination of risk significantly reduces marginal costs, and consequently, deposit spreads, whether under uniform or local pricing. We observe a larger reduction in smaller counties, where marginal costs drop by as much as 0.35 log points (representing over 40% of spreads). This cross-sectional pattern can be attributed to a similar rationale as that in Section 5.1: smaller counties rely more heavily on undiversified banks, thereby magnifying the impact of risk. In addition, we find that eliminating risk premia leads to a slight increase in markups, particularly for smaller counties. The net effect is negative, and all counties exhibit a reduction in spreads.

Figure 11. Effect of No Risk Premium, changes in (log) spreads

(A) Uniform Pricing (B) Local Pricing



7.2. *Role of Local Banks*

Next, we examine a scenario where, for each county, we replace "local" banks with the largest bank in that county (based on total assets). Here, we define a bank as local if it operates in fewer than three counties. This counterfactual is designed to capture the consolidation and M&A activity observed in the US banking industry since the Riegle-Neal Act. We assume that upon merger, the acquired bank retains the same ψ_{ij} value as the acquiring bank. Figure 12 presents the changes in (log) spreads under this counterfactual. It shows that the implied changes in the composition of banks lead to a decline in marginal costs due to lower risk premia, by almost 0.08 log points for the smallest counties. Under uniform pricing, banks' markups remain nearly unaffected, resulting in an overall reduction in deposit spreads. However, under local pricing, we observe a slightly larger increase in markups. Nevertheless, the net effect is also negative under this pricing structure.

7.3. *Aggregate Shock to Returns*

Finally, we analyze the effects of a common (i.e. economy-wide) decrease in the lending spread z. We interpret this as an adverse aggregate shock to the returns from lending. The effects of such on equilibrium outcomes can thus be viewed as an indicator of financial stability. Formally, we conduct the experiment separately for two years—1993 and 2019, reducing z by one (cross-sectional) standard deviation of $\kappa_j - z$ in both cases. Figure 13 illustrates the (net) effect on $\ln(R - R_i^D)$ by county size. Blue dots represent the predicted changes for 2019, while red dots denote those for 1993. Our analysis reveals that a lower z significantly increases

Figure 12. Removing Local Banks, changes in (log) spreads

(a) Uniform Pricing (b) Local Pricing

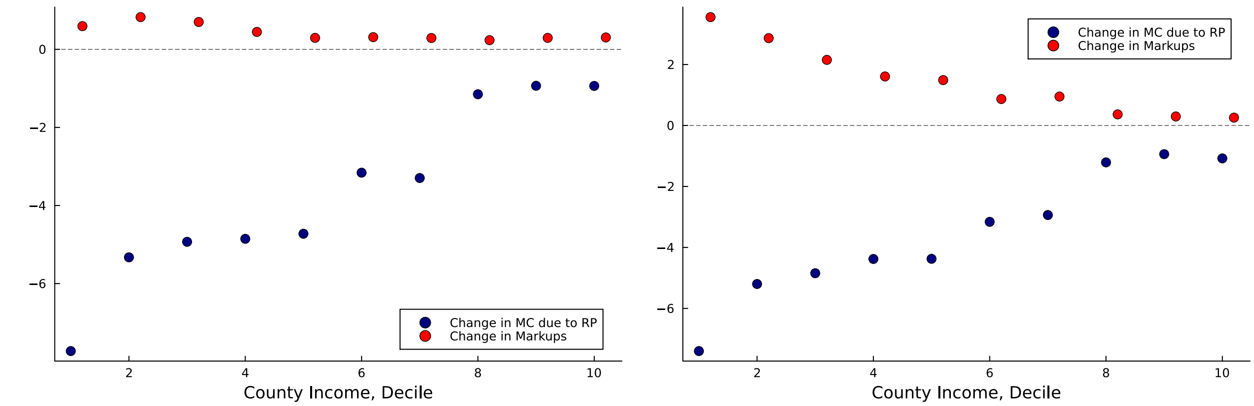
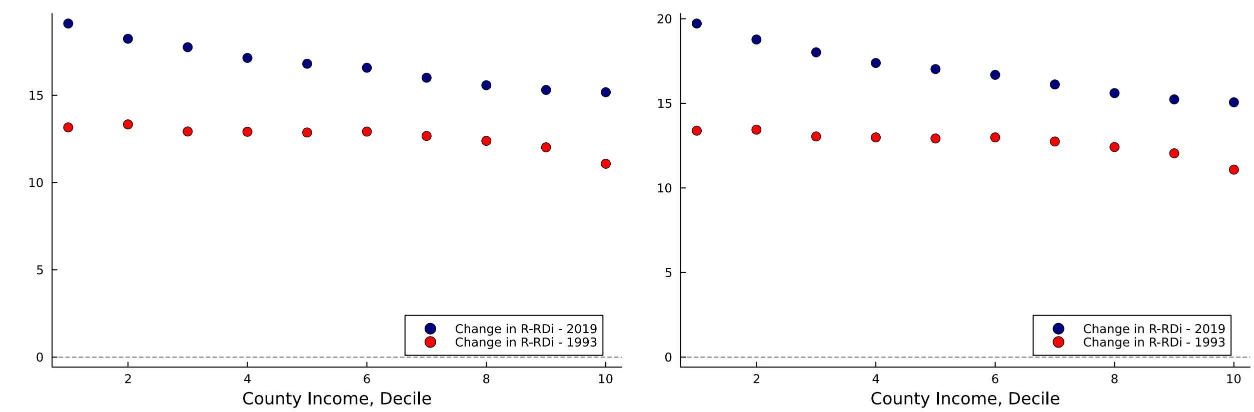


Figure 13. Changes in (log) Spreads Upon Negative Revenues Shock

(a) Uniform Pricing (b) Local Pricing



county-level spreads, with some cases showing up to a 0.20 log point increase. Notably, the rise in spreads is more pronounced in 2019 compared to 1993. In other words, in this sense, the banking system has become more vulnerable to aggregate negative shocks, even as it has reaped the benefits of diversification.

8. Conclusion

In this paper, we take a structural approach to measure the impacts of geographical expansion and consolidation within the US banking sector. We formulate a quantitative general equilibrium model with rich heterogeneity at both the bank and county levels. Oligopolistic banks operate in multiple counties with imperfectly correlated deposit demand, creating the potential for diversification through geographical expansion. We leverage detailed bank- and county-level data to discipline the rich spatial heterogeneity in the model.

The calibrated model shows that both risk premia and markups are significant contributors to the spread between deposit rates and benchmark 'illiquid' rates. Their role is particularly significant in smaller, poorer counties. Our results also suggest that the changes in the structure of the banking industry over the past few decades have resulted in meaningful reductions in risk premia in these counties.

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Appendix A. Data

A.1. *Data Sources*

County-level economic activity, urbanization, and risk-free rate. County-level economic activity data at yearly frequency since 1969 can be obtained from the BEA.[20] Classification of degree of urbanization for counties was obtained from the CDC, with counties being identified by FIPS codes.[21] The categories in this dataset, in decreasing order of urbanization, are large central metro, large fringe metro, medium metro, small metro, micropolitan counties, and non-core counties. Both large central and fringe metro counties are those in MSAs that have at least 1 million population but differ in density. Counties in medium metro areas are those in MSAs with population between 250,000 and 999,999, while small metro counties are those in MSAs with population less than 250,000. Micropolitan counties are those in micropolitan statistical areas. Non-core counties are non-metropolitan counties that are not in a micropolitan statistical area. Data for households' rate of return, R, is obtained from FRED: 5-Year High Quality Market (HQM) Corporate Bond Spot Rate (HQMCB5YR).[22] Data is at monthly frequency and we compute yearly averages.

