Geographic Funding Risk And Market Power In Deposit Markets*

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Abstract. We develop a rich yet flexible spatial banking model to study how diversification and competition shape U.S. deposit markets. Deposit rates reflect both markups and risk premia from undiversified geographic risk. Calibrated to micro data, the model reveals sizable risk premia, especially in small, poor counties, and shows that recent banking consolidation has reduced these premia. In contrast, markups changed only modestly, so depositors in less diversified areas benefited the most. Further consolidation, e.g. acquisitions of small banks by large regional ones, would lower risk premia but reduce local lending, as larger banks reallocate credit toward more profitable markets.

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 changed dramatically 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, allowing bank holding companies to acquire banks in any state. Subsequently, the 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 competition to reduced idiosyncratic risks through diversification.

In this paper, we use a structural approach to quantify these effects on bank deposit markets and through them, bank lending. We formulate a general equilibrium, spatial model of deposit-taking and lending by heterogeneous banks competing across a large number of oligopolistic markets (US counties in our empirical implementation). Banks face market-specific shocks to deposit demand, so operating in more locations reduces funding risk through diversification.[1] We derive a closed-form expression for deposit rates as the product of a standard markup and a marginal 'cost'. The latter depends on funding volatility: specifically, on how deposit inflows covary with the marginal benefit of funds. We discipline the model's rich heterogeneity using detailed bank- and county-level data, and use the calibrated framework to disentangle the effects of funding risk and markups on deposit pricing and, in turn, on aggregate deposit flows and lending.

We begin with some reduced-form evidence to motivate our analysis. We confirm that, since the 1990s, banks have significantly increased the number of counties in which they operate. This is particularly relevant given our second finding: deposit growth at the bank level is as volatile as loan growth, and more than one-third of this variation can be attributed to fluctuations in county-level deposits. We also find that banks become less exposed to fluctuations in deposit flows as they operate in more locations. On the competition front, we find that national-level market concentration in deposit markets (measured by HHI) has increased since the 1990s, while changes in county-level concentration show a more mixed pattern. While these patterns on deposit risk and market concentration are informative, their overall implications for deposit flows, interest rates, and lending are difficult to interpret without a structural framework.

[1]That banks face risk in their deposit inflows has been documented by Drechsler, Savov, and Schnabl (2017) and also features prominently in a few recent papers, e.g. Aguirregabiria et al. (2016), Corbae and D'Erasmo (2022) and Bolton et al. (2023). Our framework also allows for idiosyncratic risk in lending returns, but we find little interaction with deposit pricing, the key object of interest in this paper.

Our model features a representative household which values, in addition to consumption, liquidity services from deposit holdings. To capture imperfect substitutability across banks and locations, we use a nested aggregate with constant elasticity of substitution (CES) at each nest. Deposits at different banks within a county are aggregated into a county-level composite, which is then accumulated to generate the economy-wide bundle. The latter aggregation is subject to shocks that shift the household's preferences for deposits in a county. Since an individual bank does not operate in all counties, it is exposed to idiosyncratic risk. Curvature in bank payoffs then generates a motive for diversification. In our baseline specification, curvature arises from a combination of loan commitments and frictions in the inter-bank market, but we show that the results are quite robust to alternative sources of curvature—such as, diminishing marginal returns on lending, risk aversion, or regulatory constraints.

Banks compete by offering interest rates on deposits, assumed to be set before observing idiosyncratic shocks. How banks set rates across the different markets is the subject of some debate in the literature. A number of papers (Radecki, 1998; Heitfield and Prager, 2004; Granja and Paixao, 2021; Begenau and Stafford, 2022) argue that banks do not choose rates market-by-market but instead engage in some degree of 'uniform pricing', i.e. set similar rates across a number of markets. Our micro data on deposit rates are broadly consistent with this view, though there is residual variation at the county-level. Rather than take a stand on the exact degree of uniform pricing, we analyze separately two polar cases: in the first, banks are assumed to engage in 'uniform pricing', where each bank sets a single rate across all the markets in which it operates. In the second case, banks engage in 'local pricing', i.e. set interest rates separately for each county they operate in. The actual pricing behavior likely lies somewhere between these two polar cases. As we will show, the economic forces and the main takeaways about the effects of geographic risk and market power are similar under both assumptions, even if the exact formulae and magnitudes differ somewhat, pointing to the robustness of our insights.

The optimal deposit spread—the difference between the deposit rate and the return on an asset without liquidity benefits—is given by a markup times the marginal cost of providing deposit services. In our oligopolistic setting, markups depend on substitution elasticities and appropriately defined market shares. Intuitively, an oligopolistic bank internalizes the effect of changes in its deposit rate on county-level deposits. Since the elasticity of substitution across banks within a county is higher than the elasticity across counties, markups increase with a bank's market share. The two pricing protocols differ in the relevant notion of market share: under uniform pricing, markups depend on the bank's average market share across all counties, whereas under local pricing, the markup is county-specific and determined by the bank's share in that county.

The marginal cost includes a risk-premium component, a novel feature of our framework. Under uniform pricing, there is a single risk premium for the entire bank, which is a function of the variability of its total deposit flows. This variability, in turn, depends on the covariance matrix of county-level shocks. All else equal, the less diversified the bank, the higher this variability and thus the risk premium. Consequently, the bank charges a larger spread (or equivalently, offers a less attractive rate to depositors). Geographical diversification reduces this risk premium and, therefore, lowers effective marginal costs and deposit spreads. Under local pricing, the risk premium is bank- and county-specific, but the intuition remains similar—the more positively a county's deposit demand shock covaries with those of other counties in which the bank operates, the higher the risk premium. As with uniform pricing, diversification reduces risk, and through this channel, deposit spreads.

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—branch-level rates on certificate of deposits (CDs) and money markets (from RateWatch) and bank financial statements. Our calibration strategy has two interconnected parts. The first part leverages the richness of micro-data to estimate key parameters, such as the within- and across-market elasticities of substitution and the curvature in the banks' payoff function. The second one combines the estimated parameters from the first part with the data to recover preference and cost shifters and through that, idiosyncratic risks.

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 point to a significant risk premium-component in deposit spreads especially among smaller banks, which typically operate in a limited number of locations. For example, for banks in the smallest size decile, risk premia raise deposit spreads by over 0.40 log points—equivalent to nearly a 50% increase. The spreads of the largest banks, on the other hand, contain a much lower compensation for funding risk, with spreads pushed up by around 0.15 log points. Smaller banks also tend to have somewhat lower average market shares—and thus lower markups—than their mid-sized and larger counterparts, although the differences are small.

Across counties, risk premia drive up deposit spreads by about 0.40 log points in the smallest/poorest counties. For the median county, the risk-related increase in spreads is almost 25%.

Markups also have their largest impact in these smaller and poorer counties, adding up to 0.55 log points. Combined, the risk and markup channels increase spreads by over 0.90 log points among the smallest/poorest counties.

Next, we analyze changes in the effects of risk premia and markups on deposit spreads over the last couple of decades (specifically, between 1993 and 2019). We find that geographical expansion and the 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 almost 20%. In the aggregate, the reduction in risk premia lowered the cost of deposit services by about 3%. Changes in markups are more modest, across all counties. Under uniform pricing, the model shows markups declining by about 5% in the smallest counties and remaining more or less unchanged in the largest counties. This pattern emerges despite the rise in reduced-form measures of national concentration, highlighting the importance of a carefully calibrated structural model like ours for drawing meaningful insights about competition. Under local pricing, markups have remained largely flat over the past three decades, with little variation across locations.

Overall, the changes in the structure of the banking industry over the past three decades have benefited the smallest and poorest counties in two key ways: through diversification-induced reductions in risk premia and, to a lesser extent, lower markups. We show that the decline in risk premia was primarily driven by extensive margin dynamics—namely, bank entry and exit—with most of the effect accounted for by entry from out-of-state banks.

We leverage the tractability of our model to perform a series of counterfactual experiments. In the first, we increase curvature in bank payoffs, or equivalently, their aversion to deposit risk.[2] Deposit spreads rise with substantial regional heterogeneity: smaller counties, which rely more heavily on less diversified banks, experience the largest increases. Our second experiment studies the effects of further consolidation, specifically the acquisition of local banks. These mergers reduce risk premia, especially in smaller counties and when the acquirer is a large regional or national bank. The effect on markups is modest and the sign depends on the pricing protocol: under uniform pricing, they decline but rise under local pricing.

Next, we examine changes in the spatial distribution of economic activity, specifically with large markets growing in relative size. This is meant to capture a continued rise in spatial inequality, consistent with trends observed in recent decades. The reallocation increases banks'

[2] One interpretation of such a change is greater frictions in interbank markets.

exposure to larger, safer markets, which lowers their overall deposit funding risk. Small and medium-sized counties benefit the most, exhibiting larger reductions in deposit risk premia. As large markets become more dominant, smaller regions may also become increasingly vulnerable to shocks originating in those areas. To assess this, we consider a counterfactual in which we double the volatility of deposit demand in large counties. This directly raises risk premia and deposit spreads in large counties, but we find that nearly half the increase spills over to small and medium-sized counties.

We extend the baseline model in several directions, both to demonstrate the robustness of our analysis and to generate additional insights. First, we enrich the asset side of banks' balance sheets by allowing for multiple asset types, including "local" loans—i.e., loans linked to the branch network—and securities. This version not only yields the same expression for optimal deposit spreads—showing that our baseline decomposition holds more generally—but also allows us to trace the effects of deposit risk and bank consolidation on local lending. We find that increases in deposit risk premia can lead to large declines in lending, not only in regions where banks are less geographically diversified, but also in larger, more diversified states. In addition, we show that the acquisition of local banks by large regional banks reduces local lending in smaller regions, as larger banks tend to redirect credit toward more profitable, higher-income markets. These effects are especially pronounced in areas where smaller banks hold large market shares.

Second, we show how additional assets and sources of liquidity services (e.g. cash) can be tractably incorporated into our framework. The main change relative to the baseline framework is that the substitutability of deposits with these assets now influences equilibrium markups. We calibrate this extension to match the aggregate cash-to-deposits ratio as well as its sensitivity to exogenous changes in interest rates. We find that the effects of risk and markups on deposit spreads remain similar to those in our baseline model, both in the cross-section and over time, though markup variation plays a somewhat larger role.

Related literature. This paper contributes to several strands of the literature. Our focus on deposit flow risk is shared by Aguirregabiria et al. (2016), Corbae and D'Erasmo (2022) and Bolton et al. (2023). The first two papers also analyze geographical expansion, but treat deposit flows as exogenous. Our structural approach is complementary to recent empirical work on geographical expansion and diversification (see, for instance, Levine et al., 2021; Kundu et al., 2021; Kundu and Vats, 2021; Doerr, 2024).[3] We differ from these papers in our explicit

[3]Empirical analysis of diversification of other types of risks (notably on the lending side) are presented in Stiroh

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.

Second, these interactions also distinguish our work from that of Ji et al. (2023) and Oberfield et al. (2024), who study location choices in spatial banking models that abstract from risk. These papers highlight how primitives (e.g., size) of the markets for deposits and loans interact to determine optimal location decisions of banks. For example, Oberfield et al. (2024) show that deregulation induced large US banks to expand into markets that were relatively abundant in deposits relative to lending opportunities.[4] Our analysis, which focuses on how location choices have reshaped funding risks and concentration in deposit markets, complements their findings and helps paint a more complete picture of the effects of geographical expansion. Methodologically, our contribution is a rich yet tractable framework combined with a transparent empirical strategy that has applicability beyond the questions of interest in this paper.

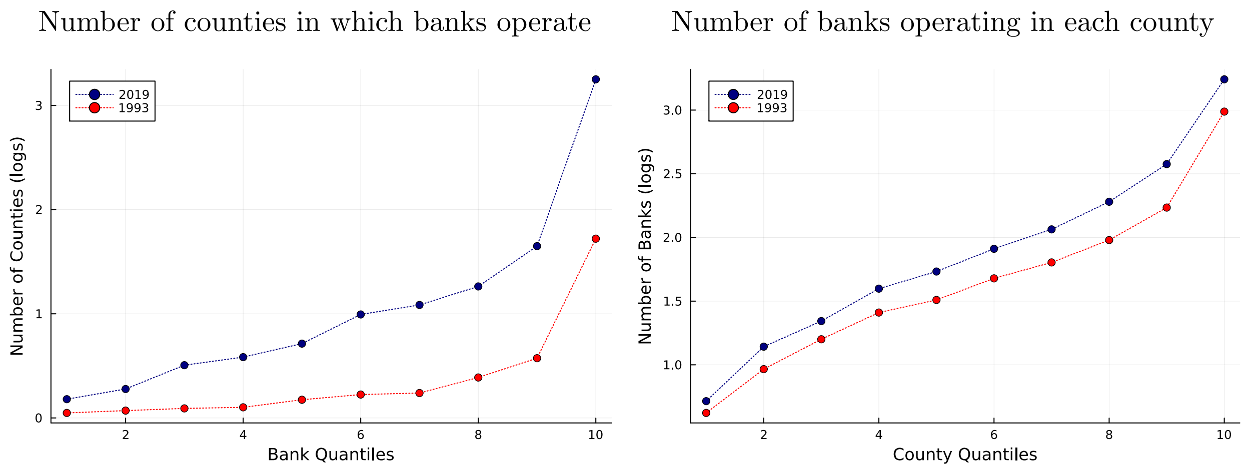
Third, our approach to modeling competition is widely used in the macroeconomics and trade literature. Key references include Atkeson and Burstein (2008), Hottman et al. (2016), Rossi-Hansberg et al. (2020) and Berger et al. (2022). We extend and adapt this well-known framework to the banking context, where oligopolistic 'firms' compete in multiple markets subject to idiosyncratic risk.

Finally, our paper relates to the literature on banks' market power. Work by Drechsler et al. (2017) and Wang et al. (2020) analyze how market power affects the transmission of monetary policy through deposit and lending channels. Similarly, Egan et al. (2017) study the implications of banks' oligopolistic competition in markets for uninsured deposits on financial fragility. Other studies examine how banks' market power affects credit supply and financial stability (Black and Strahan, 2002; Corbae and D'Erasmo, 2021; Carlson et al., 2022; Herkenhoff and Morelli, 2025), as well as adverse selection in lending markets (Crawford et al., 2018). We contribute to this literature by quantifying the aggregate effects of banks' market power on the deposit side, both in the cross-section and over time.

(2006); Laeven and Levine (2007); Baele et al. (2007); Cetorelli and Goldberg (2012); Goetz et al. (2016); Gilje et al. (2016); Chu et al. (2019); Correa and Goldberg (2020); Doerr and Schaz (2021); Goetz and Gozzi (2022); and Granja et al. (2022). Recently, D'Amico and Alekseev (2024) study bank funding and financial integration—measured using dispersion in loan rates—during the era of branching restrictions (1953-1983).

[4] In recent work, Aguirregabiria et al. (forthcoming) analyze the geographic dispersion and imbalances between deposits and local lending. Unlike our framework, their model abstracts from considerations related to banks' geographic diversification.

Figure 1. Banks Geographical Expansion



Notes: The left panel shows the average number of counties in which banks operate (in logs), by bank size—measured in total deposits. The right panel displays the number of banks operating in each county (in logs), by county size—also measured in total deposits. Red dots correspond to 1993 data; blue dots to 2019.

2. Motivating Facts

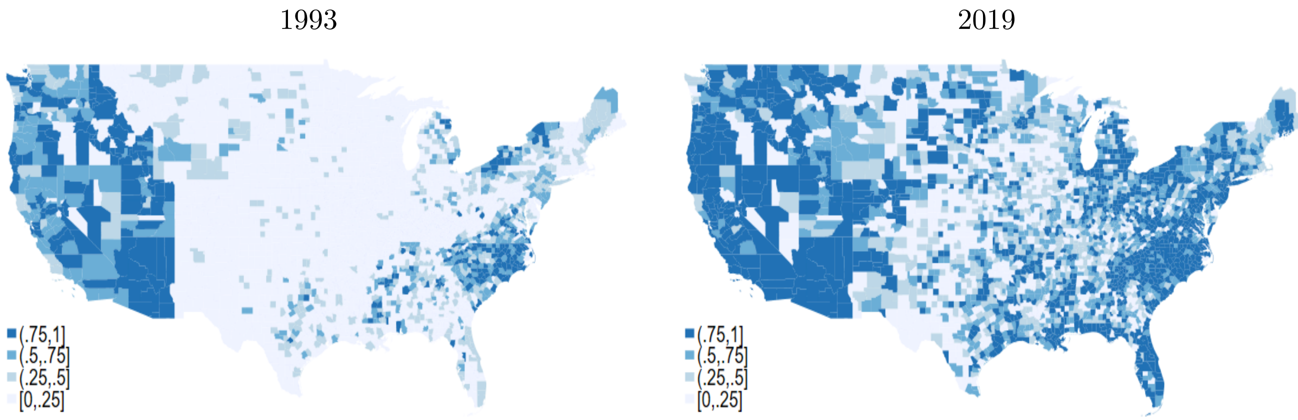
We begin by documenting banks' geographical expansion since the 1990s. The left panel of Figure 1 shows the relationship between size (measured using deciles of total deposits) and the average number of counties a bank operates in. The figure reveals that the expansion in geographic reach has been primarily driven by medium and large banks. By 2019, the largest banks in the sample (deciles 9 and 10) operated in five times as many counties as they did before the Riegle-Neal Act (1994). The right panel shows that these changes are quite broad-based: we observe an increase in the number of active banks in both smaller and larger counties.

Figure 2 depicts banks' geographical expansion from a county-perspective. For each county, it shows the share of local deposits held by banks that operate in at least 10 other counties. This share has increased markedly since the 1990s. The rise has been particularly evident in some regions (e.g. parts of the Midwest).

Next, we document some facts about cross-sectional variability in deposits. Note that these are reduced-form patterns: later, we use the model to recover the underlying structural shocks. Our purpose here is to show that idiosyncratic deposit flow risk is significant. For example, the cross-sectional standard deviation of the annual growth rate in deposits at the bank-level is 15%, comparable to the loan growth variability. Similarly, at the county level, after controlling for county and year fixed effects, the standard deviation of deposit growth is 14%.[5]

[5]These patterns are consistent with prior work documenting substantial volatility in deposits, particularly at the branch level (see, for instance, Drechsler et al., 2017). Similarly, Kundu et al. (2021) show that the volatility of the bank-level deposit-to-asset ratio is similar in magnitude to that of the loan-to-asset ratio. See Appendix

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



Notes: The maps show county-level shares of deposits held by banks that operate in 10 or more counties. The left panel is for 1993, while the right panel shows the results for 2019.

To assess the potential for diversification, we explore the role of county-level deposit growth changes in explaining the variation in total deposits at the bank-level. We define total deposits for bank j at time t as $D_{jt} = \sum_{i \in \mathcal{M}_{j,t}} D_{ijt}$, where $\mathcal{M}_{j,t}$ denotes the set of counties in which bank j operates at t. For each bank, we use the county shares based on the first year in which the bank is observed in a given county as proxy for exposure:[6]

$$\omega_{ij}^{0} = \frac{D_{ij,t(0)}}{\sum_{i \in \mathcal{M}_j} D_{ij,t(0)}}.$$

We then combine these weights with county-level deposits (net of year fixed effects) to predict bank-level deposits, $\log \widehat{D}_{jt}$.[7] Table 1 then reports the within-R^2 from the following regression:

$$\log D_{jt} = \beta \log \widehat{D}_{jt} + \gamma_j + \gamma_t + \epsilon_{jt}.$$

It shows that county-level variation in deposit flows explains about one-third of banks' residual deposit fluctuations.

Appendix B provides additional evidence suggestive of diversification gains. It shows that the volatility of bank-level deposits declines with the number of counties in which a bank operates—even after controlling for bank and year fixed effects—suggesting that geographic expansion meaningfully reduces banks' exposure to deposit risk.

Figure B.1 for details.

[6]This approach avoids understating the importance of counties that were added during bank expansion, which was common during our sample period.