Summary of Deposits (SOD). Historical data is publicly available at the FDIC website but we pull the data from a nonconfidential internal dataset from the Board of Governors.[23] The dataset is at yearly frequency with banks reporting at June each year. Some of the fields in the dataset are unique identifiers for a branch (UNINUMBR) and a bank (IDRSSD), location variables (zip code, city, county, state, etc), and volume of deposits (in thousands of USD).

Call Report Data. Bank-level balance-sheet and income statement data is reported to the FFIEC through forms 031, 041, and 051. [24] Most data is at quarterly frequency and contains a unique bank identifier (IDRSSD) that allows to merge it with the SOD data. While raw Call Reports data is publicly available, we use a dataset that is internally available at the Board of Governors that adjusts for mergers and acquisitions. Data is available from 1985:Q1 until the present. Among various fields, the dataset contains information on deposit types and its

[20] See: https://www.bea.gov/data/gdp/gdp-county-metro-and-other-areas.

[21] https://www.cdc.gov/nchs/data_access/urban_rural.htm.

[22] Source: U.S. Department of the Treasury, 5-Year High Quality Market (HQM) Corporate Bond Spot Rate [HQMCB5YR], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/HQMCB5YR.

[23] See https://www7.fdic.gov/sod/dynaDownload.asp?barItem=6.

[24] For details on forms, see https://www.ffiec.gov/ffiec_report_forms.htm.

maturities, detailed information on banks' assets and liabilities, interest income from loans, and interest expenses on deposits.

RateWatch. This is a weekly survey asking banks' branches about interest rates set on various loan types and deposits products, including certificates of deposits and money market accounts. The dataset is proprietary. It contains unique identifiers for branches and banks, as well as its locations, thus permitting to link this dataset to SOD and Call Reports. Comprehensive data is available since 2011.

A.2. *Construction of Interim Datasets*

Our analysis is done at the bank-county level, merging several datasets, so some data processing is needed prior to the analysis. SOD data is filtered to only include US states (i.e., exclude territories). We also adjust a few county names to make them consistent with names and FIPS codes in BEA's county-level economic activity dataset.[25] We then aggregate deposits data to the year-bank-county level, keeping track of the number of branches in the triplet.

The RateWatch dataset consists on three files: survey, account information, and account join. The survey file contains branches' account number, product type, and date of the survey. The account number variable is the unique identifier from RateWatch which allows us to link the three files. The account information file contains information on each account, such as institution type, location, and unique branch identifier (UNINUMBR). The account join file links branches with their self-reported rate setters, and with the date when that the relationship was formed. We can merge SOD data with RateWatch using UNINUMBR. Then, we use SOD information to associate a branch with its owning bank.

As a first step to merging RateWatch and SOD files, we collapse the survey data to yearly frequency. Then, we merge the account information with the account join file using the common account number identifier, and merge the resulting dataset with SOD using the unique branch identifier UNINUMBR. Finally, we merge this with the yearly survey data using the account number identifier.

The deposit products we use from RateWatch are interest rates on 12-month CDs (12MCD10K), 24-month CDs (24MCD10K), 60-month CDs (60MCD10K), and MMDAs (MM25K). Data is

[25] Adjustments are done for roughly 90 counties (out of 3,000 in our sample), a third of them located in Virginia, 6 in Alaska, and the rest dispersed through various US states.

cleaned from promo rates. Since data is at the product-branch-year level, we collapse it to the product-bank-county-year level by using a branch's deposits as weights.[26]

To construct a unique deposit rate at the bank-county-year level, RateWatch data is weighted by deposit product and maturity structure of time deposits using Call Reports data on deposits in domestic offices. In Call Reports, savings accounts include money market deposit accounts (MMDAs). In turn, we consider time deposits to be the sum of small time (less than $100,000) and large time ($100,000 or more) deposits. We further decompose time deposits by maturity structure, to have a weighted average of RateWatch's CDs interest rates across maturities. Time deposits up to 1 year are the sum of large and small time deposits for less or equal to 3 months, and between 3 months up to 1 year. We also compute time deposits for more than three years, and between 1 and 3 years (i.e., the residual). RateWatch and Call Report datasets are merged using IDRSSD. To be consistent with SOD timing, we only consider data at the second quarter of each year.

Since RateWatch has comprehensive data starting only on 2011, we construct an alternative database of average deposit rates based on Call Reports data starting on 1990. To this end, we pull data on volumes and interest expenses on time deposits (small and large) and savings accounts (including MMDAs), add time and savings values within expenses and volumes, and compute the ratio of interest expenses to volumes.[27] Since interest expenses are flows, we accumulate to the fourth quarter of each year before computing the ratio. In a few cases, we do not have information on time and savings deposits separately, so we use the average deposit rate in overall domestic deposits instead. We then merge this data with the risk-free rate (HQMCB5YR), compute spreads, and *winsorize* spreads at the lower and upper 1 percent.

We also use Call Reports data to compute bank-level ratios of equity, wholesale funding, and deposits to total assets. For comparison, we also compute ratios of deposits to total assets using SOD data, collapsed to the bank-level. In very few cases, the ratio based on Call Reports differs from the one based on SOD by more than 10% in absolute value, so we drop them.[28] We also drop outliers of deposits to assets ratios that are on the top 0.5 percent of the distribution, or ratios that are lower than 10 percent. We then calculate bank equity as total assets minus total liabilities, and compute its ratio to total assets. We also drop the low/top 0.1 percent of the distribution, which renders equity values that are always positive and ratios far away

[26] In this step, we assume same weights across products due to data availability issues.

[27] Of note, it is not possible to further differentiate time deposit interest expenditures by maturity.

[28] This consistency check is needed since our bank-county level deposits are based on SOD data.

from 1. Given values for deposits (d_j) and equity (e_j) to total assets, we compute wholesale funding to total assets as $h_j = 1 - d_j - e_j$ and drop observations in the low/top 0.1 percent of its distribution.

A.3. *Construction of Dataset on Bank-County-Year Deposits and Rates (2011-2019)*

We start by uploading SOD-based data at bank-county level, assuming this has the universe of deposits. We merge this data with shares of time and savings deposits constructed from Call Reports, and multiply bank-county level deposits by the bank-level shares of time and savings deposits as a way to adjust for checking accounts. We drop bank-county pairs with deposits less than 1 million USD. We then combine this with data on e_j, h_j, and d_j, and with the processed RateWatch dataset. The resulting merger covers around 80% of total deposits observed in SOD (or around 70% of raw count for bank-county pairs), so we need to impute deposit rates for the remaining bank-county pairs that are present in SOD but not on RateWatch. We do so using average deposit rates based on interest expenditures on deposits.

We then use the risk-free rate variable (HQMCB5YR) to compute deposit spreads. We then exclude counties that, despite the imputation procedure, do not have deposit rate data on all years. These are very few, and represent less than 0.1% of deposits in total. Finally, de-trend deposits based on the growth rate of aggregate loans.[29]

A.4. *Historical Data on Deposits*

In addition to 1990-2019 yearly data on average deposit rates based on Call Reports, we obtain historical data on bank-county deposits from SOD. We merge SOD and Call Report datasets for 1990-2010 using IDRRSD bank identifier and, as before, compute ratios of equity, wholesale funding, and deposits to total assets. We also follow the same steps as before to process the data: (1) apply the share of savings and time deposits (over total deposits) from Call Reports; (2) drop bank-county pairs with deposit volume less than 1 million USD; (3) drop counties that are not present for the entire period 1990-2009 (very small in magnitude, both in raw count and share of deposits); (4) de-trend deposits based on growth rate of total loans.[30]

[29]Let Y_t be the variable in levels, y_t the de-trended version, and g the growth rate. Then, $y_t = \frac{Y_t}{(1+g)^t} \iff \ln Y_t = \ln y_t - \ln(1+g) \times t$. We estimate g by running an OLS of the log of aggregate loans onto a year variable, and computing $\hat{g} = \exp\left(\hat{\beta}\right) - 1$, with $\hat{\beta}$ being the OLS estimate. We then perform the de-trending by calculating $y_t = \frac{Y_t}{(1+\hat{g})^T}$ with $T = Year(t) - 1990$.

[30]We also make sure that the set of counties in the 1990-2010 sample is also present in the 2011-2019 sample.

Of note, while SOD has data on both banks and thrifts, before 2004 Call Reports have deposit data only for depository institutions reporting forms 31-34. That means that our sample excludes thrifts reporting form 1313.

Appendix B. Motivation: Additional Evidence

B.1. *Banks' Exposure to Risk*

In this section, we illustrate the potential gains of diversification simply based on observables. To this end, we first argue that endogenous branching posits a challenge when attempting to use bank-level variables to capture banks' risk and diversification. We then detail an approach that controls for the effects of endogenous branching.

Given the wave of geographical expansion of US banks, we perform a variance decomposition exercise where we decompose bank-level deposits between number of branches (extensive margin) and deposits per branch (intensive margin). Each bank has total deposits equal to $N_{jt} \times D_{jt}/N_{jt}$. Taking logs, we can perform the following variance decomposition:

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

Table B.1 shows that both sources of growth are relevant, with the variation in the number of branches and in deposits per branch explaining on average, 48% and 66% of a bank's total deposit variance, respectively. Figure B.1 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.[31] Overall, these results suggest that county-level shocks to deposits are relatively more relevant for smaller banks.

Table B.1. Variance decomposition on deposit growth

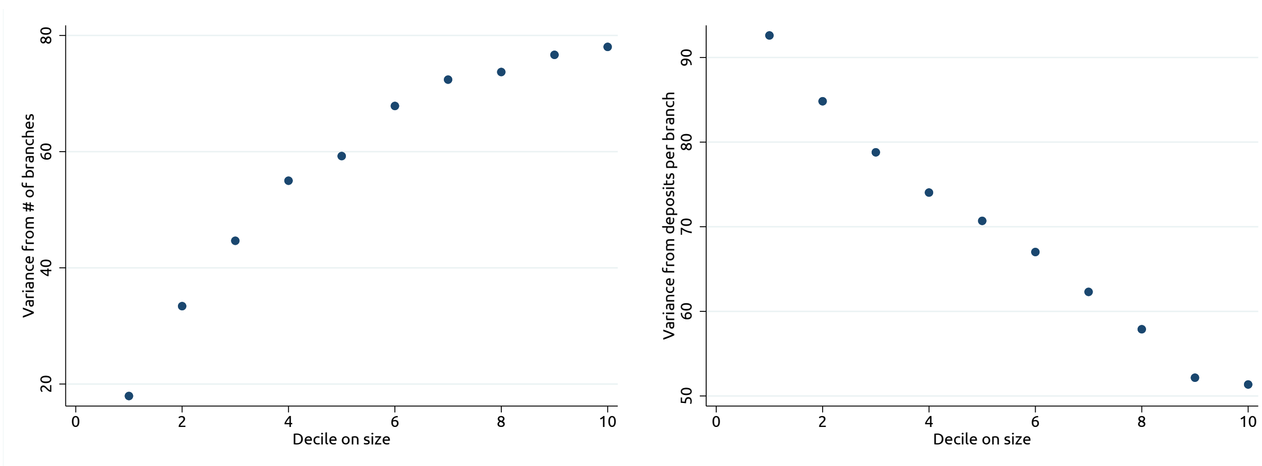
	Mean	Median
Number of branches	48%	31%
Deposits per branch	66%	55%

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.

[31] 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.

Figure B.1. Deposits variance decomposition by bank size

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



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.

We now analyze how this county-level heterogeneity affects bank-level risk. Let ω^{τ}_{ij} be a bank j's relative weight on county i at time τ, defined as $\omega^{\tau}_{ij} = \frac{D^{\tau}_{ij}}{\sum_i D^{\tau}_{ij}}$, where D^{τ}_{ij} is the total stock of deposits that bank j has on county i at time τ. For a given weight ω^{τ}_{ij}, we can then use $\Delta \ln D_{it}$ to construct bank j's weighted deposit change at time t as $\Delta \ln D^{\tau}_{jt} = \sum_i \omega^{\tau}_{ij}(\Delta \ln D_{it})$. We then compute the time-series standard deviation as

$$\sigma^{\tau}_{j} = \sqrt{\frac{1}{T}\sum_{t}\left(\Delta \ln D^{\tau}_{jt} - \overline{\Delta \ln D^{\tau}_{jt}}\right)^2}. \tag{B.2}$$

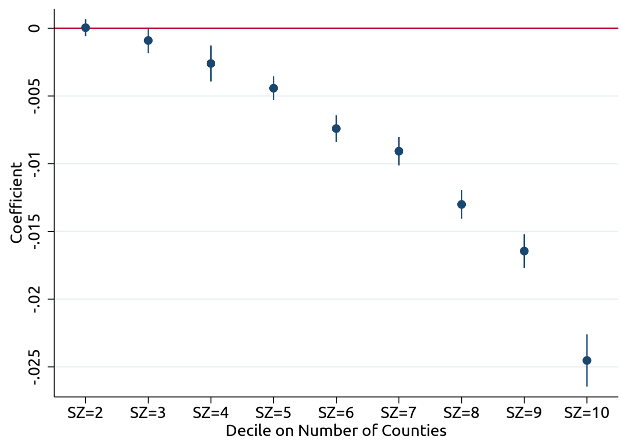
We make use of the panel of exposures $\{\sigma^{\tau}_{j}\}$ to study how deposit risk relates to different banks' characteristics. To this end, we regress σ^{τ}_{j} onto decile dummies on the number of counties the bank operates ($\{\mathbf{1}_{k,\tau}\}_{k=2}^{10}$), bank fixed effects ($\alpha_j$),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

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

Figure B.2 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.[32]