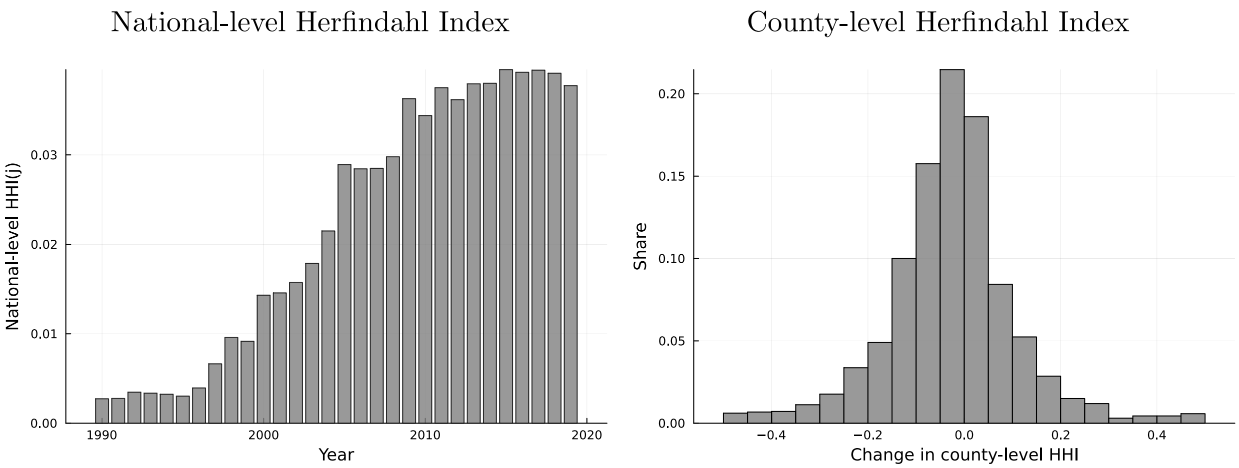
[7]Formally, we first regress county-level deposits $\log D_{it} = \log \sum_j D_{ijt}$ on year fixed effects and extract residuals $\log \widehat{D}_{it}$. The predicted deposits for bank j is then given by $\widehat{D_{jt}} = \sum_{i \in \mathcal{M}_{j,t}} \omega_{ij}^{0} \widehat{D_{it}}$ where ω_{ij}^{0} are the base-year county exposures of the bank.

Table 1. Variation in Bank-level Deposits driven by County-level Changes

	Within R^2			
FEs	All banks	≥ 5 counties	≥ 10 counties	≥ 25 counties
Bank	0.50	0.70	0.76	0.80
Year	0.53	0.62	0.60	0.55
Bank and Year	0.31	0.33	0.38	0.40

Notes: The table reports the within-R^2 from the regression $\log D_{jt} = \log \hat{D}_{jt} + \alpha_j + \alpha_t + \epsilon_{jt}$, where D_{jt} denotes actual bank-level deposits and $\hat{D}_{jt}$ is the predicted value based on exposure to county-level shocks. Each row corresponds to a different set of fixed effects (bank, year, or both), while each column presents results for different subsamples of banks: all banks, and those operating in more than 5, 10, or 25 counties..

Figure 3. Concentration in Deposit Markets



Notes: The left panel shows the national-level HHI for deposits, defined as $HHI_t = \sum_j \left(\frac{D_{jt}}{\sum_j D_{jt}}\right)^2$. The right panel shows a histogram of changes in county-level HHIs between 1993 and 2019. County-level HHI is defined as $HHI_{it} = \sum_{j\in i} \left(\frac{D_{jit}}{\sum_{j\in i} D_{jit}}\right)^2$, where D_{jit} denotes deposits held by bank j in county i at time t.

Our final set of facts pertains to market concentration. The left panel of figure 3 shows that the Herfindahl-Hirschman indices (HHI) for bank deposits at the national level (left panel) have risen steadily since the mid-1990s. The changes in county-level HHI (the right panel) show a more mixed pattern: a number of counties experienced significant increases in concentration, while many others saw a decline.[8] The overall effect on deposit markups is hard to pin down without an explicit model of competition.

The facts presented in this section show that banks' geographical expansion affected deposit markets in complicated ways. The structural model used in the rest of the paper will help us quantify these effects and conduct counterfactuals.

[8]Appendix Figure B.4 displays the level of the HHIs and highlights that deposit markets are more concentrated in smaller counties.

3. The Model

We lay out an equilibrium model of banks operating in multiple oligopolistic markets. The economy features a representative household and a large number of heterogeneous banks. The household uses its endowment to provide funds to banks in the form of equity, deposits and non-deposit funding (i.e., wholesale funding and interbank lending). Deposits provide liquidity services to the household. Banks invest (or equivalently, lend out) the funds at their disposal. For simplicity, we model all these as intra-period transactions, allowing us to work with effectively a static setting.

There is a continuum of heterogeneous deposit markets (counties), indexed by i, each with a finite number of operating banks. A given bank does not operate in all markets, exposing it to idiosyncratic risk. Banks act as oligopolists in deposit markets and compete by setting interest rates on deposits.

We start by deriving analytical expressions for a number of objects of interest, notably deposit spreads, risk premia, and markups. We exploit these to devise a simple and transparent empirical strategy in Section 4.

3.1. *Households*

The economy has a representative household, which is assumed to be endowed with $\bar{W}$ units of consumption goods. It can invest these funds in three different assets: bank equity (denoted by E), deposits (described in more detail below), or non-deposit funding to banks. In our baseline specification, deposits are the only source of liquidity services. Section 8 extends the model to incorporate other assets providing liquidity benefits (e.g., cash).

Let D_{ij} denote the household's deposits held with bank j in county i. Deposit services across different banks and markets are aggregated using a nested CES specification—the first level aggregates D_{ij} of different banks in county i to construct a county-level composite D_i. The second level then combines these composites into an economy-wide aggregate 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 substitutability 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.[9] The variable ϕ_i denotes the household's relative preference for deposits in county i and captures factors that may affect county-level demand for deposits (including, for instance, income, wealth, or economic conditions). Our empirical strategy, described in Section 4, recovers these preference shifters from the data. Analogously, ψ_{ij} is the relative preference for bank j within a given county.[10]

The household derives utility from consumption and the economy-wide deposit composite according to a function $u(C, D)$, increasing in both arguments. It solves

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

where R_{ij}^D is the interest rate offered by bank j that operates in market i, R is an exogenous rate of return on (illiquid) investments, and Π are aggregate bank profits. All non-deposit assets (i.e., wholesale funding and interbank lending) earn a return R, so the net wealth of the household is simply $\overline{W} - E - \int_0^1 \sum_{j=1}^{J_i} D_{ij} di$.

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

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

In what follows, we let $\mathcal{D}_{ij}\left(R_{ij}^D\right)$ to capture the demand function defined by Equation (3). The bank-level spreads $R - R_{ij}^D$ and the county-level spread index $R - R_i^D$ are linked through:

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

Analogously, demand for the county-level deposit composite D_i is

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

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

[9]This is similar to assumptions commonly made in the literature on oligopolistic competition in macroeconomics and trade (see, e.g., Atkeson and Burstein, 2008).

[10]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 (Verboven, 1996; Berger et al., 2022). For details, see Appendix C.1.

3.2. *Banks*

There is a large number of heterogeneous banks, indexed by j. Each bank j uses funds raised from deposits and other sources of financing (wholesale funding, interbank loans, equity) to make loans L_j or to invest in securities S_j. We let bank j operate in a subset of locations (counties) $\mathcal{M}_j$ from where it is able to raise deposits. We use the indicator function $\Lambda_j(i)$ to denote whether bank j operates in county i, i.e. $\Lambda_j(i) = 1$ if $i \in \mathcal{M}_j$ and 0 otherwise. Throughout the paper, we do not explicitly model the choice of $\mathcal{M}_j$: instead, we treat banks' location decisions as given (and directly observed from the data) and quantify their implications for risk premia, markups, and spreads.

Banks compete for deposits by setting interest rates R^D_{ij}. They act as oligopolists at the county-level—i.e. they internalize their effects on R^D_i and D_i—but take as given the aggregates R^D and D. Bank j's overall cost of a unit of deposits from county i is $R^D_{ij} + \kappa_{ij}$, where the parameter κ_{ij} captures non-interest costs. We analyze separately two polar cases for banks' rate setting behavior. In the first, banks set deposit rates separately for each county ('local pricing'). The second is a stark form of 'uniform pricing': each bank sets a single deposit rate across all the counties, i.e. we impose $R^D_{ij} = R^D_j \ \forall i \in \mathcal{M}_j$. This second formulation is motivated by an empirical literature documenting that banks often set identical 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 extremes. For instance, a bank may set the same rate across all branches of a given state, but different rates across states.[11]

Given our focus on deposit risks, we start with a flexible, general approach to returns on deposits. Let $\Pi_j\left(\{\mathcal{D}_{ij}\}_{i\in\mathcal{M}_j}\right)$ denote the realized profit from a vector of deposit flows, taking into account the optimal choices and returns/costs of lending and other sources of financing (e.g. wholesale funding and interbank borrowing).[12] This general formulation of returns allows us to connect to a large literature analyzing, both theoretically and empirically, rich models of lending and wholesale borrowing. Our goal is to derive a general expression for deposit rates—the key object of interest—as a function of $\Pi_j(\cdot)$ and the demand side.

Of course, characterizing the exact form of $\Pi_j(\cdot)$ requires additional assumptions on its key determinants, specifically: (i) returns on lending and other assets; (ii) other sources of funding, such as wholesale funding and interbank loans; (iii) the timing of banks' choices. For instance,

[11] As we will see, data are consistent with this intermediate view—there is some market-specific variation in rates even though a bank-specific component accounts for a very large fraction of the overall variation.

[12] These returns and costs may be stochastic and heterogeneous across locations or banks. At this stage, we impose no specific assumptions on them, nor on the lending technology.

as we explain next for our baseline specification, we assume that banks choose deposit rates and loans before observing the realized shocks.

Before imposing additional structure, we first characterize the bank's problem of choosing deposit rates for a general profit function Π_j. For brevity, we focus on the local pricing case. The deposit rates offered by bank j in each market it operates in are the solution to:

$$\max_{\left\{R_{ij}^D\right\}_{i\in\mathcal{M}_j}} \mathbb{E}\left[\Pi_j\left(\left\{\mathcal{D}_{ij}\left(R_{ij}^D\right)\right\}_{\forall i\in\mathcal{M}_j}\right) - \int_0^1 \left(R_{ij}^D + \kappa_{ij}\right)\mathcal{D}_{ij}\left(R_{ij}^D\right) d\Lambda_j\left(k\right)\right], \tag{6}$$

where $\Lambda_j(\cdot)$ denotes the measure indexing counties in which bank j operates.

It is instructive to express the optimal choice in terms of deposit spreads (relative to R, the return on the illiquid asset). These are given by (see Appendix C for derivations):

$$R - R_{ij}^D = \frac{\vartheta_{ij}}{\vartheta_{ij}+1}\left[\kappa_{ij} + R - \mathbb{E}\left(\Pi_{ij}'\right) - \frac{\mathbb{C}ov\left(\Pi_{ij}', \mathcal{D}_{ij}'\right)}{\mathbb{E}\left(\mathcal{D}_{ij}'\right)}\right] \tag{7}$$

Equation (7) decomposes deposit spreads into a markup and marginal cost component. The markup is given by $\frac{\vartheta_{ij}}{\vartheta_{ij}+1}$, where $\vartheta_{ij} \equiv \left(R - R_{ij}^D\right)\frac{\mathbb{E}\left(\mathcal{D}_{ij}'\right)}{\mathbb{E}\left(\mathcal{D}_{ij}\right)}$ denotes the expected price (i.e., spread) elasticity of deposit demand and $\mathcal{D}_{ij}' \equiv \frac{\partial \mathcal{D}_{ij}}{\partial\left(R-R_{ij}^D\right)}$ is the slope of deposit demand. The marginal cost component comprises the non-interest costs of raising deposits κ_{ij} and the gap between R and the expected marginal profit of an additional unit of deposits $\mathbb{E}\left(\Pi_{ij}'\right)$, with $\Pi_{ij}' \equiv \frac{\partial \Pi_j}{\partial \mathcal{D}_{ij}}$. More importantly for our analysis, the marginal cost also depends on how the marginal benefit covaries with the slope of deposit demand. Intuitively, if the benefit of an additional unit of deposits tends to be high when the slope of the demand is also relatively high (in magnitude), that location is a more attractive source of deposit funding since it generates funds precisely when their marginal value is larger. Consequently, the bank finds it optimal to offer a higher deposit rate in that market—or, equivalently, a smaller spread $R - R_{ij}^D$.

In sum, Equation (7) delivers a general insight: under uncertainty, deposit rates rise with the covariance of the slope of deposit demand with marginal benefit. In what follows, we impose additional structure that will allow us to express (7) in terms of observables and take it to data.

Baseline Specification

We start by using the CES demand system to derive a closed-form expression for markups:

$$MKP_{ij} \equiv \frac{\eta(1-s_{ij}) + \theta s_{ij}}{\eta(1-s_{ij}) + \theta s_{ij} - 1}, \qquad \text{where} \tag{8}$$

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

denotes the bank's effective share in liquidity-related expenditure in county i. The form of the markup is identical to that of Atkeson and Burstein (2008) and reflects the fact that the effective elasticity of deposit demand is a weighted average of the within-county and across-county elasticity parameters (η and θ, respectively). Given the assumption that $\eta > \theta > 1$, this implies that markups are increasing in s_{ij}, the bank's market share s_{ij}.[13]

We then specify the determinants of the profit function, $\Pi_j(\cdot)$. First, on the assets side, we assume that bank j is endowed with a linear lending technology, with returns $R + z_j$, where z_j denotes a stochastic (bank-specific) spread. One interpretation is that each bank has access to a large (potentially economy-wide) market for assets. This simple specification still allows for heterogeneity in skill or information acquisition across banks through a bank-specific spread z_j. The linear returns assumption implies the distinction between loans and other assets (such as securities) is not relevant, so we economize on notation and refer to all assets as loans. Later, in Section 7, we will analyze a richer asset structure where banks make explicit choices of securities and lending across local markets.

Second, banks have three other sources of funding, in addition to deposits. Wholesale funding H_j is available through a competitive economy-wide market. The supply of funds (from households) in this market is assumed to be perfectly elastic at R, which fixes the interest rate on H_j. Bank j is 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 $R + \frac{\nu_j}{H}_j$. Bank j is also assumed to receive E_j units of equity funding. We treat E_j as exogenous, an innocuous choice given the absence of financial or agency frictions.[14] Lastly, there is a competitive interbank lending market that opens after all the shocks have been realized. Interbank borrowing B_j is subject to costs, given by $\frac{\chi_j}{2}B_j^2$.[15] For simplicity, we will assume that the household also participates in this market with a supply curve that is perfectly elastic at R.[16] This implies that from bank j's perspective, the cost (return) of borrowing (lending) in this market is $R + \frac{\chi_j}{2}B_j$.

Third, we make explicit the timing of various decisions. Banks first choose deposit rates $\{R_{ij}^D\}$ (or equivalently, deposit spreads $\{R - R_{ij}^D\}$), wholesale funding H_j, and loans L_j. Importantly, the county-level deposit demand shifters $\{\phi_i\}$ and the loan returns z_j are unknown at the time

[13]For $s_{ij} > 0$, the bank internalizes the effects of its choices on county-level aggregates, which changes the effective demand elasticity. As $s_{ij} \to 0$, the markup becomes $\frac{\eta}{\eta-1}$, the monopolistic competition limit.

[14]It is straightforward to endogenize equity subject to issuance costs. This will have no effect on our results.

[15]This assumption, convex costs in non-deposit funding, is common in the literature (see Bernanke and Gertler, 1995; Kashyap and Stein, 1995; D'Amico and Alekseev, 2024) and is meant to capture market frictions, such as credit risk and/or agency/information frictions.

[16]This could be interpreted as capturing non-bank intermediaries, which have become increasingly important participants in the interbank Fed Funds market.

banks make these choices (but their joint distribution is known). Then, the shocks are realized, and the household chooses $\{\mathcal{D}_{ij}\}$. Banks cannot adjust their loans once shocks have been realized. Given the realized $\{\phi_i\}$ shocks, the total funds available to bank j (from deposits, wholesale funding and equity) may differ from its loan commitments L_j. In this case, the bank has to borrow or lend in the interbank market, $B_j = L_j - E_j - H_j - \int_0^1 D_{ij} \mathrm{d}\Lambda_j(i)$.

Given these assumptions, we can write the profit function as follows:

$$\Pi_j\left(\{\mathcal{D}_{ij}\}_{i\in\mathcal{M}_j}\right) = (R + z_j)L_j^* - (R + \frac{\nu_j}{2}H_j^*)H_j^* - (R + \frac{\chi_j}{2}B_j)B_j, \tag{9}$$
$$\text{where} \qquad B_j = L_j^* - H_j^* - E_j - \int_0^1 \mathcal{D}_{ij}\mathrm{d}\Lambda_j(i),$$

and L_j^* and H_j^* denote the optimal (ex-ante) choices of loan commitments and wholesale funding.

In this baseline specification, the combination of loan commitments and costs of interbank borrowing (i.e., a $\chi_j > 0$) create curvature in $\Pi_j\left(\{\mathcal{D}_{ij}\}_{i\in\mathcal{M}_j}\right)$, the source of aversion to deposit risk.[17] Given (L_j^*, H_j^*), and deposit rates, more volatile $\{\phi_i\}$ shocks increase the probability that the bank will have to tap the costly interbank market. Equation (9) directly implies:

$$\Pi'_{ij} = R + \chi_j\left(L_j^* - H_j^* - E_j - \int_0^1 D_{ij}\mathrm{d}\Lambda_j(i)\right).$$

We now analyze the bank's problem separately under local and uniform pricing.

Local Pricing

In the case where banks set a different deposit rate for each location in which they operate, their problem can be stated as follows:

$$\max_{\{R_{ij}^D\}_{\forall i\in\mathcal{M}_j}, L_j, H_j} \mathbb{E}\left\{(R + z_j)L_j - \left(R + \frac{\nu_j}{2}H_j\right)H_j - \left(R + \frac{\chi_j}{2}B_j\right)B_j - \int_0^1 \left(R_{ij}^D + \kappa_{ij}\right)\mathcal{D}_{ij}d\Lambda_j(i)\right\}$$
$$\text{s.t. } L_j = \int_0^1 \mathcal{D}_{ij}\, d\Lambda_j(i) + H_j + E_j + B_j, \tag{10}$$

Optimal deposit spreads (see Appendix C for the derivation) are given by:

$$R - R_{ij}^D = \frac{\eta(1-s_{ij}) + \theta s_{ij}}{\eta(1-s_{ij}) + \theta s_{ij} - 1}\left[\kappa_{ij} - \mathbb{E}(z_j) + \chi_j\mathbb{E}(\mathcal{D}_j)\Gamma_{ij}\right], \tag{11}$$

[17]In Section 8, we show that our results are robust to alternative sources of curvature, such as diminishing marginal returns on lending, risk aversion, or regulatory constraints. Other mechanism that would also generate curvature in a bank's profit function is costly equity issuance and capital requirements, as in Bolton et al. (2020).

where $\mathbb{E}(\mathcal{D}_j) \equiv \int_{i\in\mathcal{M}_j} \mathbb{E}(\mathcal{D}_{ij})\, di$ denotes total expected deposits and

$$\Gamma_{ij} \equiv \int_{k\in\mathcal{M}_j} \omega_{kj} \frac{\rho_{ik}\sigma_i\sigma_k}{\mu_i\mu_k} dk. \tag{12}$$

denotes the county-specific risk for bank j, with $\mu_i \equiv \mathbb{E}[\phi_i^\theta]$, $\sigma_i \equiv \mathbb{V}^{1/2}(\phi_i^\theta)$, and $\rho_{ik} \equiv \mathrm{corr}(\phi_i^\theta, \phi_k^\theta)$. The risk is the average covariance of county i's deposit demand shock with the counties bank j operates in, weighted by each county's expected share in the bank's exposure total deposits, $\omega_{kj} \equiv \frac{\mathbb{E}(\mathcal{D}_{kj})\Lambda_j(k)}{\int_{k\in\mathcal{M}_j} \mathbb{E}(\mathcal{D}_{kj})\mathrm{d}_k}$. In what follows, we define deposit risk premium as $RP_{ij} \equiv \chi_j \mathbb{E}(\mathcal{D}_j)\Gamma_{ij}$, the product of the quantity of risk ($\mathbb{E}(\mathcal{D}_j)\Gamma_{ij}$) and the price of risk (χ_j).

Equation (12) shows how idiosyncratic risk affects marginal costs and through that, deposit spreads. 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 j operates in. The higher this correlation, *ceteris paribus*, the higher is the risk premium and the spread (or equivalently, the lower is the deposit rate R_{ij}^D). Intuitively, it is optimal to charge higher deposit spreads in a county where deposit demand tends to be high when overall deposit demand from the bank's perspective is high. 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 effective marginal cost.

Uniform Pricing

We next turn to the analysis of banks' problem under uniform pricing: now, bank j is assumed to set a single rate across all markets in which it operates, i.e. $R_{ij}^D = R_j^D \ \forall i \in \mathcal{M}_j$. Given our set of baseline assumptions, the problem for bank j is as follows:

$$\max_{R_j^D, L_j, H_j} \mathbb{E}\left\{ (R+z_j) L_j - \left(R + \frac{\nu_j}{2} H_j\right) H_j - \left(R + \frac{\chi_j}{2} B_j\right) B_j - \int_0^1 \left(R_j^D + \kappa_{ij}\right) \mathcal{D}_{ij}\, d\Lambda_j(i) \right\}$$
$$\text{s.t. } L_j = \int_0^1 \mathcal{D}_{ij} d\Lambda_j(i) + H_j + E_j + B_j. \tag{13}$$

Equation (14) characterizes the optimal bank deposit spread under uniform pricing (detailed derivations are relegated to Appendix C):

$$R - R_j^D = \frac{\eta(1-s_j) + \theta s_j}{\eta(1-s_j) + \theta s_j - 1} \left[\kappa_j - \mathbb{E}(z_j) + \chi_j \mathbb{E}(\mathcal{D}_j)\Gamma_j \right], \tag{14}$$

where $s_j \equiv \sum \omega_{ij} s_{ij}$ and $\kappa_j \equiv \sum \omega_{ij} \kappa_{ij}$ represent bank-level weighted average market shares and operating costs, respectively. The bank-level risk Γ_j is defined as:

$$\Gamma_j = \int_{k \in \mathcal{M}_j} \widetilde{\omega}_{kj} \left(\int_{i \in \mathcal{M}_j} \omega_{ij} \frac{\rho_{i,k} \sigma_i \sigma_k}{\mu_i \mu_k} di \right) dk, \tag{15}$$

where $\widetilde{\omega}^D_{ij}$ is a weighted elasticity of substitution, given by:

$$\widetilde{\omega}_{ij} \equiv \frac{\mathbb{E}\left(\mathcal{D}_{ij} \Lambda_j(i)\right) \times \left(\eta(1 - s_{ij}) + \theta s_{ij}\right)}{\int_{i \in \mathcal{M}_j} \mathbb{E}\left(\mathcal{D}_{ij}\right) \times \left(\eta(1 - s_{ij}) + \theta s_{ij}\right) di}.$$

Equation (14) is similar in structure to (11), which characterized the optimal spread under local pricing. The key difference is that the relevant objects—market shares and risk —are now averaged with appropriate weights across all markets in which the bank operates. Under local pricing, markups vary by county and increase with the county-level market share s_{ij}. In contrast, under uniform pricing, markups are determined by a weighted average of market shares in all the markets the bank operates in, s_j. Similarly, the risk premium under uniform pricing, $RP_j \equiv \chi_j \mathbb{E}(\mathcal{D}_j) \Gamma_j$, depends on the average covariance—or equivalently, on the volatility of the bank's total deposits—while under local pricing, it varies by county and is a function of that county's covariance with others in the bank's portfolio.

3.3. *Lending*

The analysis so far has focused on deposit markets. Changes in deposit spreads—such as those driven by reductions in deposit volatility—also have implications for lending. While we take the demand for loans as given and treat loan returns, $\{z_j\}$, as exogenous processes, changes in deposit spreads affect overall lending through shifts in the credit supply.

From the bank's first-order conditions with respect to loans and wholesale funding:

$$L^\star_j = \frac{\mathbb{E}\left(z_j\right)}{\chi_j} + \int_{i \in \mathcal{M}_j} \mathbb{E}\left(D_{ij}\right) + H_j + E_j, \quad \text{and} \quad H^\star_j = \frac{\mathbb{E}\left(z_j\right)}{\nu_j}. \tag{16}$$

Given our CES specification for deposit demand, the change in bank-county level deposits in response to a change in spreads is $\mathcal{D}'_{ij} = \frac{(\eta-\theta)s_{ij}-\eta}{R-R^D_{ij}} \mathcal{D}_{ij}$. Using a first-order approximation, we can show that changes in bank-level lending induced by deposit risk (under uniform pricing) are given by:[18]

$$\frac{\partial \ln L^\star_j}{\partial \ln \Gamma_j} \approx \left(\left(\eta - \theta\right) s_j - \eta\right) \frac{\mathbb{E}\left(D_j\right)}{L^\star_j} \frac{\chi_j \mathbb{E}(D_j) \Gamma_j}{MC_j} < 0 \tag{17}$$

[18]The expressions under local pricing or for changes induces by variation in markups are analogous.

Thus, lower risk leads to higher lending, particularly for banks (i) with large risk premia (as a share of total marginal costs), (ii) that rely more heavily on deposits for funding, and/or (iii) with smaller market shares (and so face more elastic deposit demand). We examine the effects of changes in deposit markups and risk premia on lending more thoroughly in Section 7, using an extended version of the model with multiple assets (including 'local' loans and securities).

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 and 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.

We use two sources for deposit rates. The first one is 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.[19] 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 weighted average deposit rates across deposit products (certificates of deposit and savings accounts) using as weights bank-level balances for each deposit type from Call Reports.[20] Lastly, based on our view of a county

[19]The survey has data for before 2011 but with a significantly lower coverage of deposits.

[20]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, 1-3 years, and more than 3 years, respectively. Rates on money markets are weighted using savings account balances.

as the relevant market, we collapse the RateWatch interest rate data to the year-county-bank level using branch-level deposits as weights.[21]

We use the 5-Year High Quality Market (HQM) Corporate Bond Spot Rate as our measure of the market rate R.[22] We then compute interest rate spreads, $R - R^D_{ij}$ and $R - R^D_j$, 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 from Call Reports. This dataset has better coverage, both across banks (the Call Reports cover 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 to use a longer sample to compute the variance-covariance matrix for the county-level ϕ_i shocks.

In line with previous studies, we find evidence consistent with uniform pricing by banks. 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.[23] The residual variation, while small, suggests some degree of local pricing behavior. Later in this section, we will exploit this variation to estimate the within-county demand elasticity, η.

Table 2 shows some descriptive statistics for deposits (SOD) and spreads (Call Reports) in 2019. Our final dataset contains nearly 25,000 bank-county observations and just over 5,000 bank-level observations. 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.

4.2. *Calibration*

We describe next our calibration strategy, which proceeds in several steps. While our model is static, we introduce a time subindex, t, to highlight the set of parameters that vary from year to year, and to be more precise on the source of variation that we exploit to identify

[21] In Appendix D.4, we show that all our results are robust to an alternative definition of a local market at the MSA level, instead of at the county level. Also, in Appendix D.5, we show that results are robust to excluding data that could be linked to online banking or banks' central booking practices.

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

[23] To ensure this pattern is not driven by banks operating in only a few locations, we restrict our analysis to banks active in more than 100 counties. Of course, we cannot rule out the possibility that banks engage in local pricing but find it optimal to set very similar rates across the markets in which they operate.

Table 2. Descriptive Statistics on Deposits and Spreads

	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.

many of our parameters. Given the finite number of counties in the US, we replace integrals with summations. We begin our analysis by estimating the elasticities of substitution within- and across- counties (η and θ), which are assumed to be constant throughout our sample. Using these elasticities, we then use our model equations to recover demand and cost related parameters and shocks: $\{\phi_{it}, \psi_{ijt}, \kappa_{ijt}, \mathbb{E}z_{jt}\}_{\forall\{i,j,t\}}$. The county-level shifters ϕ_{it} are then used to estimate their joint distribution and, in particular, the variance-covariance $\{\rho_{ik}, \sigma_i, \mu_i\}_{\forall i}$, relevant to compute our measure of risk premia. Finally, we estimate the parameters indexing the weight of deposit risk on spreads, $\{\chi_j\}$—the curvature of the pricing equation.

Elasticities of Substitution

To estimate the within-county elasticity of substitution, η, we employ an instrumental variable strategy. Our instrument is a weighted average of changes in relative wages of bank tellers across all locations where a bank operates. Our identifying assumption is that changes in the average wage rate impact a bank's cost of providing deposit services, κ_{ijt}, but do not influence the relative preference parameters, ψ_{ijt}, and demand for deposits. For each bank, we construct a Bartik-type instrument by weighting county-level wage changes by the share of a bank's total deposits in that county in a base year t_0 (set to 2011). Specifically, for bank j operating in counties $k \in \mathcal{M}_j$, the instrument is given by:

$$\text{Bartik}^{\text{IV}}_{jt} \equiv \sum_{k\in\mathcal{M}_{j0}} \left(\Delta \ln \text{Wage}^{\text{Tellers}}_{kt} - \Delta \ln \text{Wage}^{\text{All Occup}}_{kt}\right) \times \frac{D_{kj0}}{D_{j0}},$$

where $\text{Wage}^{\text{Tellers}}$ denotes the Metropolitan Statistical Area (MSA)-level wages for bank tellers, and $\text{Wage}^{\text{All Occup}}$ refers to the average wage across all occupations within an MSA.[24] The

[24]Wage data are from the Bureau of Labor Statistics, where the finest level of disaggregation is the MSA.

assumption is that wages constitute a significant portion of the banks' costs of providing deposit services, κ_{ijt}, so these wage changes affect banks' marginal costs and deposit spreads.[25]

Equations (18) and (19) describe our two-stage regression. In the first stage, we regress changes in bank-county-level deposit spreads on our Bartik instrument. In the second stage, we regress changes in bank-county-level deposits on the instrumented changes in spreads. We include county-bank fixed effects to account for time-invariant characteristics specific to each bank-county pair, and county-time fixed effects to capture common variation within each county over time. Our coefficient of interest is β^D, which, based on our CES structure, can be directly mapped into the within-county elasticity of substitution (i.e., $\eta = -\beta^D$):

$$\Delta \ln(R - R^D_{ijt}) = \gamma^R_{ij} + \gamma^R_{it} + \beta^R \text{Bartik}^{\text{IV}}_{jt} + \epsilon^R_{ijt}, \tag{18}$$

$$\Delta \ln D_{ijt} = \gamma^D_{ij} + \gamma^D_{it} + \beta^D \Delta \ln\widehat{(R - R^D_{ijt})} + \epsilon^D_{ijt}. \tag{19}$$

The results are shown in Panel (A) of Table 3. Based on our preferred specification in columns (2) and (3)—which includes bank-county and county-time fixed effects—we obtain a within-county elasticity of substitution close to 3. Column (1) shows the estimated elasticity for a specification without county-time fixed effects. In this case, the point estimate is smaller, which is consistent with the insight in Berger et al. (2022). That is, although the instrument is uncorrelated with bank-specific demand shifters, it still influences equilibrium deposits through its effects on county-level variables.[26] The county-time fixed effect allows us to account for all those interactions and indirect effects, thereby recovering the true structural elasticity η.

We follow a similar approach to estimate the cross-county elasticity of substitution, θ. To do this, we aggregate our bank-level Bartik instrument at the county level, weighting by banks' county-level market shares in the base year. More specifically, the instrument is defined as $\text{Bartik}^{\text{IV}}_{it} = \sum_{j \in i} \tilde{s}_{ij0} \text{Bartik}^{\text{IV}}_{jt}$, where $\tilde{s}_{ij0}$ represents county-level market shares in the base year.[27] Changes in $\text{Bartik}^{\text{IV}}_{it}$ affect county-level banks' average marginal costs and thus deposit spreads. The identifying assumption here is that the weighted county-level relative wage changes of bank tellers are orthogonal to the demand-shifter shocks, ϕ_{it}. As before, working with *relative*

[25]We subtract the change in average wage across all occupations to remove a potential mechanical correlation with deposit demand. For instance, if all wages rise, including those for tellers, higher household income could drive up deposit demand, potentially increasing spreads.

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

[27]We use a base year so that endogenous changes in s_{ijt}, which could be correlated with spreads and deposits, do not mechanically affect our instrument. We define $\tilde{s}_{ij0} \equiv \frac{D_{ij0}}{\sum_{j \in i} D_{ij0}}$.

TABLE 3. Estimated Demand Elasticities

Panel A. Estimation of η

	$\Delta \ln D_{ijt}$		
	(1)	(2)	(3)
$\widehat{\Delta \ln R_{ijt}}$	-2.03	-2.87	-3.16
	(0.55)	(1.14)	(0.67)
Time FE	Yes	-	-
Bank-county FE	Yes	Yes	Yes
County-time FE	No	Yes	Yes
County Type	All	All	≥ 5 banks
Observations	116,298	115,182	101,870
1st stage F-stat	36.43	13.48	13.48

Panel B. Estimation of θ

	$\Delta \ln D_{it}$	
	(1)	(2)
$\widehat{\Delta \ln R_{it}}$	-2.35	-1.79
	(1.02)	(0.70)
Time FE	Yes	Yes
County FE	No	Yes
County Type	All	≥ 5 banks
Observations	17,773	10,204
1st stage F-stat	11.31	29.27

Notes: Panel A presents the estimates for the elasticity of substitution, η. Standard errors are clustered at the county-year level. Panel B shows the estimates for θ. We linearly detrend our instrument at the bank level, and we linearly detrend (log) deposits and (log) spreads at the bank-county level. In column (3), we condition on counties with more than 5 banks in a given year (the first stage regression is the same as in column 2). Standard errors are clustered at the county level and all variables are linearly detrended (in logs) at the county level.

wage changes mitigates concerns that the instrument could be correlated with deposit demand. We argue that this assumption is reasonable, especially for counties where many large banks operate, as their exposure to local conditions tends to be smaller.

Equations (20) and (21) describe our two-stage regression, analogous to the approach used for estimating η. Under our CES demand system, the coefficient α^D can be directly mapped to the cross-county elasticity of substitution, θ:

$$\Delta \ln(R - R_{it}^D) = \gamma_i^R + \gamma_t^R + \alpha^R \text{Bartik}_{it}^{\text{IV}} + \epsilon_{it}^R, \tag{20}$$

$$\Delta \ln D_{it} = \gamma_i^D + \gamma_t^D + \alpha^D \Delta \ln \widehat{(R - R_{it}^D)} + \epsilon_{it}^D. \tag{21}$$

The estimates for θ are shown in Panel B of Table 3. We obtain an estimate of approximately 2, which aligns with our modeling assumption that the elasticity of substitution across counties is lower than within counties.

Recovering Shocks and Time-varying Parameters

Given the elasticities η and θ, the optimality conditions of the model can be used to recover the yearly county-level shocks $\{\phi_{it}\}_{\forall\{i,t\}}$ and the relative demand shifters $\{\psi_{ijt}\}_{\forall\{i,j,t\}}$ parameters. Combining the definition for D_i in Equation (1) with bank-county level demand function (3)

Table 4. Time-varying Parameters: Summary Statistics

Parameter	Description	Mean	Cross Sectional SD	Skewness
ψ_{ijt}	Relative preference for bank j	0.39	0.23	0.39
$k_{ijt} - z_{jt}$ (pp)	Non-interest expenses	0.99	0.45	-8.69
$k_{jt} - z_{jt}$ (pp)	Non-interest expenses (UP)	0.73	0.65	-10.11

Notes: The table reports summary moments for the estimated parameters, based on 2019 data.

and the county-level ideal price index (4), we obtain the bank-county level demand shifters:

$$\psi_{ijt} = \frac{\hat{\psi}_{ijt}}{\left(\sum_j \hat{\psi}_{ijt}^{\eta}\right)^{\frac{1}{\eta}}}, \qquad \text{where} \tag{22}$$

$$\hat{\psi}_{ijt} = \left(R - R_{ijt}^{D}\right) D_{ijt}^{\frac{1}{\eta}} \left(\sum_j \left(R - R_{ijt}^{D}\right) D_{ijt}^{\frac{1}{\eta}}\right)^{-1}. \tag{23}$$

Equation (22) imposes a normalization (specifically, $\sum_{j\in i} \psi_{ijt}^{\eta} = 1$).[28] Once we have the $\{\psi_{ijt}\}$, we can use Equations (1), (4), and (8) to directly compute the county-level $\{D_{it}\}_{\forall\{i,t\}}$ and $\left\{R - R_{it}^{D}\right\}_{\forall\{i,t\}}$ as well as the market shares $\{s_{ijt}\}_{\forall\{i,j,t\}}$.

The next step is to recover the realized shocks $\{\phi_{it}\}_{\forall\{i,t\}}$. Combining the definition for D in Equation (1) with the economy-wide demand function and price index in Equation (5), we get

$$\phi_{it} = \frac{\hat{\phi}_{it}}{\left(\sum_j \hat{\phi}_{it}^{\theta}\Lambda_i\right)^{\frac{1}{\theta}}}, \qquad \text{where} \tag{24}$$

$$\hat{\phi}_{it} = \left(R - R_{it}^{D}\right) D_{it}^{\frac{1}{\theta}} \left(\sum_i \left(R - R_{it}^{D}\right) D_{it}^{\frac{1}{\theta}}\Lambda_i\right)^{-1}. \tag{25}$$

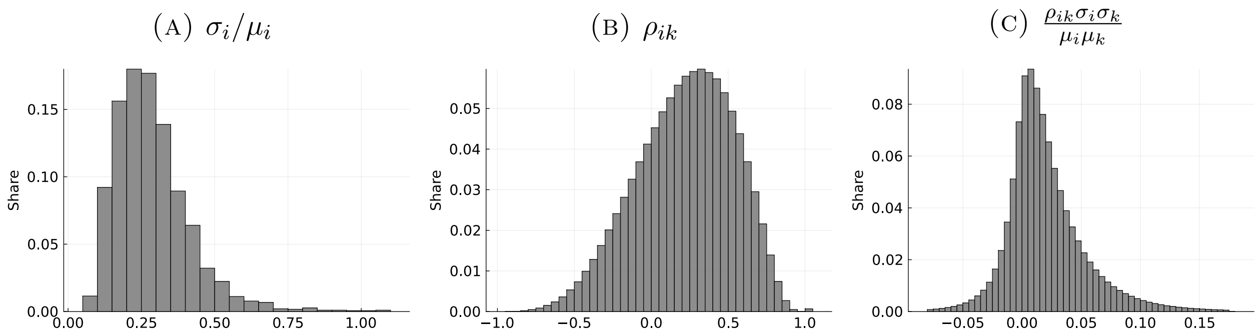
As before, the first expression reflects a normalization ($\sum_i \phi_{it}^{\theta}\Lambda_i = 1$).[29] Table 4 summarizes the moments for $\{\psi_{ijt}\}$ and $\{\phi_{it}\}$.

Given a panel of observed shocks $\{\phi_{it}\}$, we can then directly estimate $\{\rho_{ik}, \sigma_i, \mu_i\}_{\forall\{i,k\}}$. Figure 4 depicts these estimates. Panel (A), which shows the distribution of the coefficient of variation, σ_i/μ_i, indicates a non-trivial amount of risk. The histogram of pairwise correlations, ρ_{ik}, in Panel (B) suggests an important role for geographical diversification. Panel (C) presents the histogram of the covariance terms, which are relevant for the risk premium component of spreads—as shown in Equations (11) and (12).

[28]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).

[29]We detrend $\{\hat{\phi}_{it}\}_{t=1990}^{2019}$ at the county level to ensure that our estimates of the covariance matrix are not distorted by county-level trends. Using an aggregate trend produces similar results.

FIGURE 4. Estimated Moments for the $\{\phi_{it}\}$ Distribution



Notes: The figure depicts summary moments of the estimated $\{\phi_i\}$ shocks.

Curvature of the Pricing Equation

The last step of the calibration involves recovering the remaining parameters that characterize marginal costs: $\{\kappa_{ij}, \mathbb{E}z_{jt}\}_{\forall\{i,j,t\}}$ and $\{\chi_j\}_{\forall\{j\}}$. In our formulation, χ_j indexes the degree of frictions in the inter-bank lending market. We use the model's optimal pricing equation and observed deposit spreads to estimate χ_j. Since this strategy does not directly depend on the specific micro-foundation for χ_j, it renders our estimates robust to alternative mechanisms that lead to a risk premium of this form.[30]

In theory, one could estimate χ_j for each bank separately. However, data limitations force us to impose some structure.[31] We posit that χ_j is systematically related to bank size. Specifically, as a baseline, we assume that χ_j is inversely proportional to expected total deposits. This assumption reduces the exercise to estimating a single parameter $\chi \equiv \chi_j \mathbb{E}(D_j)$. 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 Γ_{ijt} term) rather than curvature heterogeneity (later in this section, we show the effect of moving to a more flexible specification). Under this assumption, rearranging the optimal pricing equation (11), and allowing for a time subscript t, we obtain the following regression specification:

$$MC_{ijt} = \kappa_{ijt} - \mathbb{E}z_{jt} + \chi\Gamma_{ijt}, \tag{26}$$

where $MC_{ijt} \equiv \frac{R - R^D_{ijt}}{MKP_{ijt}}$. Since the risk term Γ_{ijt} is likely correlated with the cost shifters, one cannot estimate χ through OLS. In order to identify χ, one would need to isolate the variation in Γ_{ijt} that is orthogonal to changes in κ_{ijt}. To this end, we exploit variation in Γ_{ijt} that is only

[30] E.g. diminishing returns in lending or risk aversion. See Appendix C.