[32]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

Figure B.2. Banks' Exposure to Deposit Fluctuation Risk, by Size



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

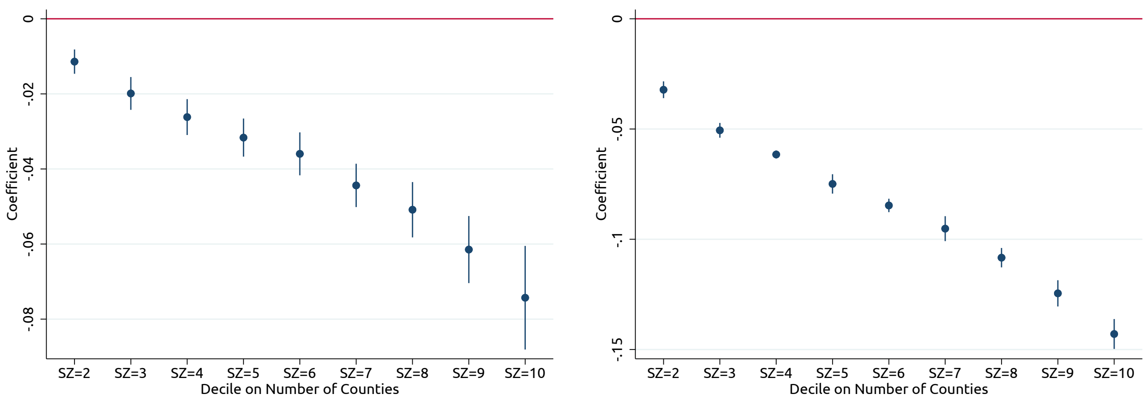
Although not shown, similar results hold when considering deciles on bank size (as proxied by deposits).

Figure B.3 shows a similar analysis but based on originations of small business loans (panel (A)) and morgages (panel (B)). Data for small business loans is obtained from the Community Reinvestment Act (CRA), while data for mortgage originations is obtained from the Home Mortgage Disclosure Act (HMDA). In both cases, we observe that banks operating in more counties are less exposed to risk on loan originations. We can observe a similar pattern whenm studying exposures to loan delinquencies, as shown in Figure B.4. Panel (A) shows results when computing delinquencies from the Consumer Financial Protection Bureau (CFPB). Panel (B), in turn, uses fluctuations in county-level nonfarm personal income as a proxy for delinquency rates as an attempt to capture a broader set of loans than just consumers'.

of observations. Furthermore, if the panel is balanced, the computation from equation (B.2) 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 B.3. Banks' Exposure to Loan Originations, by Size

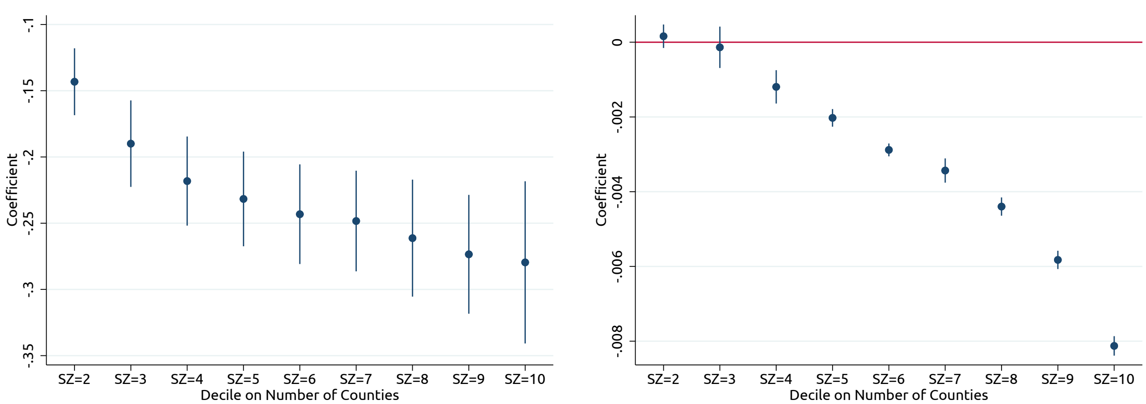
Small Business Loans | Mortgages



Notes: Own elaboration based on Community Reinvestment Act and Home Mortgage Disclosure Act

Figure B.4. Banks' Exposure to Delinquency, by Size

Delinquency Rates | Personal Income (Nonfarm)



Notes: Consumer Financial Protection Bureau and Bureau of Economic Analysis

Appendix C. The Model: Derivations and Additional Material

C.1. *Microfoundation for CES Demand System*

In this section, we provide some microfoundation for the CES demand system assumed in the baseline model. Following Verboven (1996), we assume there are heterogeneous depositors making independent discrete decisions. In particular, assume there is a unit measure of ex-ante identical depositors $\ell \in [0,1]$, each with random i.i.d. preference $\zeta_{\ell ij}$ for depositing funds at ij branch which follows Gumbel distribution:

$$F(\boldsymbol{\zeta}) = \exp\left[-\sum_{i=1}^{N}\left(\sum_{j=1}^{N_i} e^{-(1+\bar{\eta})\zeta_{ij}}\right)^{\frac{1+\bar{\theta}}{1+\bar{\eta}}}\right].$$

The depositor values deposit services, but faces an opportunity cost $y_\ell = d_{\ell ij}\left(R - R_{ij}^D\right)$. In this framework, the $\bar{\eta}$ parameter rises the correlation of draws within a location (higher within-location substitution). In turn, the $\bar{\theta}$ parameter lowers the overall variance of draws across all banks (higher across-location rate competition).

After drawing $\boldsymbol{\zeta}$, the depositor chooses ij that solves

$$\max_{ij}\left\{\ln d_{\ell ij} + \zeta_{ij}\right\} = \max_{ij}\left\{\ln y_\ell - \ln\left(R - R_{ij}^D\right) + \zeta_{ij}\right\}.$$

The depositor's optimization yields

$$Prob_\ell\left(R_{ij}^D, R_{-ij}^D\right) = \underbrace{\frac{\left(R - R_{ij}^D\right)^{-(1+\bar{\eta})}}{\sum_{j=1}^{N_i}\left(R - R_{ij}^D\right)^{-(1+\bar{\eta})}}}_{Prob_\ell(\text{Choose bank } j|\text{ Choose location } i)} \underbrace{\frac{\left(\sum_{j=1}^{N_i}\left(R - R_{ij}^D\right)^{-(1+\bar{\eta})}\right)^{\frac{1+\bar{\theta}}{1+\bar{\eta}}}}{\sum_{i=1}^{N}\left(\sum_{j=1}^{N_i}\left(R - R_{ij}^D\right)^{-(1+\bar{\eta})}\right)^{\frac{1+\bar{\theta}}{1+\bar{\eta}}}}}_{Prob_\ell(\text{Choose location } i\ )},$$

so that we can compute D_{ij} as

$$D_{ij} = \int Prob_\ell\left(R_{ij}^D, R_{-ij}^D\right) d_{\ell ij} dF(y) = Prob_\ell\left(R_{ij}^D, R_{-ij}^D\right)\frac{Y}{R - R_{ij}^D}.$$

We can define the indexes

$$R - R_i^D \equiv \left[\sum_{j=1}^{N_i}\left(R - R_{ij}^D\right)^{-(1+\bar{\eta})}\right]^{\frac{-1}{1+\bar{\eta}}} \quad \text{and} \quad R - R^D \equiv \left[\sum_{i=1}^{N}\left(R - R_i^D\right)^{-\left(1+\bar{\theta}\right)}\right]^{\frac{-1}{1+\bar{\theta}}}.$$

Note that $D \times (R - R^D) = \sum_i \sum_j D_{ij} \left(R - R_{ij}^D\right) = Y$. Then, substituting for Y and using the indexes, we get

$$D_{ij} = \left(\frac{R - R_{ij}^D}{R - R_i^D}\right)^{-\eta} \left(\frac{R - R_i^D}{R - R^D}\right)^{-\theta} D,$$

with $\eta = \bar{\eta} + 2$ and $\theta = \bar{\theta} + 2$.