[31] We have over 16,000 banks in our data, but only 9 years' worth of data from RateWatch. Moreover, many banks are active for only part of the sample period, further limiting our ability to estimate bank-specific χ_j.

driven by changes in the demand shifters ψ_{ijt}. These changes affect the county-level demand for bank j and through that influence the county-level weights ω_{ij} that are used to construct the risk premium measure, as shown in Equation (12). Our identifying assumption is that changes in ψ_{ijt} are orthogonal to fluctuations in the operating costs κ_{ijt}.

Equations (27) and (28) describe our two-stage regression for the local pricing case.

$$\Delta\Gamma_{ijt} = \kappa^{\Gamma}_{ij} + \kappa^{\Gamma}_{it} + \kappa^{\Gamma}_{jt} + \zeta^{\Gamma}\Delta\log\psi_{ijt} + \epsilon^{\Gamma}_{ijt}, \tag{27}$$

$$\Delta\ln MC_{ijt} = \kappa^{MC}_{ij} + \kappa^{MC}_{it} + \kappa^{MC}_{jt} + \zeta^{MC}\,\widehat{\Delta\Gamma_{ijt}} + \epsilon^{MC}_{ijt}. \tag{28}$$

In the first stage, we regress changes in bank-county-level deposit risk on our estimated ψ_{ijt}. In the second stage, we regress changes in bank-county-level marginal costs on the instrumented changes in risk. Both regressions include a set of fixed effects (county-bank, county-time, and bank-time), so the relevant variation is within a bank-county pair. The coefficient of interest is ζ^{MC}, which can be directly mapped into χ.

Equations (27)-(28) are derived assuming local pricing. A potential concern is that they focus on a narrow source of variation—within bank-county pairs—which may be limited when banks engage in uniform pricing. To address this, we run a similar specification at the bank level under uniform pricing. We first aggregate our bank-county level demand shifter to a bank level instrument, by weighting changes in ψ_{ijt} with the relative size of that county. Specifically, the first-stage instrument is given by: $\overline{\psi}_{jt} = \sum_{i\in\mathcal{M}_j}\omega_{ij0}\,\psi^{\eta}_{ijt}\mathbb{E}\left(D_{it}\right)$, where ω_{ij0} denotes bank j's relative exposure to county i in the base year. Using this instrument, our 2SLS regression follows from:[32]

$$\Delta\Gamma_{jt} = \kappa^{\Gamma}_{j} + \kappa^{\Gamma}_{j}\,t + \kappa^{\Gamma}_{t} + \zeta^{\Gamma}\Delta\log\overline{\psi}_{jt} + \epsilon^{\Gamma}_{jt}, \tag{29}$$

$$\Delta\ln MC_{jt} = \kappa^{MC}_{j} + \kappa^{MC}_{t} + \zeta^{MC}\,\widehat{\Delta\Gamma_{jt}} + \epsilon^{MC}_{jt}. \tag{30}$$

Table 5 presents the estimates for ζ^{MC} (or equivalently, χ). The results are consistent across both the local and uniform pricing specifications. Based on these estimates, we set $\chi = 0.03$ for our model calibration. In Appendix Figure D.1, we explore a more flexible specification by sorting banks into bins based on their total deposits and estimating χ separately within each group. The resulting estimates are quite close to those in Table 5, and suggest that χ tends to rise with bank size. This implies that our results (with $\chi = 0.03$) likely represent a lower bound for the overall impact of risk premia on spreads, particularly for larger banks.

[32] In the first stage, we include an interaction between the bank fixed effect, κ^{R}_{j}, and the year, t, to account for potential bank-level trends in the growth rate of the instrument.

Table 5. Estimated Curvature, χ

	Local Pricing:				Uniform Pricing
	(1)	(2)	(3)	(4)	(5)
$\widehat{\Delta\Gamma_{ijt}}$	0.031	0.023	0.047	0.04	0.017
	(0.0099)	(0.0106)	(0.0113)	(0.0123)	(0.0061)
Bank-year FE	Yes	Yes	Yes	Yes	-
County-year FE	Yes	Yes	Yes	Yes	-
Bank-county FE	No	Yes	No	Yes	-
Bank and year FE	-	-	-	-	Yes
County type	All	All	≥ 5	≥ 5	-
Observations	102,454	102,301	91,175	90,992	32,000

Notes: The table displays the estimates for χ. For the local-pricing specification, standard errors are clustered at the county-year level. For the uniform-pricing case, the table reports robust standard errors.

To conclude, given a value for χ, we use Equation (26) to back out the exogenous component of marginal costs, namely $\{\kappa_{ijt} - \mathbb{E}z_{jt}\}_{\forall\{i,j,t\}}$. Table 4 shows summary statistics.

5. Contributions of Markups and Risk Premia to Deposit Spreads

In this section, we use the calibrated model to quantify the contributions of markups and risk premia to deposit spreads.[33] To this end, we use a first-order approximation of Equation (14) around some value for marginal cost $MC^{\star}$:

$$\ln\left(R - R^D_{jt}\right) \approx \ln MKP_{jt} + \frac{\chi}{MC^*}\Gamma_{jt} + \frac{1}{MC^*}\left(\kappa_{jt} - \mathbb{E}z_{jt} + \chi\right) + \left(\ln MC^* - 1\right), \tag{31}$$

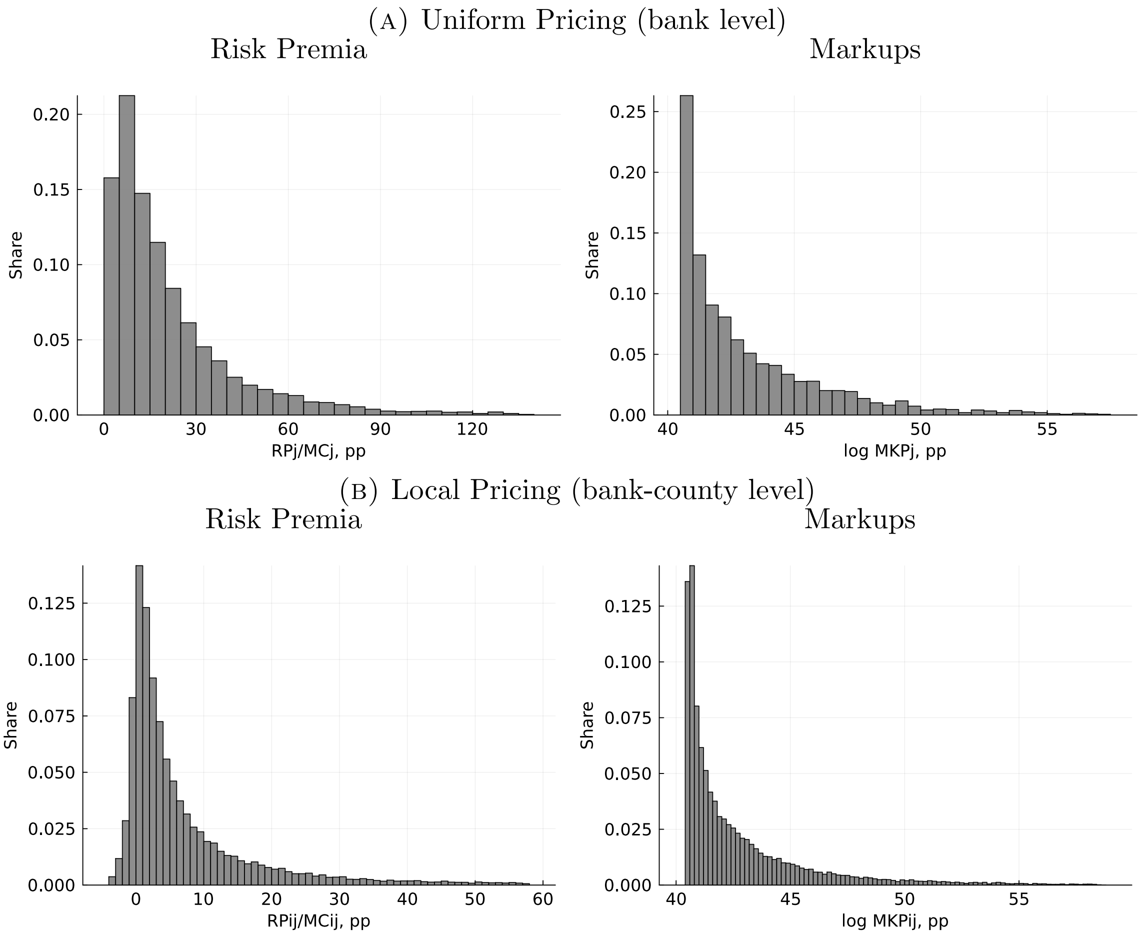
where $\ln MKP_{jt}$ and $\frac{\chi}{MC^*}\Gamma_{jt}$ capture the markup and risk premium (RP) components of spreads, respectively. We use an analogous decomposition under local pricing, based on Equation (11).

5.1. *Cross-sectional Patterns*

We start by analyzing 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 $\frac{\chi}{MC^*}\Gamma_{jt}$ and $\ln MKP_{jt}$, i.e., the contributions of risk premia (left panels) and markups (right panels) to (log) spreads (in percentage points). The top panel depicts the bank-level distribution for the uniform pricing case, while the bottom panel shows the bank-county-level distribution under local pricing. Both display considerable heterogeneity, whether across banks or bank-county

[33]Throughout the paper, we define the boundaries of the deposit market at the county level. In Appendix D, we show that our results are robust to alternative market definitions, e.g. if the boundaries are at the MSA level.

Figure 5. Contributions to (log) Spreads

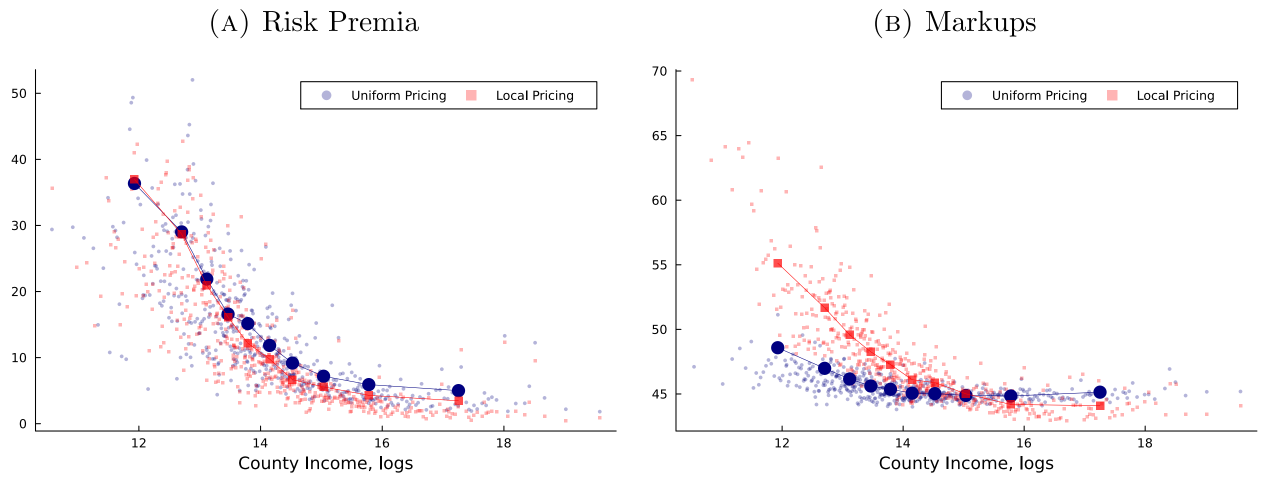


Notes: The figure presents histograms of the components of deposit spreads—risk premia and markups—based on the decomposition in Equation (31) for 2019. The top panel shows the results under the uniform-pricing scenario, while the bottom panel displays the outcomes under local pricing. Units are log points $\times 100$.

pairs. For the median bank, the risk premium accounts for about 25% of its marginal costs and markups for over 40%. At the ij-level, the effects of risk premia are relatively smaller, on average accounting 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, shift the bank-county risk distribution to the left. Still, the ij-level distribution exhibits a long right tail, indicating that risk can account for a sizable share of banks' marginal costs in some markets.

Next, we explore how the effects of risk premia and markups covary with county and bank characteristics. The county-level effects are computed as weighted averages of the bank-county level, using the model-implied market shares s_{ij} as weights. For example, under uniform pricing, the contribution of risk premia and markups to county-level spreads are, respectively,

Figure 6. Contributions to (log) Spreads, by County



Notes: The figure displays the markup and risk premia components of deposit spreads by county income, based on the decomposition in Equation (31). Blue dots represent results under uniform pricing, while red squares correspond to the local-pricing case. Larger (darker) markers denote average values within each decile of the county income distribution. Units are log points $\times 100$.

$\sum_{j\in\mathcal{J}_i} s_{ijt}\,\frac{\chi}{MC_i^*}\Gamma_{jt}$, and $\sum_{j\in\mathcal{J}_i} s_{ijt}\ \ln MKP_{jt}$, where $\mathcal{J}_i$ denotes the set of banks operating in i.[34] The definitions are analogous under local pricing.

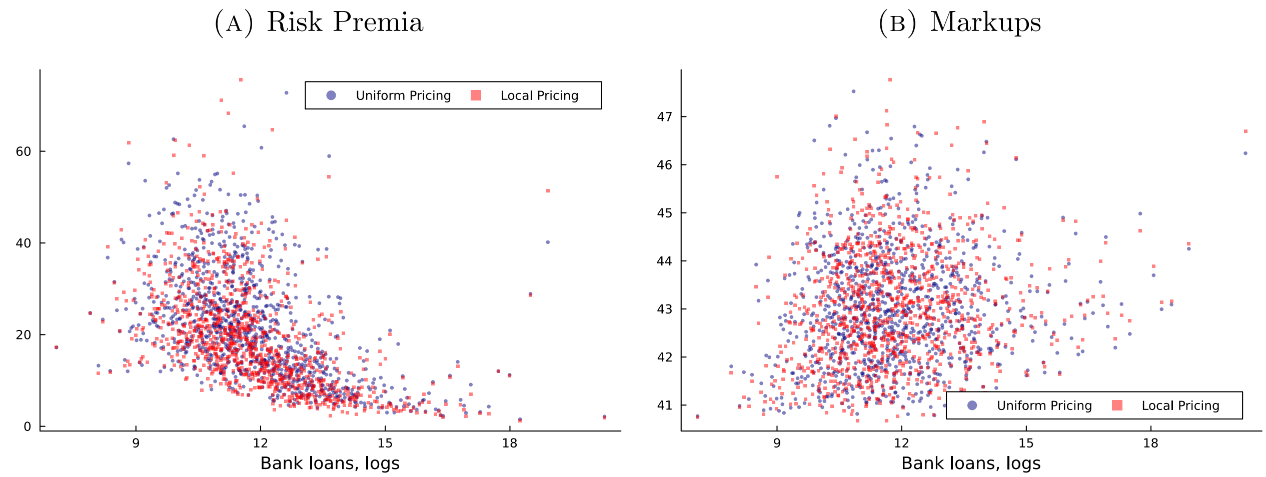
Panel (A) of Figure 6 shows the contribution of risk premia by county income. Blue dots show the results under uniform pricing, and red squares represent the local-pricing case. Larger dots indicate average values for each county income decile. Under both scenarios, we find that the effects of risk on 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 0.40 log points. Panel (B) depicts the effects of markups, which also decline with county size. Markups are typically higher under local pricing (except for the largest two deciles). Combined, the risk and markup forces drive up spreads by around 0.90 log points in the smallest/poorest counties.

We now turn to bank-level patterns. Under uniform pricing, we can directly use the decomposition in Equation (31), since it is at the bank level. For the local-pricing case, we first aggregate the bank-county-level variables using banks' deposit shares, i.e., $\sum_{i\in\mathcal{M}_j} \omega_{ijt}^D \frac{\chi\Gamma_{ijt}}{MC_{jt}^*}$ and $\sum_{i\in\mathcal{M}_j} \omega_{ijt}^D \ln MKP_{ijt}$, respectively, and then apply the decomposition in Equation (31).[35]

Panel (A) of Figure 7 shows that risk premia have a greater impact on spreads offered by smaller banks, which typically operate in fewer markets. The effect is substantial: for banks in the bottom decile, risk premia increase spreads by about 0.50 log points. Since larger banks

[34]For this exercise, we approximate marginal costs around the county average, i.e., $MC_i^* = \sum_{j\in\mathcal{J}_i} s_{ij} MC_j$.
[35]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. Contributions to (log) Spreads, by Bank



Notes: The figure shows the decomposition of deposit spreads into markups and risk premia by bank size, proxied by total loans, using Equation (31). Blue dots represent results under uniform pricing, while red squares correspond to local pricing. Units are log points $\times 100$.

operate in many markets, their risk premium is small (close to zero for the top national banks). 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.

5.2. *Changes Across Time*

Next, we use the model to decompose changes in banks' deposit spreads over time. Our goal is to quantify the effects of changes in banks' geographical presence on county-level markups, marginal costs, and risk premia. To this end, we compute changes in these components 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, we show that the patterns are similar under local pricing.[36]

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

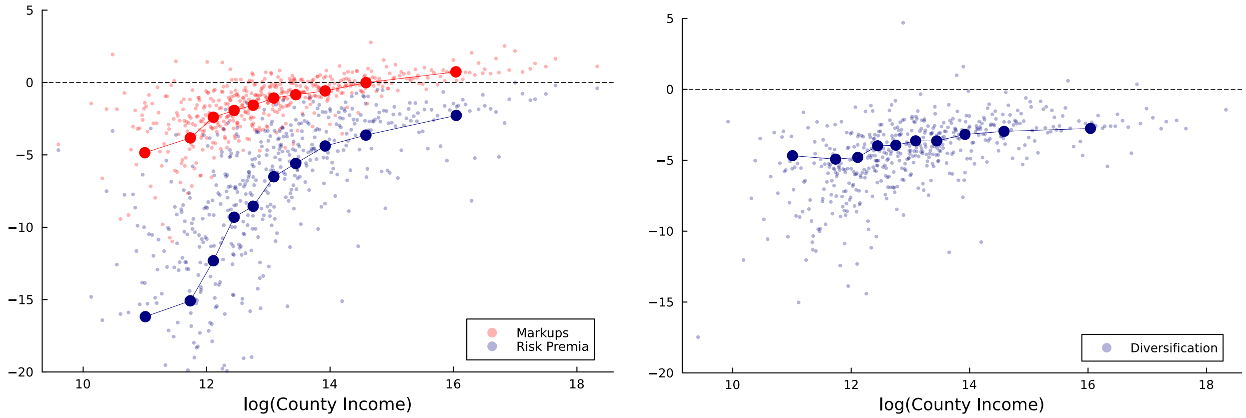
$$\Delta \ln(R - R^D_{it}) \approx \Delta \sum_{j \in \mathcal{J}_{it}} s_{ijt} \ln MKP_{jt} + \frac{\chi}{MC^*_i} \Delta \sum_{j \in \mathcal{J}_{it}} s_{ijt} \Gamma_{jt} + \frac{1}{MC^*_i} \Delta \sum_{j \in \mathcal{J}_{it}} s_{ijt} (\kappa_{jt} - \mathbb{E} z_{jt}), \quad (32)$$

[36]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).

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

(A) Markups and Risk Premia

(B) Diversification



Notes: Using the decomposition in Equation (32), Panel (A) shows the change in the markup and risk premia components of deposit spreads between 1993 and 2019, by deciles of county income, under the uniform-pricing case. Blue dots represent model-implied changes in risk premia, while red dots capture changes in markups. Panel (B) further breaks down the change in risk premia into contributions from *diversification* gains, based on Equation (33). Units are log points $\times 100$.

where the operator Δ defines changes across periods $t = 1$ and $t = 0$. The first two terms in the right hand side, $\Delta \sum_{j \in \mathcal{J}_{it}} s_{ijt} \ln MKP_{jt}$ and $\frac{\chi}{MC_i^*} \Delta \sum_{j \in \mathcal{J}_{it}} s_{ijt} \Gamma_{jt}$, capture county-level changes in deposits spreads driven by changes in markups and risk premia, respectively.[37]

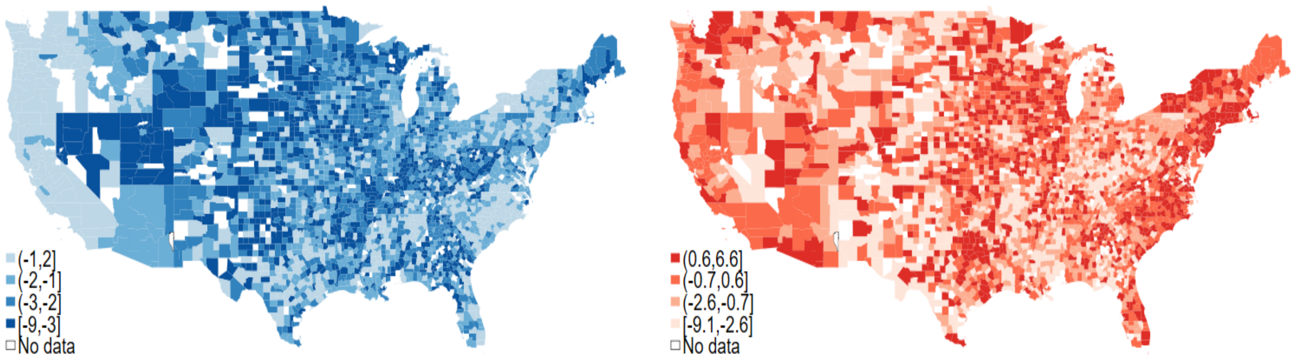
Panel (A) of Figure 8 depicts the changes in markups and risk premia, by county size. The reduction in spreads from lower risk premia is much larger in smaller (poorer) counties and implies a reduction of deposit spreads by over 15%. For larger counties, on the other hand, the effects of risk premia on marginal costs are smaller (since they are served largely by that were already well-diversified). Perhaps surprisingly, we find that markups actually *decreased* for smaller counties and implied a 5% reduction (on average) in deposit spreads.

Figure 9 shows a county-level map of the U.S. with a decomposition of changes in spreads. The largest risk-related reductions were observed in Wyoming, South Dakota, West Virginia, Oklahoma, and Nebraska (Panel A). For larger/richer locations (such as California or the Northeast), reductions in risk premia were modest, in part because those locations were served by diversified banks even before the Riegle-Neal Act. The changes in markups, shown in Panel (B), are milder: markups rose slightly in the Northeast (particularly in Connecticut, New York, and New Jersey) and in Nevada but generally declined, particularly in the Midwest and South regions.

[37]To 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



Notes: Based on the decomposition in Equation (32), the maps illustrate county-level changes in the risk premium and markup components of deposit spreads between 1993 and 2019 under the uniform-pricing case. Darker blue shades represent larger declines in spreads due to reductions in risk premia, while darker red shades indicate greater increases in spreads driven by rising markups. Units are log points $\times 100$.

We can further decompose the changes in risk premia into variation in the extent of diversification and other movements in deposit risk (for instance, the composition of a bank's deposits shifting toward less volatile counties). For each bank j and date t, we define the following measure of diversification:

$$Diver_{jt} \equiv \Gamma_{jt} - \Gamma_{jt} \mid_{\rho=1} = \Gamma_{jt} - \int_{k \in \mathcal{M}jt} \tilde{\omega}_{kjt} \left(\int_{i \in \mathcal{M}j} \omega_{ijt} \frac{\sigma_i \sigma_k}{\mu_i \mu_k}, di \right) dk, \tag{33}$$

where $\Gamma_{jt} \mid_{\rho=1}$ is our (bank-level) measure of deposit risk under the assumption that all counties are perfectly correlated (but the other moments and weights remain the same). We then use Equation (32) 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 $\frac{\chi}{MC_i^*} \Delta \sum_{\mathcal{J}_{it}} s_{ijt} Diver_{jt}$. On average, we find that changes in diversification account for almost half of the drop in risk premia—Panel (B) of Figure 8.

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

$$\Delta \sum_{j\in\mathcal{J}_{it}} s_{ijt}\Gamma_{jt} = \underbrace{M_{i1}\Big(\sum_{j\in\{\tilde{J}_{i1}\}} \frac{s_{ij1}}{M_{i1}}\Gamma_{j1} - \sum_{j\in\{\hat{J}_i\}} \frac{s_{ij1}}{1-M_{i1}}\Gamma_{j1}\Big)}_{\text{Entrants vs. Survivors}} + \underbrace{M_{i0}\Big(\sum_{j\in\{\hat{J}_i\}} \frac{s_{ij0}}{1-M_{i0}}\Gamma_{j0} - \sum_{j\in\{\tilde{J}_{i0}\}} \frac{s_{ij0}}{M_{i0}}\Gamma_{j0}\Big)}_{\text{Survivors vs. Exiters}}$$
$$+ \underbrace{\sum_{j\in\{\hat{J}_i\}} \Big(\frac{s_{ij1}}{1-M_{i1}}\Gamma_{j1} - \frac{s_{ij0}}{1-M_{i0}}\Gamma_{j0}\Big)}_{\text{Within Survivors}}. \tag{34}$$

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 $t = 1$ to that of the average survivor.[38] 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 for exiters relative to survivors. We define the sum of these two terms as the extensive margin. The last term on the right-hand side captures changes in risk across surviving incumbents.

We then use Equation (32) to map the extensive-margin and surviving-incumbents components into changes in county-level spreads. Panel A of Figure 10 shows these results by county size. Over half of the decline in risk premia came through changes in the extensive margin, particularly for smaller counties. Given its relative magnitude, we further decompose the extensive margin into within-state and out-of-state entrants and exiters. An out-of-state entrant is a bank that operated in county i only in 2019 (but not in 1993) and, in 1993, was not operating in the state to which county i belongs.[39] We find that more than half of the extensive-margin change can be attributed to out-of-state entrants and exiters (Panel B), consistent with the relaxation of geographic restrictions under the Riegle-Neal Act.

Aggregate Changes

Using a decomposition similar to Equation (32), we can decompose aggregate changes in deposit spreads as follows:

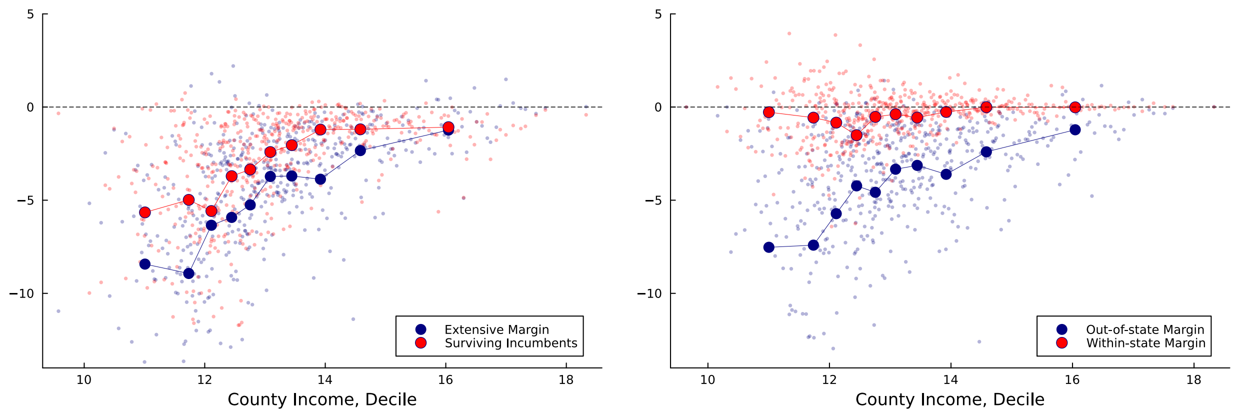
$$\Delta \ln(R - R_t^D) \approx \Delta \int_i s_{it} \left\{ \sum_{j\in\mathcal{J}_{it}} s_{ijt} \ln MKP_{jt} + \sum_{j\in\mathcal{J}_{it}} s_{ijt} \frac{\chi\Gamma_{jt}}{MC_i^*} + \sum_{j\in\mathcal{J}_{it}} s_{ijt} \frac{\kappa_{jt} - \mathbb{E}z_{jt}}{MC_i^*} \right\} \mathrm{d}i\,, \tag{35}$$

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

[39] The definition for an out-of-state exiter is analogous. Within-state entrants and exiters are banks that only operated in county i during 2019 (1993), but in 1993 (2019), the bank was operating in the state to which county i belongs. See Appendix C.4 for further details on this decomposition.

FIGURE 10. Changes in (log) Spreads, 1993-2019: Role of the Extensive Margin

(A) New entrants vs incumbents (B) Out-of-state Banks



Notes: Following the decomposition in Equation (34), Panel (A) shows changes in risk premia driven by the extensive margin (entrant and exiter banks) and by surviving incumbents. Panel (B) further decomposes the extensive margin to highlight the role of out-of-state entrants and exiters. Units are log points $\times 100$.

where s_{it} denotes the county-level market shares. This decomposition captures not only county-level variation in markups and risk premia but also compositional shifts. For instance, risk premia may fall because due to the relative growth of counties with with low risk premia in the pre-period. To isolate those effects, we consider an alternative decomposition in which the shares s_{it} are held fixed at their pre Riegle-Neal Act values, s_{i0}.

Table 6 presents the aggregate effects on deposit spreads from changes in markups and risk premia, for the uniform-pricing and local-pricing cases. Specifically, it shows the contribution of each channel to changes in the national deposit spread (log points $\times$ 100) as well as for three broad county groups (small, medium, and large). Appendix Table D.1 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 premia pushed spreads down by around 3 log points, while markup changes contributed to around a 1.5 log point increase. These small effects are not surprising, since aggregate changes are mostly driven by large counties, for which we find small changes in both risk premia and markups (Figure 8). For smaller counties, however, changes in banks' geographical presence had sizable effects on spreads: for the "small" and "medium" groups, changes in risk premia and markups account for more than half of the observed decrease in deposit spreads during the considered period. The magnitudes of these changes are similar under uniform and local pricing.

Table 6. Changes Across Time: The Role of Markups and Risk Premia

	Uniform pricing				Local Pricing			
	Risk Premium		Markup	Net	Risk Premium		Markup	Net
	Total	Diver			Total	Diver		
National Level								
Aggregate	-2.1	-2.5	1.4	-0.6	-2.0	-2.2	1.7	-0.3
Aggregate (fixed s_i shares)	-3.4	-2.7	0.7	-2.7	-3.5	-2.6	0.4	-3.1
By Group of Counties								
Small Counties (<p10)	-18.9	-5.1	-5.3	-24.1	-15.5	-6.9	-1.1	-16.5
Medium Counties	-6.7	-3.5	-1.3	-8.0	-5.9	-3.9	-0.6	-6.5
Large Counties (>p90)	-2.1	-2.5	0.8	-1.3	-2.4	-2.1	0.0	-2.4

Notes: The table decomposes the change in log aggregate spreads, $\ln(R - R^D) \times 100$, from 1993 to 2019 into markup and risk premium components, using (35). The row labeled 'fixed s_i shares' holds county weights fixed at their 1993 levels. The 'Diver' column reports the portion of the risk premium change attributable to diversification. The last three rows present results by county income groups: small (10^{th} percentile), medium ($45^{th} - 55^{th}$ percentiles), and large (90^{th} percentile).

6. Counterfactual Experiments

In this section, we use our model to analyze the effects of various changes —from the structure of the banking industry to demographics—on markups, risk premia, and deposit spreads. We use the year 2019 as the benchmark and focus on the uniform pricing case. We begin by specifying a functional form for the household's preferences over consumption and deposit services. Specifically, we assume a quasi-linear function $U(C, D) = C + \xi \log D$. Optimality implies the following relationship between the aggregate deposit composite and spreads: $R - R^D = \frac{U_D}{U_C} = \xi D^{-1}$. Plugging in 2019 values for $R - R^D$ and D yields an estimate for ξ. Appendix C.8 describes our solution algorithm.

Our first exercise analyzes an increase in χ, the curvature in bank payoffs or equivalently, in banks' aversion to deposit risk. In our baseline model, such a change can be interpreted as arising from higher frictions in the interbank lending market.[40] Formally, we increase χ for all banks by 25% For the median county in our sample, this adjustment raises the risk premia component of deposit spreads from approximately 0.10 log points to 0.125 log points. Panel (A) of Table 7 presents the relative changes in county-level deposit spreads across small, medium, and large counties (classified according to their income). Although the shock affects banks in all locations, the increase in spreads is most pronounced (almost 4%) in small counties; in larger counties, the effects are more subdued. Overall, these results underscore the disproportionate

[40]As we show in Section 8, the upward adjustment in χ can alternatively be understood as an indication of heightened bank risk aversion or more pronounced diminishing returns in lending.

TABLE 7. Counterfactuals

	Δ Deposit Spreads			Risk Premia			Markups		
	Small	Medium	Large	Small	Medium	Large	Small	Medium	Large
A. Higher curvature									
Increase χ_j	3.74	1.90	0.78	3.21	1.51	0.60	-0.06	-0.02	0.02
B. M&A, acquired banks operate in only 1 county									
Acquirer bank:									
B.1 Top local bank	2.64	0.62	-0.16	-1.74	0.22	0.18	0.77	0.42	0.06
B.2 Top regional bank	4.52	1.28	0.15	-12.33	-1.46	-0.10	-1.41	-0.00	0.06
B.3 Top national bank	5.78	2.08	0.38	-12.43	-1.53	-0.13	-1.00	0.24	0.11
C. M&A, acquired banks operate in at most 2 counties									
Acquirer bank:									
C.1 Top local bank	5.89	2.21	-0.33	-4.73	0.70	0.39	2.12	0.97	0.17
C.2 Top regional bank	11.52	3.24	0.38	-26.97	-3.43	-0.17	-2.39	-0.03	0.16
C.3 Top national bank	14.49	4.85	0.78	-27.59	-3.78	-0.27	-1.79	0.37	0.23
D. Changes in demographics									
D.1 Increase μ_i	-9.22	-4.28	-0.05	-7.47	-2.90	0.04	0.00	-0.19	-0.06
D.2 Increase σ_i / μ_i	1.95	2.45	5.88	1.88	2.38	4.75	0.03	0.06	0.13

Notes: The table reports log changes in deposit spreads, risk premia, and markups relative to the 2019 baseline, in log points ×100. Columns display average changes for three groups of counties—small, medium, and large—classified by total income. Panel A shows the effect of increasing the curvature parameter χ in banks' profit functions. Panels B and C report outcomes under different merger and acquisition scenarios (see main text for details). Panel D examines the impact of demographic shifts. All results correspond to the uniform-pricing specification.

impact that elevated frictions in the national interbank lending market can have on regions where the bank deposit base is less diversified.

Our second counterfactual examines the impact of further consolidation in the banking sector. In particular, we consider the acquisition of relatively undiversified banks by larger institutions, a continuation of the M&A patterns seen over recent decades. We consider separately two sets of target banks—those that operate in a single county and those that operate in at most two counties.[41] We consider three types of acquirers: the largest local bank operating in the same county as the target, the largest regional bank operating in the same state, and the largest national bank. We define a local bank as one that operates in 10 or fewer counties; a regional bank operates in more than 10 but fewer than 100 counties; and a national bank operates in 100 or more counties.[42] Following a merger, the deposit demand for the acquirer bank j in county i is given by $\psi_{ijt}^{\eta} + \sum_k \psi_{ikt}^{\eta}$, where ψ_{ikt} denotes the demand shifters of the acquired banks.[43] For our uniform pricing case, we also assume that the merged entity inherits the acquirer's non-interest cost k_j.

[41]We impose mild restrictions: specifically, banks with assets above the 95th national percentile are omitted. This is to exclude acquisitions of very large, single-county banks (usually online banks).
[42]Under these definitions, our sample includes 4,758 local banks, 277 regional banks, and 20 national banks.
[43]Recall that the shifters are normalized so that $\sum_j \psi_{ijt}^{\eta} = 1$.

Panel (B) of Table 7 presents the results when acquired banks operate only in a single county. In this case, deposit spreads tend to rise following the merger. The changes are more pronounced in small counties, where the acquired banks have large market shares. The rise in spreads is because the acquirers' non-interest costs $\{k_j\}$ are generally higher than those of the targets. This is partly offset by a reduction in the risk premia component, particularly when the acquiring bank is either regional or national. Markups decline slightly despite the reduction in the number of banks and higher county-level concentration. This happens because, under uniform pricing, markups depend on banks' average market shares rather than on county-specific concentration. Acquirer banks in this experiment have, on average, slightly lower market shares across all their locations relative to the targets. In Appendix Table D.3, we show results under local pricing, assuming that the acquiring branch inherits the same non-interest cost structure $\{k_{ij}\}$ as the acquired branch. This assumption leads to a reduction in deposit spreads. The effects on risk premia and markups remain similar to those reported in Table 7. Panel (C) shows results when acquired banks operate in at most two locations. In this case, changes in risk premia are roughly twice as large. These exercises highlight the potential for further diversification gains in the banking system at the end of our sample.

Our third experiment examines the impact of changes in the spatial distribution of economic activity. Specifically, we analyze a scenario in which the largest deposit markets become relatively larger (Panel D). This is a simple way to capture the continued rise in spatial inequality, consistent with trends observed in recent decades (e.g., Gaubert et al., 2021). Formally, we increase market size (μ_i) by 10% for all large counties, while holding total deposits constant by proportionally reducing μ_i in all other counties.[44] This reallocation increases banks' overall exposure to larger markets, which also happen to be relatively less risky. This lowers risk premia, with the largest reductions in small and medium-sized counties.

Our final exercise aims to quantify the exposure of smaller counties to changes originating in larger counties. Specifically, we double the volatility of deposit demand in large counties. Unsurprisingly, this leads to higher risk premia and spreads for large counties. More interestingly, spreads in small/medium counties also rise significantly (almost half as much as in large counties). If large counties become relatively larger, these spillovers could become even larger.

Appendix D describes a few more counterfactual exercises. First, we examine (separately) the impact of a 1 percentage point increase in the non-interest cost k_j for local, regional, and national banks. We find that when local banks experience higher costs, small counties see a

[44] We classify counties above the 90th percentile in income as "large." We hold fixed the ratio $\frac{\rho_{ik}\sigma_i\sigma_k}{\mu_i\mu_k}$ to avoid mechanically affecting risk premia.

notable reduction in risk premia, as market shares shift toward more diversified regional and national banks. This partially offsets the effect of higher costs. In contrast, higher costs for larger banks lead to increased risk premia, amplifying the effect. Second, we study how changes in households' relative preferences (captured by the the relative demand shifters, ψ_{ij}) across bank types affect deposit spreads and risk premia. When households' preferences shift away from local banks, regional and national banks gain market share, resulting in lower risk premia, particularly in small and medium-sized counties.

7. Local Lending

The analysis so far assumed that banks' lending opportunities are not directly related to the locations of their branches. Moreover, returns were linear, which made the distinction between different types of assets (loans, securities, etc.) irrelevant. In this section, we relax these assumptions with two modifications to our baseline model. First, we allow banks to hold two types of assets: local loans L_j and securities S_j. The former can only be extended in states where the bank has branches, i.e., $L_j = \int_{\mathcal{M}^{\mathcal{S}}{}_j} L_{ij} di$ where $\mathcal{M}^{\mathcal{S}}{}_j$ is the set of states in which bank j has at least one branch. We assume that loan markets operate at the state level, partly for tractability and partly to capture the fact that lending activity is arguably less 'local' (i.e. branch-intensive) than deposit-taking.[45] This captures forms of lending where physical proximity to the borrower is useful, e.g., loans to small businesses. Second, we introduce curvature in the return functions for both loans and securities, capturing diminishing marginal returns. We will show that, even with these changes, the optimal pricing equation remains identical to the baseline version. Here, we present only the main equations, relegating detailed derivations to Appendix C.

We start by characterizing bank j's gross interest revenue, denoted $Rev(A_j)$, as a function of total assets $A_j = L_j + S_j$:

$$Rev\left(A_j\right) \equiv \max_{\{L_{kj}\}_{\forall k \in \mathcal{M}^{\mathcal{S}}{}_j}, S_j} \mathbb{E} \int_{\mathcal{M}^{\mathcal{S}}{}_j} \left(R + z_j - \frac{1}{2}\alpha_i \alpha_j L_{ij}\right) L_{ij} di + \left(R + z_j - \frac{1}{2}\beta_j S_j\right) S_j, \tag{36}$$

$$\text{s.t. } A_j = \int_{\mathcal{M}^{\mathcal{S}}{}_j} L_{kj} dk + S_j.$$

This specification allows for diminishing marginal returns on both types of assets. For loans, we parameterize curvature as a combination of market-specific and bank-specific components

[45] In a slight abuse of notation, we use the subscript i to index the loan market as well.