C.2. *Local Lending*

Some of banks' lending, such as local business loans or commercial real estate loans, is done at the local level. With this in mind, we consider a model extension in which lending is done entirely at the locations in which banks are located. This implies changes to the curvature of banks' lending technology, and that lack of diversification from part of banks could potentially have larger effects on county-level lending relative to the baseline model.

The timing assumption under this model extension is very close to the baseline. Banks first choose $R - R_{ij}^D$ and then shocks are realized. Then, households provide deposits and banks allocate lending to each county, $\{L_{ij}\}$. This means that bank j's problem can be divided into two stages:

$$\max_{\left\{R - R_{ij}^D\right\}} \mathbb{E}\left[Rev_j\left(L_j\right) - \left(R + \frac{\nu_j}{2}\right) H_j - \sum_k \left(R_{kj}^D + k_{kj}\right) \mathcal{D}_{kj} \Lambda_{kj}\right]$$

$$Rev_j\left(L_j\right) = \max_{\left\{L_{kj}\right\}} \sum_k \left(R + z - \frac{\omega_j}{2} L_{kj}\right) L_{kj} \Lambda_{kj}$$

$$\text{s.t. } L_j = \sum_k L_{kj} \Lambda_{kj}$$

The optimal pricing similar to baseline, and similar analysis follows:

$$R - R_{ij}^D = \frac{(\eta - \theta) s_{ij} - \eta}{1 + (\eta - \theta) s_{ij} - \eta} \times \left[k_{ij} - z + \hat{\omega}_j \mathbb{E}\left[L_j\right] \left(1 + d_j \sum_k \omega_{kj}^D \frac{\rho_{ik} \sigma_i \sigma_k}{\mu_i \mu_k}\right)\right]$$

with $\omega_j = \frac{\omega_j}{\left(\sum_k \Lambda_{kj}\right)}$.

C.3. *Solution Algorithm*

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

(1) Guess spreads $R - R_{ij}^{D(0)}$. If in uniform pricing, then $R - R_{ij}^{D(0)} = R - R_j^{D(0)}$.
(2) Use price index definitions to compute $R - R_{it}^D$ and $R - R_t^D$ (using realized ϕ_{it}).

(3) Compute $D_t = \xi^{\frac{1}{\gamma}} \left(R - R_t^D\right)^{\frac{-1}{\gamma}}$ and $\mathbb{E}\left[D_i\right] = \mu_i \left(\frac{R-R_t^D}{R-R_{it}^D}\right)^{\theta} D_t$.

(4) Compute $\mathbb{E}\left[D_{ij}\right] = \psi_{ij}^{\eta} \left(\frac{R-R_{it}^D}{R-R_{ijt}^D}\right)^{\eta} \mathbb{E}\left[D_i\right]$.

(5) Compute $\mathbb{E}\left[L_j\right] = \sum_i \mathbb{E}\left[D_{ij}\right] \Lambda_{ij} + H_j + E_j$.

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

(7) Compute $RP_{ij} = w_j^D \sum_k w_{kj}^D \frac{\rho_{ik}\sigma_i\sigma_k}{\mu_i\mu_k}, MC_{ij} = (k-z)_{ij} + \chi\left(1 + RP_{ij}\right)$.

(8) Compute spreads, to be substituted in step 10 below $R - R_{ij,NEW}^D = MKP_{ij} \times MC_{ij}$.

(9) Uniform pricing (updates $R - R_j^D$)

$$
\begin{aligned}
\widetilde{w}_{ij}^D =& \frac{\mathbb{E}\left[D_{ij}\right]\left(\eta\left(1-s_{ij}\right)+\theta s_{ij}\right)\Lambda_{ij}}{\sum_i \mathbb{E}\left[D_{ij}\right]\left(\eta\left(1-s_{ij}\right)+\theta s_{ij}\right)\Lambda_{ij}} \\
RP_j =& w_j^D \sum_k \tilde{w}_{kj}^D \left(\sum_i w_{ij}^D \frac{\rho_{i,k}\sigma_i\sigma_k}{\mu_i\mu_k}\right) \\
MC_j =& (k-z)_j + \chi\left(1 + RP_j\right) \\
s_j =& \frac{\sum_i \mathbb{E}\left[D_{ij}\right]\Lambda_{ij} s_{ij}}{\sum_i \mathbb{E}\left[D_{ij}\right]\Lambda_{ij}} \\
MKP_j =& \frac{\eta\left(1-s_j\right)+\theta s_j}{\eta\left(1-s_j\right)+\theta s_j - 1} \\
R - R_j^D =& MKP_j \times MC_j
\end{aligned}
$$

(10) Update spreads, $R - R_{ij}^{D(1)} = R - R_{ij,NEW}^D$. If in uniform pricing, then $R - R_{ij}^{D(1)} = R - R_j^D$.

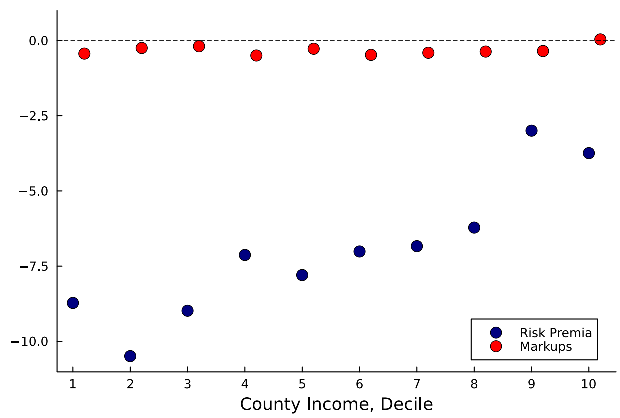
(11) Iterate until convergence of spreads.

Appendix D. Quantitative Analysis: Additional Material

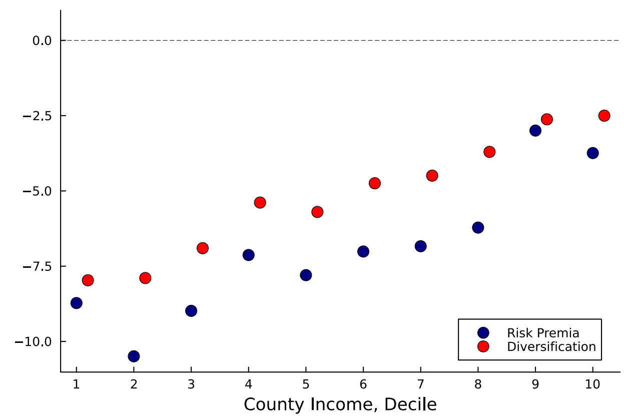
D.1. *Changes Across Time under Local Pricing*

Figure D.1. Changes in (log) Spreads under Local Pricing, 1993-2019, by County

(A) Changes in Markups and Risk Premia



(B) Decomposition of Changes in Risk Premia



D.2. *Alternative Definition of Local Markets: MSA Regions*

We consider an alternative definition of a local market. In our baseline analysis, we have defined a market based on county-level regions. In this section, we repeat our analysis using the Metropolitan Statistical Area (MSA) as the definition of local market. All the baseline results are robust to this different specification of a market.