—$\alpha_i \alpha_j$.[46] We define $\varrho_j \equiv \int_{i \in \mathcal{M}^S_j} \frac{1}{\alpha_i} di$, as the average curvature across all locations in which a bank operate. From Equation (36), the optimal bank-level choices of loans and securities are given by $L_j = \ell_j A_j$ and $S_j = (1 - \ell_j) A_j$, where

$$\ell_j \equiv \frac{\varrho_j \beta_j}{\varrho_j \beta_j + \alpha_j}. \tag{37}$$

Given L_j, the optimal amount of loans in each k is given by

$$L_{ij} = \frac{L_j}{\varrho_j \alpha_i}. \tag{38}$$

Thus, a bank's lending in i is a function of the curvature in that market relative to the average curvature of the bank. Total lending in state i is then: $L_i = \frac{1}{\alpha_i} \sum_{j \in i} \frac{L_j}{\varrho_j}$.

Substituting in Equation (36), we get that banks' interest income is given by:

$$Rev\left(A_j\right) = \left(R + z_j\right) A_j - \frac{1}{2} \vartheta_j A_j^2 \qquad \text{where} \qquad \vartheta_j \equiv \frac{\alpha_j}{\varrho_j} l_j. \tag{39}$$

Given this revenue function, one can show that the optimal deposit spreads are given by:

$$R - R^D_j = \frac{\eta\left(1 - s_j\right) + \theta s_j}{\eta\left(1 - s_j\right) + \theta s_j - 1} \left[\kappa_j - \mathbb{E} z_j + \vartheta_j A_j + \chi_j \mathbb{E}\left(D_j\right) \int_{k \in \mathcal{M}_j} \omega_{ij} \frac{\rho_{ik} \sigma_i \sigma_k}{\mu_i \mu_k} dk\right], \tag{40}$$

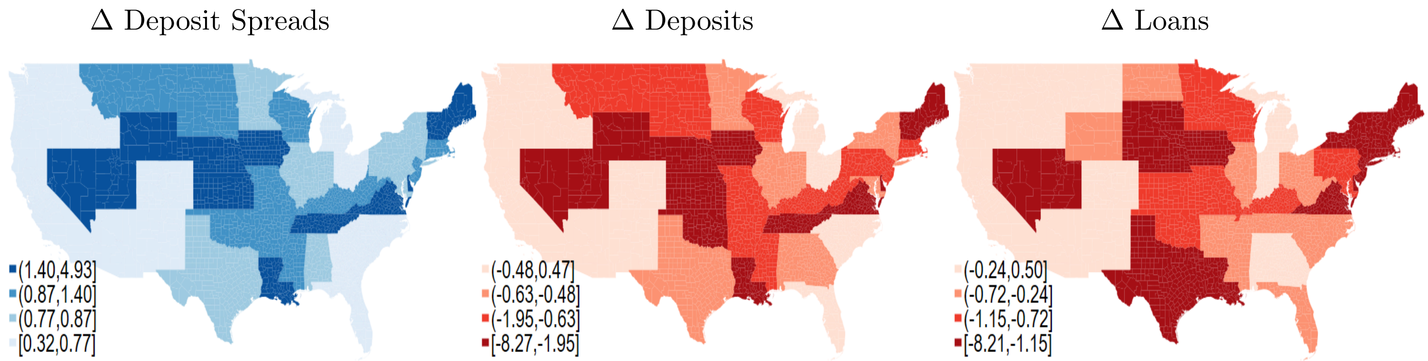
with s_j and κ_j being defined as in Section 3. Note that this pricing equation is almost identical to the one of our baseline model.[47] The only difference is the $\vartheta_j A_j$ term, which reflects the effect of bank-level curvature in asset returns. This implies that the decompositions of deposit spreads in the preceding sections go through unchanged.

More interestingly, this version of the model allows us to examine how industry structure affects lending at the local level. To this end, we first estimate the state-level parameters $\{\alpha_i\}$ using data on small business loan originations. Specifically, we choose $\{\alpha_i\}$ to minimize the distance between model-implied shares of loans by location ($\{L_i/L\}$) and their empirical counterparts (see Appendix C.5 for details).[48] To recover the bank-level parameters, we follow a similar strategy as in the baseline: assume ϑ_j is inversely proportional to total assets—that is, $\vartheta_j A_j = \vartheta$, where ϑ is identical across banks. Given this, we can recover (α_j, β_j) using the optimality conditions above.

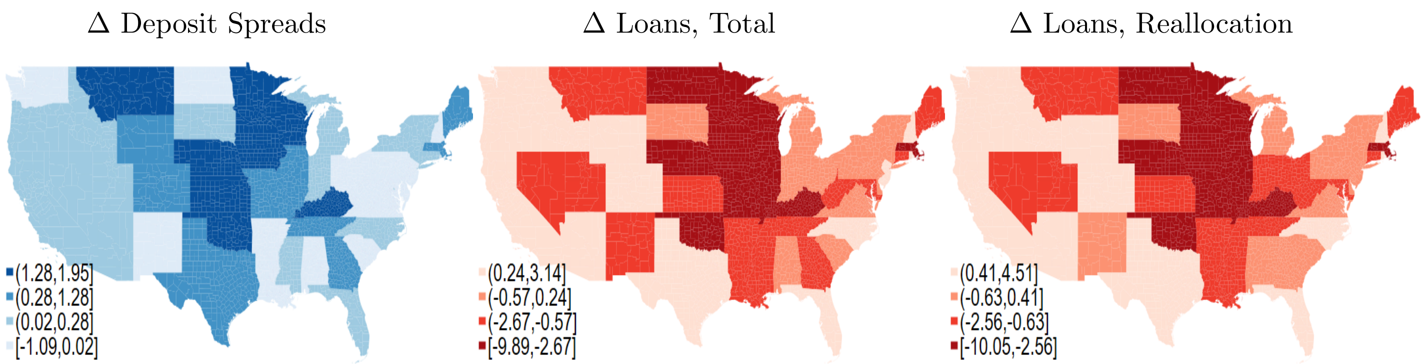
[46] In Section 8.2, we also allow for heterogeneity in market-level returns, z_{ij}.
[47] It is easy to show that this robustness also obtains under local pricing.
[48] This estimation is computationally demanding—even at the state level—since a change in a given α_i impacts all banks operating in that location.

Figure 11. Changes in Lending and Deposit Spreads

(A) Higher Bank Curvature



(B) Mergers and Acquisition



Notes: The maps display state-level changes in deposit spreads (under uniform pricing), deposit quantities, and lending for two counterfactual experiments. Panel (A) shows the effects of an increase in the curvature parameter χ. The left panel shows changes in deposit spreads, the middle panel shows change in expected deposits, and the right panel shows changes in loans. Panel (B) presents results from an M&A scenario in which top regional banks acquire banks operating in a single market. The left panel displays changes in deposit spreads following the mergers, the middle panel shows the total change in lending, and the right panel isolates the portion attributable to the "reallocation channel." Units are log points $\times 100$.

We then revisit the counterfactual exercises from Section 6, focusing explicitly on implications for lending. We restrict attention to the uniform pricing case here, leaving details for local pricing to the appendix.

First, we examine the counterfactual in which banks' curvature parameter χ increases (Panel A of Figure 11). This leads to larger deposit risk premia, implying wider spreads (left map) and lower deposits (middle map), particularly in states (e.g. in the Midwest) served by less diversified banks. Interestingly, the right map shows the effects on lending are more broad-based: they fall not only in states with the large drops in deposits, but also in states like New York, Massachusetts, and Texas. Intuitively, (relatively) geographically undiversified banks play a non-trivial role in local lending markets in these states, even though their effect on deposit markets is very modest.

Next, we analyze the acquisition of local banks—defined as those operating in a single county—by the largest regional banks, as defined in Table 7. Panel B of Figure 11 displays the results. The most substantial declines in local lending occur in the Midwest and South. These reductions are primarily driven by a "reallocation channel" (the right panel) which shows the effect on local lending from directly reallocating all assets (both loans and securities) from the acquired bank to the acquirer. Since large regional banks tend to invest more heavily in larger markets compared to local banks, regions with a significant presence of local banks experience larger reductions in lending from this type of consolidation. The change in industry structure also leads to higher deposit spreads—and thus lower deposit funding—in Midwestern and Southern states. These funding-side effects modestly amplify the initial reallocation-driven reduction in lending.

8. Extensions and Robustness

We present two extensions of our baseline model. First, we introduce other assets that provide liquidity, such as cash. Second, we consider an alternative timing assumptions in which the curvature of banks' profits arise from diminishing marginal returns on loans.

8.1. *Other Liquid Assets*

In our baseline model, deposits were the sole source of liquidity. In this subsection, we extend our framework to allow for multiple assets providing liquidity benefits. We modify the preferences of the representative household as follows: $u\left(C,X\right) = C - \xi \log(X)$, where X denotes a liquidity composite defined by the following aggregator

$$X = \left(\int \phi_i X_i^{\frac{\theta-1}{\theta}} di\right)^{\frac{\theta}{\theta-1}}, \tag{41}$$

where X_i is a county-level composite of liquidity services from a portfolio of assets:

$$X_i = \left(\sum_l \zeta_l X_{li}^{\frac{\varepsilon-1}{\varepsilon}} + D_i^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}}. \tag{42}$$

The parameter ε captures the elasticity of substitution between liquidity services from different assets, while the parameters $\{\zeta_l\}_{\forall l}$ reflect share weights. Under this specification, the $\{\phi_i\}$ shocks affect county-level demand for all liquidity services, not just deposits. For simplicity and clarity of exposition, we consider a single additional asset—cash—which pays a gross return of 1 and has share parameter ζ. Appendix C.6 presents the full derivations for the general case with an arbitrary set of assets.

We denote the household's cash holdings in county i by M_i. The county-level demands for cash, deposits, and overall liquidity services are, respectively:

$$\frac{R-1}{R-R_i^X}=\zeta\left(\frac{M_i}{X_i}\right)^{-\frac{1}{\varepsilon}}, \qquad \frac{R-R_i^D}{R-R_i^X}=\left(\frac{D_i}{X_i}\right)^{-\frac{1}{\varepsilon}}, \qquad \frac{R-R_i^X}{R-R^X}=\phi_i\left(\frac{X_i}{X}\right)^{-\frac{1}{\theta}}, \tag{43}$$

with ideal spread indices defined as:

$$R-R_i^X=\left(\zeta^{\varepsilon}\left(R-1\right)^{1-\varepsilon}+\left(R-R_i^D\right)^{1-\varepsilon}\right)^{\frac{1}{1-\varepsilon}}, \tag{44}$$

$$R-R^X=\left(\int \phi_i^{\theta}\left(R-R_i^X\right)^{1-\theta}di\right)^{\frac{1}{1-\theta}}. \tag{45}$$

The individual bank's deposit demand in county i remains as in Equation (3). Combining this with Equation (43), we have:

$$D_{ij}=\psi_{ij}^{\eta}\left(\frac{R-R_{ij}^D}{R-R_i^D}\right)^{-\eta}\left(\frac{R-R_i^D}{R-R_i^X}\right)^{-\varepsilon}\phi_i^{\theta}\left(\frac{R-R_i^X}{R-R^X}\right)^{-\theta}X. \tag{46}$$

When setting spreads, banks now internalize not only their impact on the county-level deposit spread R_i^D, as in the baseline model, but also on the county-level liquidity price index R_i^X. Hence, the elasticity of demand is now a weighted average of the three structural elasticity parameters η, ε, and θ:

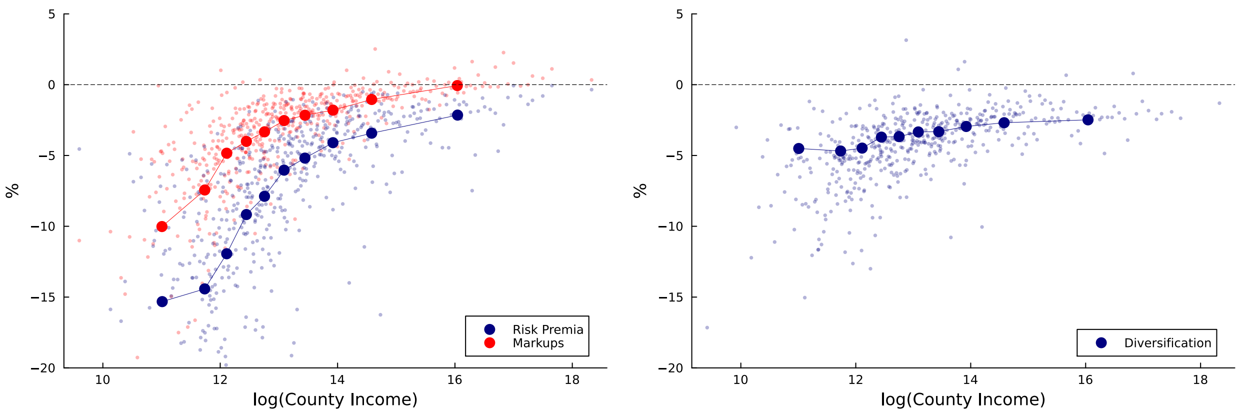
$$\frac{d\ln D_{ij}}{d\ln\left(R-R_{ij}^D\right)}=-\left[(1-s_{ij})\eta+s_{ij}\widehat{\theta}_i\right], \tag{47}$$

where $\widehat{\theta}_i=\theta(1-s_i^M)+s_i^M\varepsilon$ and $s_i^M\equiv 1-\frac{R-R_i^D}{R-R_i^X}\frac{D_i}{X_i}$ represents the market share of cash. This nests our baseline model when $s_i^M=0$. Compared to the baseline, markups now vary in the cross-section and over time due to fluctuations in cash market shares s_i^M.

We calibrate ε by targeting the elasticity of the aggregate cash-to-deposit ratio with respect to R. Specifically, we use monetary policy shocks as instruments for exogenous variation in R, estimating the reduced-form elasticity of cash-to-deposits (see Appendix D.7). Note this reduced-form elasticity differs from the structural parameter ε because changes in R also affect equilibrium deposit spreads. Our estimation yields $\varepsilon=1.24$, smaller than our estimate for θ. We allow the share parameter ζ to vary over time, setting it to match the aggregate cash-to-deposit ratio.

Figure 12. Changes in (log) Spreads, 1993-2019, by County — Cash Extension

(A) Markups and Risk Premia (B) Diversification



Notes: Following the decomposition in Equation (32), Panel (A) shows changes in the markup and risk premium components of deposit spreads between 1993 and 2019 under the uniform-pricing model with the cash extension, by county income deciles. Blue dots indicate model-implied changes in risk premia, while red dots represent changes in markups. Panel (B) further decomposes the change in risk premia into contributions from "diversification gains," as defined in Equation (33). Units are log points $\times 100$.

Panel (A) of Figure 12 shows changes in risk premia and markups between 1993 and 2019.[49] The estimated reduction in risk premia remains similar to the baseline (see Figure 8), while the decline in markups is more pronounced. This is because the market share of cash, s_i^M, declined significantly, from an average of 39% in 1993 to 15% in 2019. Given that $\varepsilon < \theta$, the resulting increase in $\widehat{\theta}_i$ pushes down markups. Panel (B) decomposes the changes in risk premia into contributions from diversification gains. The results remain quantitatively similar to the baseline, with diversification gains explaining a larger share of the reduction in risk premia for smaller counties. Overall, introducing cash leads to a very similar narrative about the evolution of risk and market power over time.

8.2. *Alternative Timing and Source of Curvature*

In our baseline specification, the risk premium component of deposit spreads arises due to a combination of loan commitments and costly rebalancing in the interbank market. We now consider a modified version where banks can adjust their loan commitments after shocks have been realized but face diminishing marginal returns on lending. In Appendix C.7, we study a related timing assumption combined with a linear lending technology. In that setting, curvature

[49]While not shown, the cross-sectional effects of risk premia and markups on deposit spreads are quantitatively similar to the baseline. Markup effects show the same patterns as in the baseline, albeit with somewhat larger magnitudes.

in banks' problem is introduced either by assuming that banks directly dislike variability in deposits or by regulatory constraints that penalize deposit volatility. Importantly, we show that the equations characterizing optimal deposit spreads in these alternative specifications closely parallel those from our baseline model.

Banks raise funds from households through equity, wholesale funding, and deposits, which operate as in the baseline model. However, instead of *ex ante* loan commitments, we now assume that banks allocate the total funds available to them *ex post*—that is, after deposit shocks are realized.[50] Crucially, the lending technology now features decreasing marginal returns: the return on loans is $R + z_j - \frac{\chi_j}{2} L_j$, where $\chi_j > 0$ indexes the degree of diminishing returns.

The timing of events is as follows. First, banks choose deposit rates R^D_{ij} and wholesale funding H_j. Second, all shocks are realized, and households allocate deposits across banks by choosing $\{\mathcal{D}_{ij}\}$. Third, banks make and collect on loans. As a result, the quantity of loans L_j is stochastic and depends on the realized $\{\phi_i\}$ shocks.

Under these assumptions, the *ex post* return function $\Pi_j(\cdot)$ is given by:

$$\Pi_j(\{D_{ij}\}) = \left(R + z_j - \frac{\chi_j}{2} L_j\right) L_j - \left(R + \frac{\nu_j}{2} H^*_j\right) H^*_j, \tag{48}$$
$$\text{where} \quad L_j = E_j + H^*_j + \sum_i D_{ij},$$

so that $\Pi'_{ij} \equiv \frac{d\Pi_j}{dD_{ij}} = R + z_j - \chi_j L_j$. Under local pricing, optimal deposit spreads are characterized by (see Appendix C.7 for derivations):

$$R - R^D_{ij} = \frac{\eta(1 - s_{ij}) + \theta s_{ij}}{\eta(1 - s_{ij}) + \theta s_{ij} - 1} \left[k_{ij} - \mathbb{E}(z_j) + \chi_j \mathbb{E}(L_j)(1 + \widetilde{\Gamma_{ij}}) - \frac{\mathbb{C}ov(z_j, \phi^\theta_i)}{\mu_i}\right], \tag{49}$$
$$\text{where} \qquad \widetilde{\Gamma_{ij}} \equiv \omega^D_j \int_{k \in \mathcal{M}_j} \omega_{kj} \frac{\rho_{ik}\sigma_i\sigma_k}{\mu_i \mu_k}\, dk,$$

and $\omega^D_j \equiv \frac{\int_{k\in\mathcal{M}_j} \mathbb{E}(D_{kj})\, dk}{\mathbb{E}(L_j)}$ denotes the share of total loans financed by deposits. The term $\widetilde{\Gamma_{ij}}$ corresponds to the baseline model's risk term scaled by the deposit share ω^D_j.

Equation (49) closely parallels the baseline pricing equation, with two key differences. First, it includes an additional term that penalizes bank size, reflecting the curvature in lending technology. Second, and more importantly, it features a covariance term that captures the relationship between lending returns and deposit demand shocks. When $\mathbb{C}ov(z_j, \phi^\theta_i) > 0$, i.e.,

[50] For simplicity, we abstract from ex post interbank borrowing and lending. Including it would yield a more complex expression for the curvature term—reflecting curvature in both markets—but would not change the main conclusions.

when deposit flows into county i tend to occur in periods of high returns, the bank optimally sets a lower deposit spread in that location.

To assess the quantitative relevance of the covariance term, we proxy z_j using bank-level average loan returns from Call Report data and compute $\frac{\mathbb{C}ov(z_j,\phi_i^\theta)}{\mu_i}$ directly. Our estimates show that this term is small, with a median value of -1.21×10^{-5} (5th and 95th percentiles are -1.68×10^{-3} and 1.13×10^{-3}, respectively). In other words, accounting for the interaction between lending returns and deposit shocks has little impact on our estimates of risk premia in deposit spreads. Consequently, the spread decompositions under this specification are nearly identical to those in the baseline.[51]

These conclusions extend to the uniform pricing case as well. For completeness, we show the optimal spreads and risk premia under that protocol:

$$R - R_j^D = \frac{\eta(1-s_j)+\theta s_j}{\eta(1-s_j)+\theta s_j - 1}\left[\kappa_j - \mathbb{E}(z_j) + \chi_j \mathbb{E}(L_j)(1+\widetilde{\Gamma}_j) - \int_0^1 \tilde{\omega}_{kj}\frac{\mathbb{C}ov(z_j,\phi_k^\theta)}{\mu_k}\,d\Lambda_j(k)\right], \tag{50}$$

where the bank-level risk term is defined as:

$$\widetilde{\Gamma}_j \equiv \omega_j^D \int_{k\in\mathcal{M}_j}\tilde{\omega}_{kj}\int_{i\in\mathcal{M}_j}\omega_{ij}\frac{\rho_{ik}\sigma_i\sigma_k}{\mu_i\mu_k}\,di\,dk. \tag{51}$$

We can also extend this setup to allow for local lending, where each bank allocates loans across the locations in which it operates. Unlike the baseline local-lending model, we now allow for heterogeneity in loan returns across locations, indexed by z_{kj}. For a given total loan amount L_j, the bank chooses $\{L_{kj}\}_{k\in\mathcal{M}_j}$ to maximize:

$$Rev_j(L_j) = \max_{\{L_{kj}\}}\int_{k\in\mathcal{M}_j}\left(R + z_{kj} - \frac{\chi_j}{2}L_{kj}\right)L_{kj}\,dk, \tag{52}$$

$$\text{subject to} \quad L_j = \int_{k\in\mathcal{M}_j} L_{kj}\,dk,$$

where $Rev_j(L_j)$ is the bank's total revenue from allocating L_j across markets. One can show that the optimal allocation of loans takes the form:

$$L_{kj}^*(L_j) = \frac{1}{\chi_j}(z_{kj} - \bar{z}_j) + \frac{L_j}{\int_{k\in\mathcal{M}_j} dk}, \tag{53}$$

[51] The size penalty does not materially affect our results, as we impose $\chi = \chi_j\mathbb{E}(L_j)$ in our estimation. The only minor difference arises from the ω_j^D term, which scales the risk term by the share of deposits in total loans.

where $\bar{z}_j \equiv \frac{\int_{k\in\mathcal{M}_j} z_{kj}\,dk}{\int_{k\in\mathcal{M}_j} dk}$ is the bank's average loan return across locations. Substituting this allocation back into the objective yields:

$$Rev_j(L_j) = \left(R + \bar{z}_j - \frac{\widetilde{\chi}_j}{2} L_j\right) L_j, \quad \text{with} \quad \widetilde{\chi}_j \equiv \frac{\chi_j}{\int_{k\in\mathcal{M}_j} dk}. \tag{54}$$

Substituting this into the general return function, we get:

$$\Pi_j(\{D_{ij}\}) = \left(R + \bar{z}_j - \frac{\widetilde{\chi}_j}{2} L_j\right) L_j - \left(R + \frac{\nu_j}{2} H_j^*\right) H_j^*, \tag{55}$$

$$\text{where} \quad L_j = E_j + H_j^* + \int_{i\in\mathcal{M}_j} D_{ij}\,di.$$

This return function takes the same form as in Equation (48), implying that the pricing equations for deposit spreads remain unchanged.

9. Conclusion

In the preceding sections, we perform a structural evaluation of the effect of idiosyncratic risk and market power in banking combining a rich multi-market model with granular data at the bank- and county-level. The calibration uncovers a significant role for risk premia in the deposit rate variation, both in the cross-section and over time. We exploit the tractability of the model to conduct a number of counterfactual experiments exploring the implications of continued consolidation in the industry, increasing spatial inequality and shocks.

There are several avenues for future research. Our analysis takes branch location choices of banks as exogenous. While this assumption has no bearing on our empirical strategy—our estimates for parameters related to risks and costs remain valid—it abstracts from changes in location choices in our counterfactual experiments. Formally incorporating this margin is conceptually straightforward but computationally almost infeasible in this setting with multiple sources of risk and heterogeneity, both across banks and markets. We leave this, along with the development of a full-fledged dynamic model, as challenging yet promising directions for future work. Similarly, given our focus on deposit markets, we adopted a more simplified approach on the lending side. Incorporating risk and market power considerations in lending markets is another valuable extension.

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Appendix A. Data

A.1. *Data Sources*

Summary of Deposits (SOD). Publicly available through the Federal Deposit Insurance Corporation (FDIC), the SOD is the annual survey of branch office deposits. It records bank-reported information as of June each year. It includes unique identifiers for branches (UNINUMBR) and banks (IDRSSD), location data (zip code, city, county, state), and branch-level deposits.

Call Reports. Reported quarterly to the Federal Financial Institutions Examination Council (FFIEC) via forms 031, 041, and 051, these reports provide detailed bank-level balance sheet and income statement data. Each bank is identified via IDRSSD, which enables us to link them with SOD. While Call Report data is publicly available, we use an internally maintained version by the Board of Governors that adjusts for mergers and acquisitions. The data spans from 1985:Q1 and includes information on deposit types and maturities, detailed assets and liabilities, interest income from loans, and interest expenses on deposits.

RateWatch. This proprietary weekly survey collects product-level interest rates from bank branches, covering deposit products such as CDs and money market accounts. It contains identifiers for branches and banks, as well as location information, which enables linkage to SOD and Call Reports. Comprehensive data coverage begins in 2011.

County-level economic activity and rate of return. Annual county-level economic activity data since 1969 is obtained from the Bureau of Economic Analysis (BEA). For R, the return on illiquid investment, we use the 5-Year High Quality Market Corporate Bond Spot Rate (HQMCB5YR) available via FRED. The series is monthly; we compute annual averages.

A.2. *Construction of Datasets*

We combine these sources to construct an annual bank-county-level panel. Throughout, we focus on time and savings deposits, excluding checking accounts. To do so, we scale branch-level deposits from SOD using the bank-level ratio of time and savings deposits to total deposits from Call Reports. Since Call Report data prior to 2004 excludes deposit details for thrifts reporting on form 1313, we exclude those institutions from our analysis. We aggregate branch-level deposits from SOD to the bank-county-year level, tracking the number of branches within each triplet.[52]

Bank-county deposit rates from RateWatch. We use RateWatch to construct bank-county-year interest rates. The data comes from three files: 'survey', 'account information', and 'account join'. The 'survey' file records account numbers, product types, interest rates, and survey dates. These are linked using a unique RateWatch account identifier. The 'account information' file contains institutional details, including branch location and the FDIC branch identifier (UNINUMBR). The 'account join' file links branches to their designated rate setters—not all branches choose their own deposit rates. We merge these files sequentially using the account number, then link to SOD using UNINUMBR. Finally, we use SOD to associate each branch with its parent bank.

To prepare the RateWatch data, we first collapse the survey component to yearly frequency. We then merge account information with account join data, followed by a merge with SOD via UNINUMBR. Lastly, we combine this with the yearly survey using the account identifier. The resulting dataset covers approximately 80% of total deposits in SOD, representing around 70% of bank-county observations.

We use four deposit products: 12-, 24-, and 60-month certificates of deposit (12MCD10K, 24MCD10K, 60MCD10K), and money market deposit accounts (MM25K). Promotional rates are excluded. As the data is at the branch-product-year level, we collapse it to the bank-county-product-year level, weighting by branch-level deposits.[53]

To compute a composite deposit rate at the bank-county-year level, we use Call Report data on time deposit maturities to weight RateWatch interest rates. Specifically, we calculate each bank's share of time deposits in three buckets: under 1 year, 1-3 years, and over 3 years. These shares are used to compute weighted averages of CD rates. Next, we use the ratio of time deposits to total time and savings deposits (including MMDAs) to combine CD and MMDA rates. All data is aligned to SOD reporting dates by using only second-quarter observations.

Bank-level deposit rates from Call Reports. In our analysis, we rely on RateWatch data for our local pricing specification. A key limitation, however, is that comprehensive coverage begins only in 2011. To address this, we construct a proxy for bank-level deposit rates using Call Reports, which serves as the basis for our uniform-pricing specification. Specifically, we collect time-series data on deposit volumes and interest expenses for time deposits and savings accounts

[52]We restrict SOD data to the 50 US states and adjust some county names for consistency with BEA county-level GDP data.

[53]We assume equal weights across products due to limited data on product-level volumes.

(including MMDAs) starting in 1990. For each bank, we compute the ratio of annualized interest expenses to volumes by summing each component over the calendar year.[54] When this breakdown is missing, we fall back on the average interest rate across all domestic deposits.

Bank funding structure. Finally, we use Call Reports data to compute bank-level ratios of deposits, equity, and wholesale funding to total assets. We define bank equity as total assets minus total liabilities. Given values for deposits (d_j) and equity (e_j) to total assets, we compute wholesale funding to total assets as $h_j = 1 - d_j - e_j$. We also compute ratios of bank loans to assets and securities to assets.

Appendix B. Motivation: Additional Evidence

Deposit Risk and Geographical Diversification. To motivate our main analysis, this section illustrates the potential gains from banks' geographic diversification. Figure B.1 presents two panels: the left panel shows the distribution of bank-level changes in deposits and loans, while the right panel shows county-level changes in deposits. For the bank-level analysis, we estimate the regression

$$\Delta \log x_{jt} = \gamma_t + \gamma_j + \epsilon^x_{jt},$$

where x_{jt} denotes either loans or deposits, and γ_t and γ_j are year and bank fixed effects. The histogram displays the residuals, expressed in percentage points. For the county-level analysis, we estimate

$$\Delta \log D_{it} = \gamma_t + \gamma_i + \epsilon_{it},$$

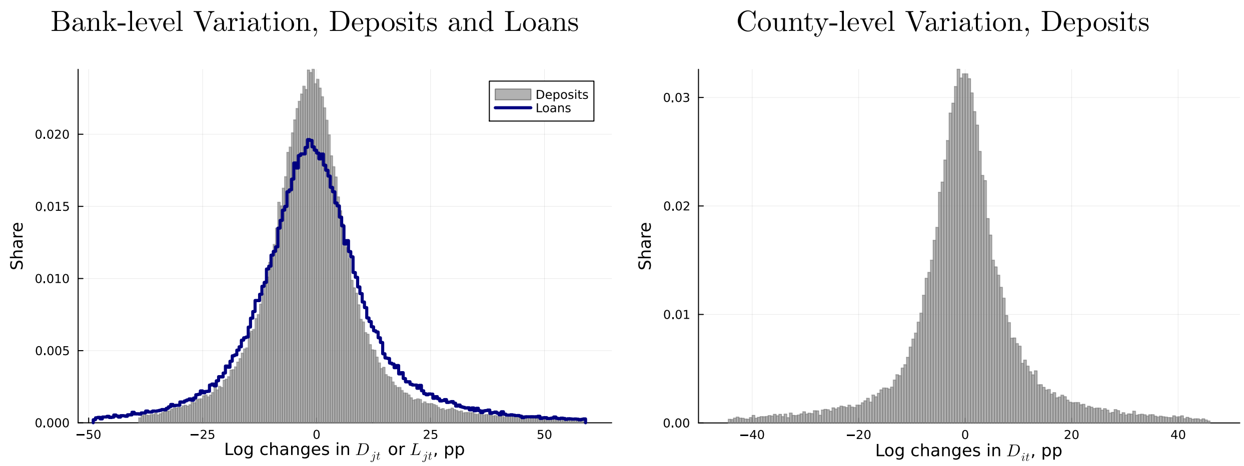
where γ_i are county fixed effects.

Two main results emerge. First, bank-level deposit growth is as volatile as loan growth, highlighting the relevance of deposit risk. Second, county-level deposit growth also exhibits substantial volatility: even after accounting for county and year fixed effects, the interquartile range remains wide, with the 25th percentile at -4.8% and the 75th percentile at 4.6%.

The preceding analysis highlights that banks face significant deposit risk. Constructing a measure of exposures to deposit shocks is challenging since banks' branching decisions are a potentially key source of deposit variability, especially for larger institutions. That is, because branch networks evolve, exposures are time-varying and not directly captured by second moments of deposit growth in bank-level time series. To address this, we assume a stationary

[54] Granular data on interest expenses by deposit maturity is unavailable.

Figure B.1. Bank- and County-level Variation: Deposits vs. Loans



Notes: The left panel shows the volatility of bank-level deposit growth and bank-level loan growth, after controlling for bank and year fixed effects. The right panel shows the volatility of county-level deposit growth, after controlling for county and year fixed effects.

covariance matrix of deposit growth at the county level and exploit time-series variation using weights based on banks' deposit shares across counties.

More specifically, we analyze how cross-county heterogeneity translates into bank-level deposit volatility. Let ω_{ij}^{τ} denote bank j's deposit share in county i at time τ, defined as $\omega_{ij}^{\tau} = \frac{D_{ij}^{\tau}}{\sum_{i \in \mathcal{M}_j} Dij^{\tau}}$, where D_{ij}^{τ} is the stock of deposits bank j holds in county i at time τ, and $\mathcal{M}_j$ is the set of location in which bank j operates at. We then construct bank j's deposit changes (in pp), induced by changes in county-level deposits, as $\Delta \ln D_{jt}^{\tau} = \sum_{i \in \mathcal{M}_j} \omega_{ij}^{\tau} \Delta \ln D_{it}$, where D_{it} are county-level deposits in period t. The time-series standard deviation is given by

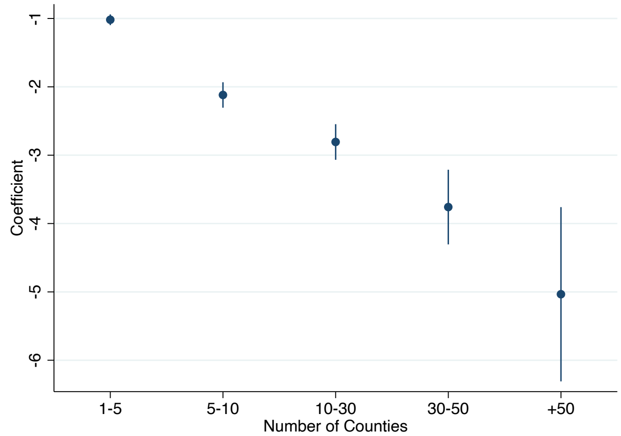
$$\sigma_j^{\tau} = \sqrt{\frac{1}{T} \sum_t \left(\Delta \ln D_{jt}^{\tau} - \overline{\Delta \ln D_{jt}^{\tau}} \right)^2}. \tag{B.1}$$

We use the yearly panel σ_j^{τ} over 1995-2019 to study how exposure to deposit volatility varies with bank characteristics. Specifically, we regress σ_j^{τ} on dummies ($\mathbb{I}_k^{\tau}$) for the number of counties in which a bank operates, along with bank (α_j) and time (α_{τ}) fixed effects:

$$\sigma_j^{\tau} = \beta_1 + \sum_{k \in K} \beta_k \times \mathbb{I}_k^{\tau} + \alpha_j + \alpha_{\tau} + \epsilon_{j\tau}. \tag{B.2}$$

Figure B.2 plots the estimated β_k coefficients from Equation (B.2). Exposure to deposit volatility declines monotonically with the number of counties a bank serves, with banks operating

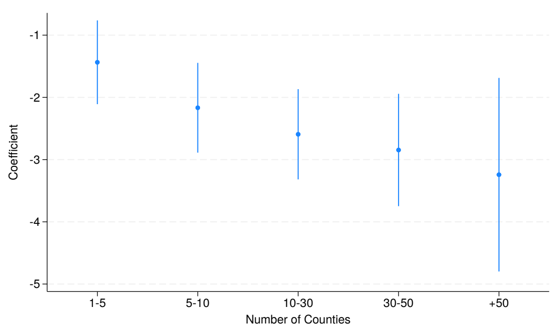
FIGURE B.2. Banks' Exposure to Deposit Fluctuation Risk



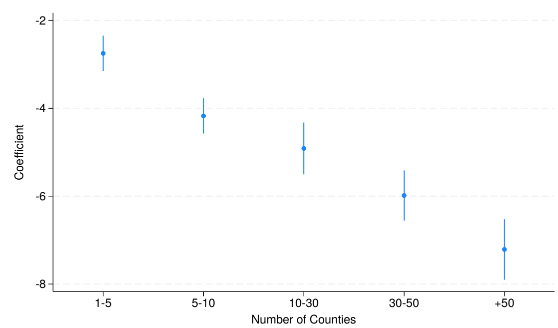
Notes: The figure displays the estimated β_k coefficients from Equation (B.2), using annual deposit data from 1995 to 2019. Units are in percentage points.

FIGURE B.3. Banks' Exposure to Loan Origination Risk

(A) Small Business Loans



(B) Mortgages



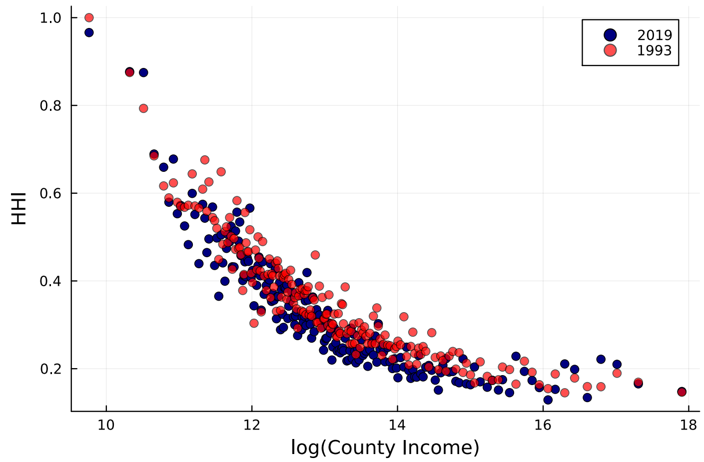
Notes: The figure shows results from the regression in Equation (B.2), using loan origination data—rather than deposits—to compute the σ_j^{τ} variable. Panel (A) presents results for small business loan originations from the Community Reinvestment Act. Panel (B) displays results for mortgage originations from the Home Mortgage Disclosure Act. The sample period is 2005-2019. Units are in percentage points.

in more than 50 counties having 4 pp lower deposit volatility than banks operating in 1-5 counties.[55] Similar results hold when sorting by bank size (not shown).

Figure B.3 extends this analysis to loan originations, also in pp. Panel (A) focuses on small business loans and Panel (B) on mortgages.[56] Small business loan data come from the Community Reinvestment Act (CRA), and mortgage data from the Home Mortgage Disclosure Act (HMDA), both from the Federal Reserve Board. In both cases, exposure to risk in loan origination declines with geographic reach.

[55]Because the panel is unbalanced (due to exits and M&A), we restrict the sample to banks with at least 10 years of data to ensure stable variance estimates. Results are robust to alternative thresholds.
[56]The sample period is 2005-2019. Loan originations data are not consistently available prior to 2005.

FIGURE B.4. County-level Concentration in Deposit Markets



Notes: The figure shows the county-level Herfindahl-Hirschman Index in deposit markets for 1993 (red dots) and 2019 (blue dots), calculated as $HHI_{it} = \sum_{j\in i}\left(\frac{D_{jit}}{\sum_{j\in i} D_{jit}}\right)^2$, where D_{jit} denotes deposits held by bank j in county i at time t.

Concentration. In Section 2, we showed that there were both positive and negative changes in county-level HHIs between 1993 and 2019. Figure B.4 shows that smaller counties tend to exhibit higher Herfindahl-Hirschman indices, both in 1993 (red dots) and 2019 (blue dots).

Appendix C. The Model: Derivations and Additional Material

C.1. *Microfoundation for CES Demand System*

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

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

Depositors value deposit services but face an opportunity cost $y_\ell = d_{\ell ij}(R - R^D_{ij})$. In this framework, the parameter $\bar{\eta}$ governs the correlation of draws within a location (i.e., the degree of substitution across banks within a county), while $\bar{\theta}$ governs the variance of draws across locations (i.e., substitution across counties). After drawing $\boldsymbol{\zeta}$, depositor ℓ chooses the ij pair that solves:

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

The probability that depositor ℓ chooses branch ij is:

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

We can then compute D_{ij} as:

$$D_{ij} = \int \text{Prob}_\ell(R^D_{ij}, R^D_{-ij}) \cdot d_{\ell ij}\, dF(y) = \text{Prob}_\ell(R^D_{ij}, R^D_{-ij}) \cdot \frac{Y}{R - R^D_{ij}}.$$

Define the price indexes:

$$R - R^D_i \equiv \left[\sum_{j=1}^{N_i}(R - R^D_{ij})^{-(1+\bar{\eta})}\right]^{-1/(1+\bar{\eta})},$$

$$R - R^D \equiv \left[\sum_{i=1}^{N}(R - R^D_{i})^{-(1+\bar{\theta})}\right]^{-1/(1+\bar{\theta})}.$$

Note that total deposits satisfy $D\left(R - R^D\right) = \sum_i \sum_j D_{ij}(R - R^D_{ij}) = Y$. Substituting for Y and using the indexes above, we obtain:

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

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

C.2. *General Bank Problem: Derivation of the Pricing Equation*

We provide the derivation for optimal deposits spreads under our most general specification—Equation (7) in the main text. Let $\Pi_j\left(\{D_{ij}\}_{i\in\mathcal{M}_j}\right) \equiv \widehat{\Pi}_j\left(\{D_{ij}\}_{i\in\mathcal{M}_j}, \left\{L^*_{ij}\right\}_{i\in\mathcal{N}_j}, F^*_j\right)$ denote bank's realized profits net of all financing costs, except those related to deposits, from receiving a vector of deposit inflows $\{D_{ij}\}_{i\in\mathcal{M}_j}$ across the $\mathcal{M}_j$ set of markets in which it operates. The $\left\{L^*_{ij}\right\}_{i\in\mathcal{N}_j}$ denotes the optimal loans made by bank j in location k across the set $\mathcal{N}_j$ of locations —which does not need to be equal to the $\mathcal{M}_j$ set. The return on these loans may be stochastic and heterogeneous across locations or banks. At this point, we do not need to make any assumptions on them. Lastly, the F_j^* captures bank j's all other sources of funding, which include wholesale funding, inter-bank loans, equity, and others.