Figure D.2. County-level Risk Premia and Markups

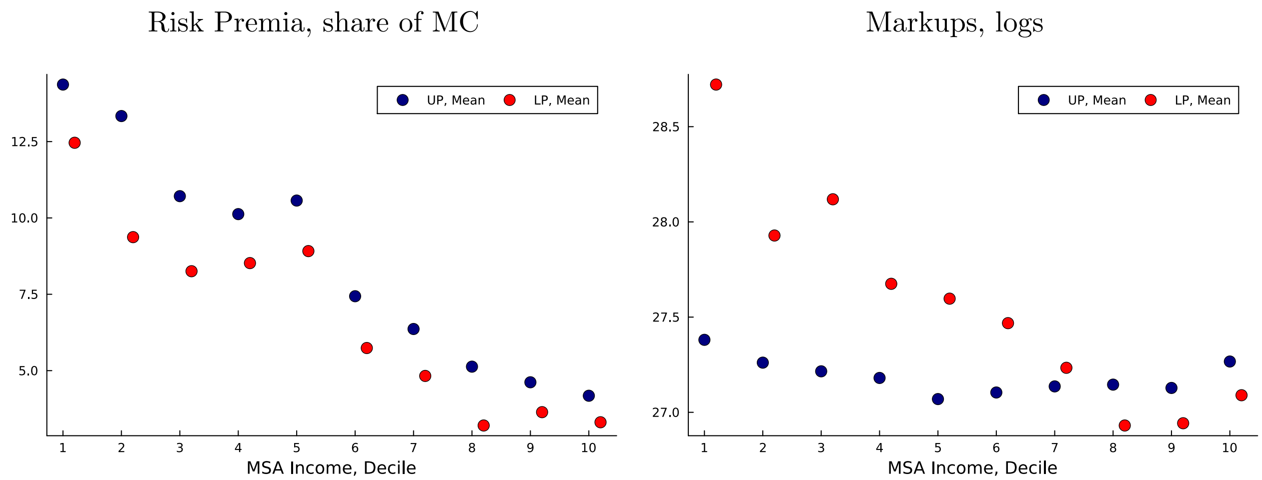


Figure D.3. Bank-level Risk Premia and Markups

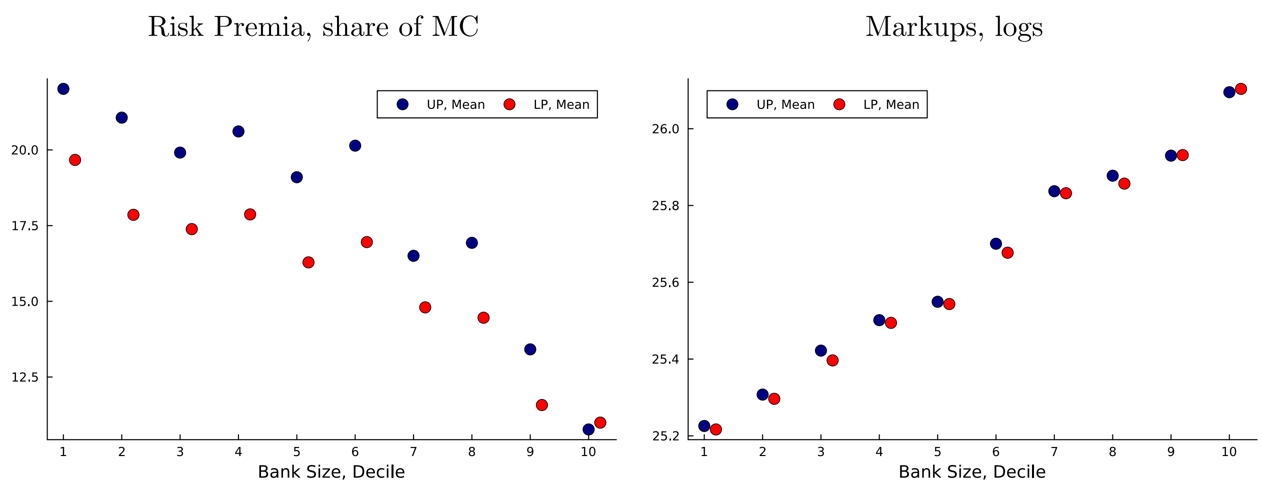
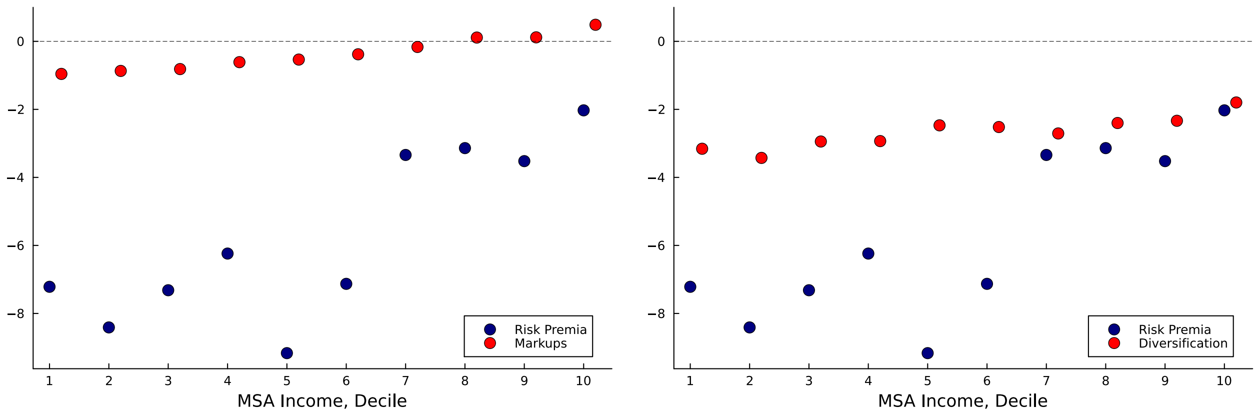


Figure D.4. Changes in (log) Spreads, 1993-2019, by County

(a) Changes in Markups and Risk Premia (b) Decomposition of Changes in Risk Premia



D.3. *On the Role of Online Banking and Central Booking*

In our baseline analysis, we've included all banks reporting deposit holdings in the SOD dataset. However, it's important to note that some of these banks may operate primarily online, rendering the geographical location of their branches irrelevant for assessing their regional risk and market concentration. For example, banks like Ally Bank serve customers nationwide despite having limited physical branches. Additionally, some banks may not consistently report deposit holdings across branches, opting instead to aggregate all deposits under one branch—a practice known as central booking. This can distort assessments of deposit concentration and geographical risk for individual branches.

In this section, we filter the data to refine our analysis by excluding these types of banks. First, we exclude counties for which their ratio of deposits to total income is 10 times higher than the 99th percentile. Second, within the subset of the top 1% largest banks (based on their deposits), we exclude those where over 99% of deposits are concentrated within a single county. For 2019, we find that about 15% of total deposits meet either one of these criteria. However, this percentage was significantly smaller in the early 1990s (less than 5%), which suggests an growing prevalence of either online banking or central booking practices.

The figures that follow present the results after removing online banks and banks employing central booking practices from the analysis. Our baseline results are robust to these filters.

FIGURE D.5. County-level Risk Premia and Markups

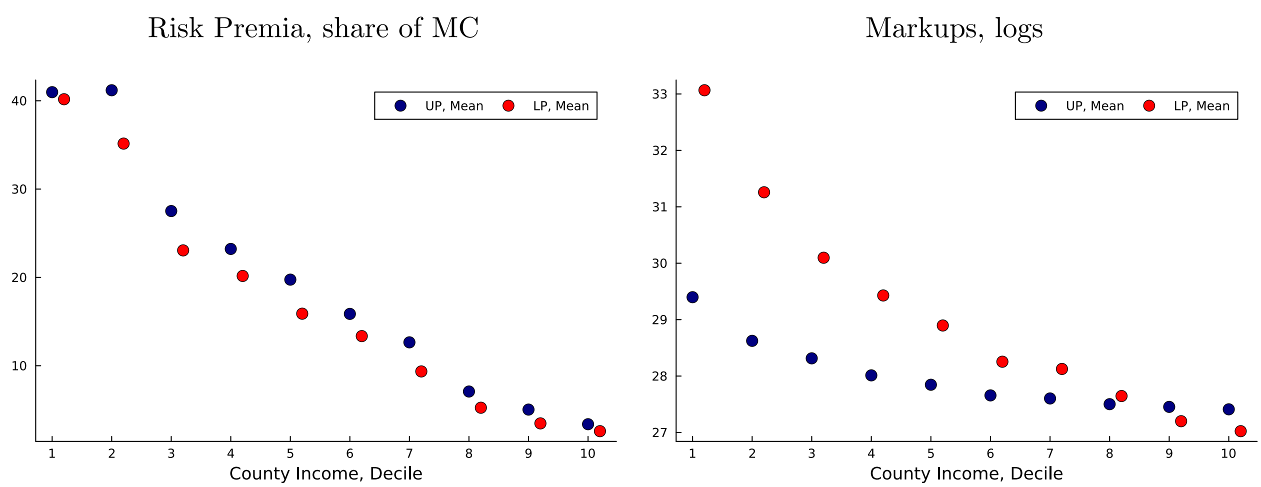


Figure D.6. Bank-level Risk Premia and Markups

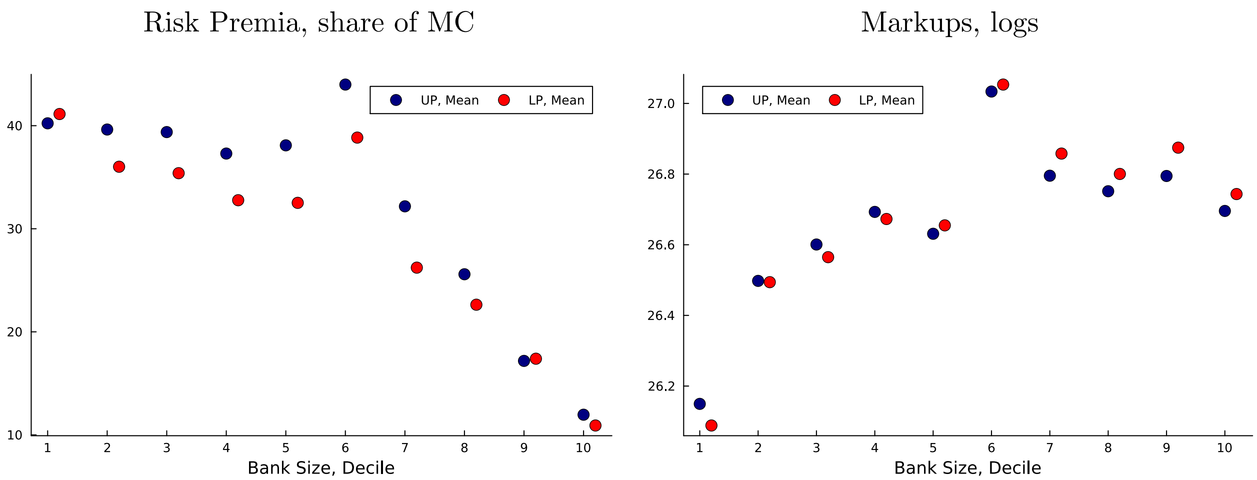
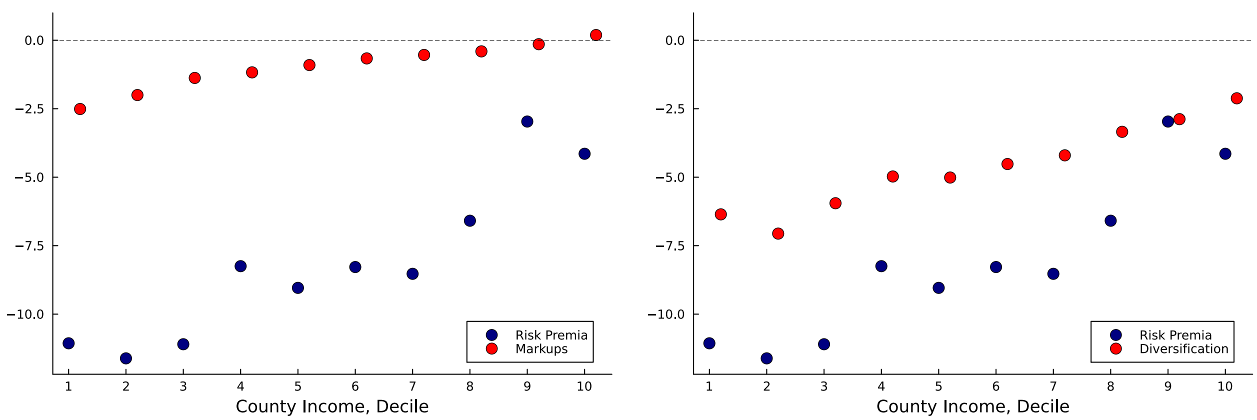


Figure D.7. Changes in (log) Spreads, 1993-2019, by County

(a) Changes in Markups and Risk Premia (b) Decomposition of Changes in Risk Premia



D.4. *Lower Cross-Country Elasticity of Substitution*

In this appendix, we analyze how sensitive our main results are to changes in the cross-country elasticity of substitution, θ. To this end, we calibrate the model based on $\theta = 2$ and repeat our main analysis of Section 5. This calibration leads to an aggregate markups of 37% in 2019 (in our baseline calibration, we target an aggregate markup of 30%). Since changes in θ affect our risk premium measure, we estimate again the χ parameter. We find a slightly higher estimate 0.014 (relative to the 0.01 of our baseline calibration). We use that higher estimate for this analysis.

All of our main cross-sectional patterns hold under the lower cross-county elasticity calibration. Figure D.8 shows that smaller counties continue to exhibit larger risk premia and higher markups.

When analyzing changes in deposit spreads across time (1993 versus 2019), we find a smaller role for risk premia and a larger role of markups. Table D.1 shows that the total contribution of risk premia to the decline in spreads is around 6%, compared to 10% in our baseline calibration. As for markups, we find that they contributed to a 5% increase in spreads, while in our baseline they accounted for only 3%. Figure D.10 shows a larger heterogeneity in markup changes. We find a much larger decline in markups in poorer counties (up to 10%) relative to our baseline analysis. On the other hand, markups increase more in larger counties.

FIGURE D.8. County-level Risk Premia and Markups

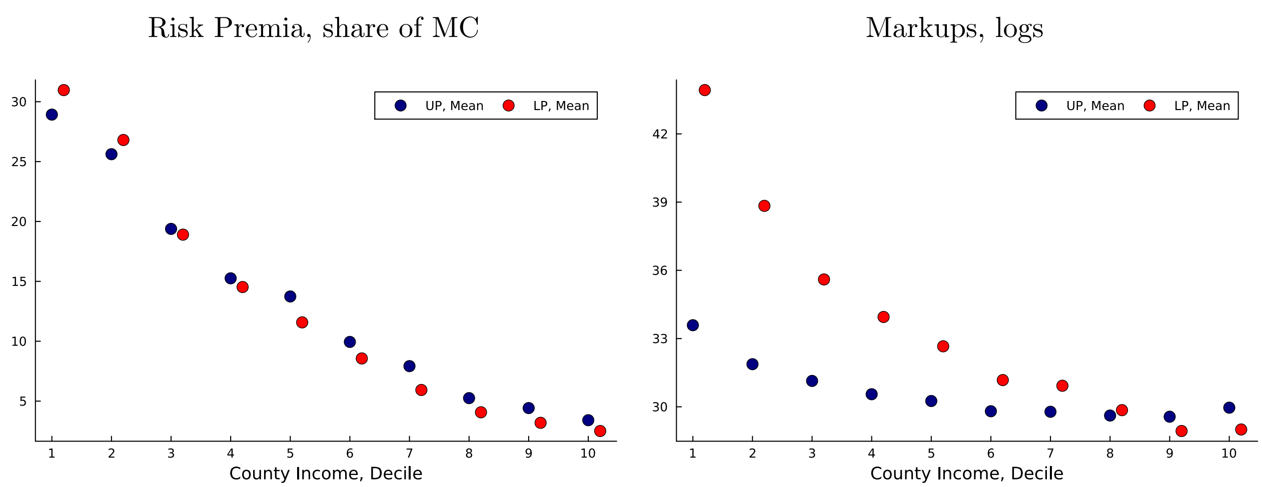


FIGURE D.9. Bank-level Risk Premia and Markups

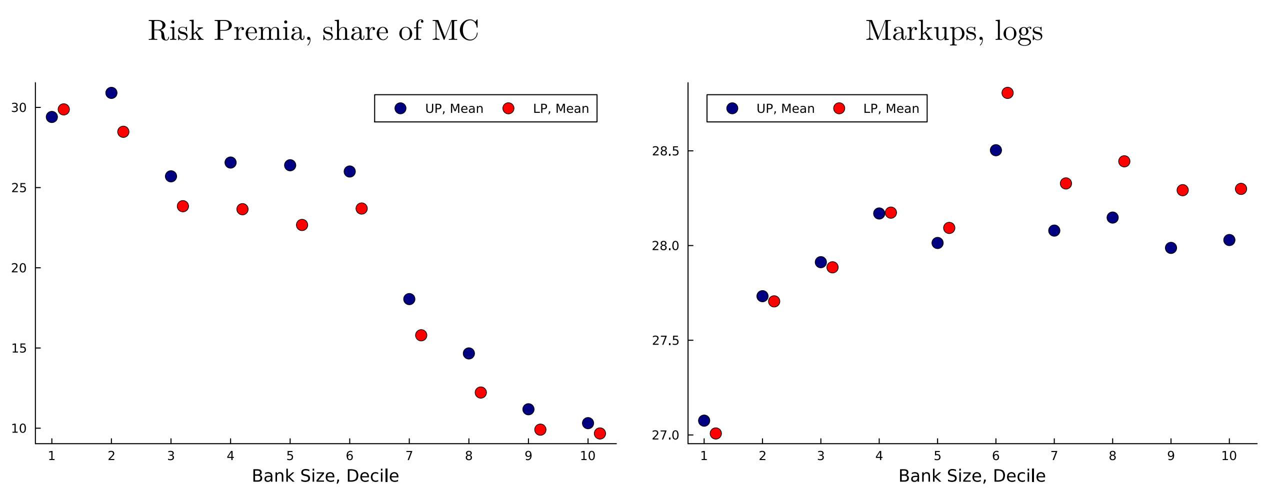


Table D.1. Changes Across Time: The Role of Diversification and Markups

(a) Contribution to changes in spreads (log points)

	Uniform pricing				**Local Pricing**			
	Risk Premium		Markup	Net	Risk Premium		Markup	Net
	Total	Diver			Total	Diver		
National Level								
Aggregate	-2.1	-1.8	1.7	-0.4	-2.1	-1.5	2.2	0.1
Aggregate (fixed shares)	-2.4	-2.0	0.7	-1.7	-2.4	-2.1	0.6	-1.8
By Group of Counties								
Small Counties (<p10)	-9.4	-5.0	-7.9	-17.3	-6.8	-6.6	-1.6	-8.4
Medium Counties	-5.4	-3.2	-1.7	-7.1	-4.9	-3.6	-0.7	-5.5
Large Counties (>p90)	-1.9	-1.8	1.0	-1.0	-2.1	-1.7	0.2	-1.8

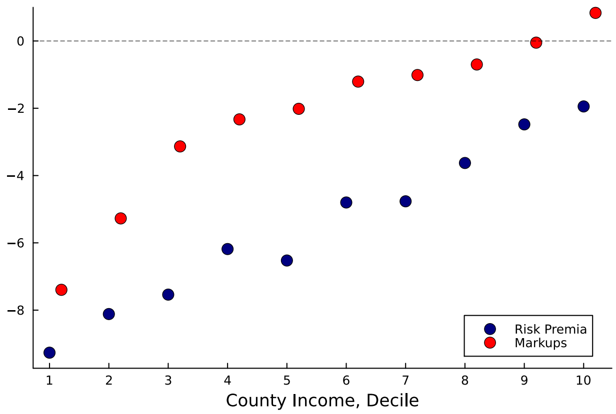
(b) Share of total change in spreads

	Uniform pricing				**Local Pricing**			
	Risk Premium		Markup	Net	Risk Premium		Markup	Net
	Total	Diver			Total	Diver		
National Level								
Aggregate	6.9%	5.7%	-5.5%	1.4%	6.7%	4.9%	-7.0%	-0.3%
Aggregate (fixed shares)	7.8%	6.6%	-2.4%	5.4%	7.8%	6.7%	-1.8%	6.0%
By Group of Counties								
Small Counties (<p10)	34.8%	18.7%	29.3%	64.0%	25.0%	24.6%	6.0%	31.0%
Medium Counties	25.5%	15.2%	7.8%	33.3%	23.0%	17.1%	3.1%	26.1%
Large Counties (>p90)	6.9%	6.6%	-3.5%	3.5%	7.4%	6.2%	-0.9%	6.5%

Notes: Panel (A) shows a decomposition of changes in log spreads, $\Delta log(R-R^D)$, between 1993 and 2019 into a risk premium and a markup component. Top rows show the aggregate effect. Bottom rows show the results by groups of counties. Panel (B) shows the share of $\Delta log(R-R^D)$ accounted by changes risk premia and markups. That is, $\frac{\chi\Delta RP_j/MC_j^0}{\Delta log(R-R^D)}$ and $\frac{\Delta log(MKP)}{\Delta log(R-R^D)}$. Since spreads have decreased during the considered period, a positive (negative) value means that the particular channel led to a reduction (increase) in spread.

FIGURE D.10. Changes in (log) Spreads, 1993-2019, by County

(A) Changes in Markups and Risk Premia



(B) Decomposition of Changes in Risk Premia