Assuming that the bank makes all its choices before observing the realization of shocks, then:

$$\left\{L_{ij}^*\right\}_{i\in\mathcal{N}_j}, F_j^* = \underset{\left\{L_{ij}\right\}_{i\in\mathcal{N}_j}, F_j}{\operatorname{argmax}} \mathbb{E}\left[\widehat{\Pi}_j\left(\left\{D_{ij}\right\}_{i\in\mathcal{M}_j}, \left\{L_{ij}\right\}_{i\in\mathcal{N}_j}, F_j\right)\right]. \tag{C.1}$$

Given these definitions, the bank problem can thus be written as in Equation (6) in the main text, which we rewrite below for convenience:

$$\max_{\left\{R_{ij}^D\right\}_{i\in\mathcal{M}_j}} \mathbb{E}\left[\Pi_j\left(\left\{\mathcal{D}_{ij}\left(R_{ij}^D\right)\right\}_{\forall i\in\mathcal{M}_j}\right) - \int_0^1 \left(R_{ij}^D + \kappa_{ij}\right)\cdot\mathcal{D}_{ij}\left(R_{ij}^D\right) d\Lambda_j\left(k\right)\right], \tag{C.2}$$

where $\Lambda_j(\cdot)$ denotes the measure indexing counties in which bank j operates and $\mathcal{D}_{ij}\left(\cdot\right)$ captures the demand for deposits faced by bank j in county i, which is a function of deposit rates.

Using the envelope theorem, the first-order condition with respect to R_{ij}^D is as follows:

$$\mathbb{E}\left(\Pi'_{ij}\frac{\partial D_{ij}}{\partial R_{ij}^D}\right) - \mathbb{E}\left(\mathcal{D}_{ij}\right) - \left[R_{ij}^D + k_{ij}\right]\mathbb{E}\left(\frac{\partial D_{ij}}{\partial R_{ij}^D}\right) = 0,$$

where $\Pi'_{ij} \equiv \frac{\partial \Pi_j(.)}{\partial D_{ij}}$ is the bank-level marginal benefit from an additional unit of deposits in location i. It is useful to rewrite the previous equation in terms of the derivative of deposits with respect to deposit spreads, $R - R_{ij}^D$. To this end, we define $\mathcal{D}'_{ij} \equiv \frac{\partial \mathcal{D}_{ij}}{\partial R - R_{ij}^D}$ Then, the previous equation is given by:

$$-\mathbb{E}\left(\Pi'_{ij}D'_{ij}\right) - \mathbb{E}\left(\mathcal{D}_{ij}\right) + \left[R_{ij}^D + k_{ij}\right]\mathbb{E}\left(\mathcal{D}'_{ij}\right) = 0.$$

Dividing by $\mathbb{E}\left(\mathcal{D}'_{ij}\right)$, adding R to both sides, and after rearranging terms, we have that:

$$R - R_{ij}^D = -\frac{\mathbb{E}\left(\mathcal{D}_{ij}\right)}{\mathbb{E}\left(\mathcal{D}'_{ij}\right)} + k_{ij} + R - \frac{\mathbb{E}\left(\Pi'_{ij}D'_{ij}\right)}{\mathbb{E}\left(\mathcal{D}'_{ij}\right)}.$$

Working with the last term in the right-hand side, it is straightforward to show that

$$\frac{\mathbb{E}\left(\Pi'_{ij}D'_{ij}\right)}{\mathbb{E}\left(\mathcal{D}'_{ij}\right)} = \left(1 + \frac{\mathbb{C}ov\left(\Pi'_{ij}, D'_{ij}\right)}{\mathbb{E}\left(\mathcal{D}'_{ij}\right)\mathbb{E}\left(\Pi'_{ij}\right)}\right)\mathbb{E}\left(\Pi'_{ij}\right).$$

Combining the last two equations, we get Equation (7) in the main text.

C.3. *Baseline Model: Derivation of the Pricing Equations*

Local Pricing. We provide additional derivations for optimal deposit spreads under local pricing. As described in the main text, for a given equity E_j, each bank chooses deposit spreads $R - R^D_{ij}$ in each county i in which it operates, loans L_j, and wholesale funding H_j to solve the problem in Equation (10). After replacing B_j with the bank's balance sheet equation, the problem can be written as follows:

$$\max_{\left\{R-R^D_{ij}\right\},L_j,H_j} \mathbb{E}\Bigg[z_j L_j - \int_0^1 \left(R - R^D_{kj} - \kappa_{kj}\right)\mathcal{D}_{kj}\Lambda_j(k) - \frac{\tau_j}{2}E_j^2 - \frac{\nu_j}{2}H_j^2 + \\ - \frac{\chi_j}{2}\left(L_j - \int_0^1 \mathcal{D}_{kj}\Lambda_{kj}(k) - H_j - E_j\right)^2\Bigg].$$

It is straightforward to get the first order conditions for L_j and H_j. They are given by

$$\begin{aligned} z_j =& \chi_j \mathbb{E}\left(L_j - \int_0^1 \mathcal{D}_{kj}\Lambda_j(k) - H_j - E_j\right), \\ \nu_j H_j =& \chi_j \mathbb{E}\left(L_j - \int_0^1 \mathcal{D}_{kj}\Lambda_j(k) - H_j - E_j\right). \end{aligned}$$

As for deposits spreads, the first order condition with respect to $R - R^D_{ij}$ is

$$\mathbb{E}\left[-\mathcal{D}_{ij}\Lambda_j(i) - (R - R^D_{ij} - \kappa_{ij})\mathcal{D}'_{ij}\Lambda_j(i) + \chi_j\left(L_j - \int_0^1 \mathcal{D}_{kj}\Lambda_j(k) - H_j - E_j\right) \times \mathcal{D}'_{ij}\Lambda_j(i)\right] = 0.$$

Replacing with the first order condition for L_j and after dividing by $\mathbb{E}\left(\mathcal{D}'_{ij}\Lambda_j(i)\right)$, we can rewrite the previous expression as follows:

$$R - R^D_{ij} = -\frac{\mathbb{E}\left(\mathcal{D}_{ij}\right)}{\mathbb{E}\left(\mathcal{D}'_{ij}\right)} + (k_{ij} - z_j) + \chi_j \frac{\mathbb{C}ov\left(\mathcal{D}'_{ij}, \int_0^1 \mathcal{D}_{kj}\Lambda_j(k)\right)}{\mathbb{E}\left(\mathcal{D}'_{ij}\right)} \tag{C.3}$$

From the household's optimality conditions —Equations (3) and (5) in the main text— we can directly get an expression for $\mathcal{D}'_{ij}$:

$$\mathcal{D}'_{ij} = \mathcal{D}_{ij}\frac{1}{R - R^D_{ij}}\left[\frac{\theta - \eta}{\theta}\frac{d\ln D_i}{d\ln R - R^D_{ij}} - \eta\right]. \tag{C.4}$$

Combining Equations (4) and (5) and after taking logs, we get

$$\ln D_i = \theta \ln \phi_i + \theta \ln\left(R - R^D\right) + \frac{\theta}{\eta - 1}\ln\left(\sum_{j=1}^{J_i}\psi^{\eta}_{ij}\left(R - R^D_{ij}\right)^{1-\eta}\right) + \ln D,$$

which implies that $\frac{d\ln D_i}{d\ln R-R_{ij}^D} = -\theta\frac{\psi_{ij}^{\eta}\left(R-R_{ij}^D\right)^{1-\eta}}{\sum_{j=1}^{J_i}\psi_{ij}^{\eta}\left(R-R_{ij}^D\right)^{1-\eta}}$. Substituting this last expression into equation (C.4):

$$\begin{aligned}\mathcal{D}_{ij}' =& \mathcal{D}_{ij}\frac{1}{R-R_{ij}^D}\left[(\eta-\theta)\frac{\psi_{ij}^{\eta}\left(R-R_{ij}^D\right)^{1-\eta}}{\sum_{j=1}^{J_i}\psi_{ij}^{\eta}\left(R-R_{ij}^D\right)^{1-\eta}}-\eta\right]\\ =& \mathcal{D}_{ij}\frac{1}{R-R_{ij}^D}\left[(\eta-\theta)s_{ij}-\eta\right],\end{aligned} \tag{C.5}$$

where in the second equality we make use of our definition for county-level market shares, s_{ij}. Substituting (C.5) back into Equation (C.3), we get:

$$R-R_{ij}^D = \frac{\eta(1-s_{ij})+\theta s_{ij}}{\eta(1-s_{ij})+\theta s_{ij}-1}\left[\kappa_{ij}-z_j+\chi_j\frac{\mathbb{C}ov\left(\mathcal{D}_{ij}\,,\,\int_0^1\mathcal{D}_{kj}d\Lambda_j(i)\right)}{\mathbb{E}\left(\mathcal{D}_{ij}\right)}\right], \tag{C.6}$$

Lastly, by further working with the CES structure of our problem, it is easy to show that:

$$\begin{aligned}\frac{Cov\left(\mathcal{D}_{ij}\,,\,\mathcal{D}_{kj}\Lambda_{kj}\right)}{\mathbb{E}\left(\mathcal{D}_{ij}\right)} &= \mathbb{E}\left(\mathcal{D}_{kj}\Lambda_{kj}\right)\frac{\mathbb{C}ov\left(\phi_i^{\theta}\phi_k^{\theta}\right)}{\mathbb{E}\left(\phi_i^{\theta}\right)\mathbb{E}\left(\phi_k^{\theta}\right)}\\ &\equiv \mathbb{E}\left(\mathcal{D}_{kj}\Lambda_{kj}\right)\frac{\rho_{ik}\sigma_i\sigma_k}{\mu_i\mu_k}.\end{aligned} \tag{C.7}$$

Replacing into Equation (C.6), after some algebraic manipulation we get our baseline pricing equation under local pricing:

$$R-R_{ij}^D = \frac{\eta(1-s_{ij})+\theta s_{ij}}{\eta(1-s_{ij})+\theta s_{ij}-1}\left[\kappa_{ij}-z_j+\chi_j\mathbb{E}\left(D_j\right)\int_{k\in\mathcal{M}_j}\omega_{ij}\frac{\rho_{ik}\sigma_i\sigma_k}{\mu_i\mu_k}dk\right], \tag{C.8}$$

with $\mathbb{E}\left(D_j\right)\equiv\int_0^1\mathbb{E}\left(\mathcal{D}_{kj}\Lambda_j(k)\right)$ and $\omega_{ij}\equiv\frac{\mathbb{E}\left[\mathcal{D}_{kj}\Lambda_{kj}\right]}{\mathbb{E}\left(D_j\right)}$.

Uniform Pricing. For the uniform-pricing case, each bank j sets a single deposit rate R_j^D across all the markets in which it operates. Its problem is as follows:

$$\begin{aligned}\max_{R-R_j^D,L_j,H_j}\mathbb{E}\Bigg[&z_jL_j-\int_0^1\left(R-R_j^D-\kappa_{kj}\right)\mathcal{D}_{kj}\Lambda_j(k)-\frac{\tau_j}{2}E_j^2-\frac{\nu_j}{2}H_j^2+\\ &-\frac{\chi_j}{2}\left(L_j-\int_0^1\mathcal{D}_{kj}\Lambda_{kj}(k)-H_j-E_j\right)^2\Bigg]\end{aligned}$$

The first-order conditions with respect to L_j and H_j are analogous to our local-pricing case. On the other hand, the optimality condition with respect to deposit spreads $R - R_j^D$ is

$$\mathbb{E}\Bigg[- \int_0^1 \mathcal{D}_{kj}\Lambda_j(k) - \int_0^1 (R - R_j^D - \kappa_{kj})\mathcal{D}'_{kj}\Lambda_j(k) + \\ + \chi_j \left(L_j - \int_0^1 \mathcal{D}_{kj}\Lambda_{kj}(k) - H_j - E_j \right) \times \int_0^1 \mathcal{D}'_{kj}\Lambda_j(k) \Bigg] = 0.$$

Replacing with the first-order condition for L_j, and after dividing by $\mathbb{E}\left(\int_0^1 \mathcal{D}'_{kj}\Lambda_j(k)\right)$, we can rewrite the previous expression as follows:

$$R - R_j^D = -\frac{\int_0^1 \mathbb{E}\mathcal{D}_{kj}\Lambda_j(k)}{\int_0^1 \mathbb{E}\mathcal{D}'_{kj}\Lambda_j(k)} + (\kappa_j - z_j) + \chi_j \frac{\mathbb{C}ov\left[\int_0^1 \mathcal{D}'_{kj}\Lambda_j(k)\ ,\ \int_0^1 \mathcal{D}_{kj}\Lambda_{kj}(k)\right]}{\int_0^1 \mathbb{E}\mathcal{D}'_{kj}\Lambda_j(k)}, \tag{C.9}$$

where $\kappa_j \equiv \frac{\int_0^1 \kappa_{kj}\mathbb{E}\mathcal{D}'_{kj}\Lambda_j(k)}{\int_0^1 \mathbb{E}\mathcal{D}'_{kj}\Lambda_j(k)}$ is a weighted-average of banks' operating costs. Using again the fact that $\mathcal{D}'_{ij} = \mathcal{D}_{ij}\frac{1}{R-R_j^D}\left[(\eta - \theta)s_{ij} - \eta\right]$ (Equation C.5), we can rewrite the first term in the right-hand side of Equation C.9 as:

$$-\frac{\int_0^1 \mathbb{E}\mathcal{D}_{kj}\Lambda_j(k)}{\int_0^1 \mathbb{E}\mathcal{D}'_{kj}\Lambda_j(k)} = -\frac{R - R_j^D}{(\eta - \theta)s_j - \eta},$$

where $s_j \equiv \frac{\int_0^1 s_{kj}\mathbb{E}\left(\mathcal{D}_{kj}\Lambda_j(k)\right)}{\int_0^1 \mathbb{E}\left(\mathcal{D}_{kj}\Lambda_j(k)\right)}$ is a bank weighted-average market share. In addition, using $\frac{Cov\left(\mathcal{D}_{ij}\,,\mathcal{D}_{kj}\Lambda_{kj}\right)}{\mathbb{E}[\mathcal{D}_{ij}]} = \mathbb{E}\left(\mathcal{D}_{kj}\Lambda_{kj}\right)\frac{\rho_{ik}\sigma_i\sigma_k}{\mu_i\mu_k}$ (Equation C.7), the covariance term can be expressed as:

$$\frac{\mathbb{C}ov\left[\int_0^1 \mathcal{D}'_{kj}\Lambda_j(k)\ ,\ \int_0^1 \mathcal{D}_{kj}\Lambda_{kj}(k)\right]}{\int_0^1 \mathbb{E}\mathcal{D}'_{kj}\Lambda_j(k)} = \mathbb{E}\left(\mathcal{D}_j\right) \times \int_{i\in\mathcal{M}_j} \tilde{\omega}_{ij}\left(\int_{k\in\mathcal{M}_j}\omega_{kj}\frac{\rho_{ik}\sigma_i\sigma_k}{\mu_i\mu_k}dk\right)di,$$

where $\tilde{\omega_{ij}} \equiv \frac{[(\eta-\theta)s_{ij}-\eta]\mathbb{E}(\mathcal{D}_{ij}\Lambda_j(i))}{\int_0^1\left[(\eta-\theta)s_{kj}-\eta\right]\mathbb{E}\left(\mathcal{D}_{kj}\Lambda_j(k)\right)}$ is a weighted-average elasticity of substitution. Replacing these last two expressions in Equation C.9, we get our pricing equation under uniform pricing:

$$R - R_j^D = \frac{\eta(1 - s_j) + \theta s_j}{\eta(1 - s_j) + \theta s_j - 1}\left[(\kappa_j - z_j) + \chi_j\mathbb{E}\left(\mathcal{D}_j\right) \times \int_{i\in\mathcal{M}_j}\tilde{\omega}_{ij}\left(\int_{k\in\mathcal{M}_j}\omega_{kj}\frac{\rho_{ik}\sigma_i\sigma_k}{\mu_i\mu_k}dk\right)di\right].$$

C.4. *Model Decompositions - Extensive Margin and Out-of-State Banks*

In the main text, we decomposed county-level changes in risk premia to analyze the role of entrants and exiters. In particular, Equation (34), which we rewrite below, shows that county-level changes in risk can be written as follows:

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

where $\{\hat{J}_i\}$ denotes the set of survivors, $\{\tilde{J}_{i0}\}$ the set of exiters, and $\{\tilde{J}_{i1}\}$ the set of entrants, and $M_{it} \equiv \sum_{j\in\tilde{J}_{it}} s_{ijt}$ is the combined market share of banks in county i that operate only in period t, with $t \in 0, 1$. We refer to the sum of the first two terms on the right-hand side of the previous expression as the "extensive margin".

In what follows, we further decompose the extensive margin into out-of-state and within-state exiters and entrants. To this end, we first define α_i^1 be the fraction (relative to M_i^1) of out-of-state entrants (and new banks). Similarly, we define α_i^0 to be the fraction (relative to M_i^0) of out-of-state exiters (and dead banks). With these definitions, and after some algebra, one can show that:

$$\Delta \sum_{j\in\mathcal{J}_{it}} s_{ijt}\Gamma_{jt} = \underbrace{\alpha_i^1 M_i^1\left(\sum_{\{\tilde{j}_1\}_i} \frac{s_{ij}^1}{\alpha_i^1 M_i^1}\Gamma_{ij}^1 - \sum_{\{\hat{j}\}_i} \frac{s_{ij}^1}{1-M_i^1}\Gamma_{ij}^1\right)}_{\text{Out-of-state Entrants vs. Survivors}} - \underbrace{\alpha_i^0 M_0^0\left(\sum_{\{\tilde{j}_0\}_i} \frac{s_{ij}^0}{\alpha_i^0 M_i^0}\Gamma_{ij}^0 - \sum_{\{\hat{j}\}_i} \frac{s_{ij}^0}{1-M_i^0}\Gamma_{ij}^0\right)}_{\text{Survivors vs Out-of-state Exiters}}$$
$$+ \underbrace{\left(1-\alpha_i^1\right) M_i^1\left(\sum_{\{\tilde{j}_1^\star\}_i} \frac{s_{ij}^1}{\left(1-\alpha_i^1\right) M_i^1}\Gamma_{ij}^1 - \sum_{\{\hat{j}\}_i} \frac{s_{ij}^1}{1-M_i^1}\Gamma_{ij}^1\right)}_{\text{Within-state Entrants vs. Survivors}}$$
$$- \underbrace{\left(1-\alpha_i^0\right) M_i^0\left(\sum_{\{\tilde{j}_0^\star\}_i} \frac{s_{ij}^0}{\left(1-\alpha_i^0\right) M_i^0}\Gamma_{ij}^0 - \sum_{\{\hat{j}\}_i} \frac{s_{ij}^0}{1-M_i^0}\Gamma_{ij}^0\right)}_{\text{Survivors vs. Within-state Exiters}}$$
$$+ \underbrace{\sum_{\{\hat{j}\}_i} \frac{s_{ij}^1}{1-M_i^1}\Gamma_{ij}^1 - \sum_{\{\hat{j}\}_i} \frac{s_{ij}^0}{1-M_i^0}\Gamma_{ij}^0}_{\text{Within Survivors}} \tag{C.10}$$

The sum of the first two terms on the right-hand-side of Equation (C.10) capture the "out-of-state extensive margin." That is, changes in risk premia driven by banks entering or exiting the state in which county i is located. The sum of the third and fourth terms capture the "within-state extensive margin," which is driven by banks that enter or exit county i but were already operating in the state in which i is located. In Figure 10 of the main text, we show that more than half of the extensive-margin is explained by out-of-state entrants and exiters.

C.5. *Local Lending*

In this section, we provide details on analytical derivations for the local lending version of the model presented in Section 7. Bank j can provide credit in the form of loans across the locations (states) in which they have branches, $L_j = \int_{\mathcal{M}_j^S} L_{ij} di$, or in form of securities, S_j, so that total assets are $A_t = L_j + S_j$. As in the baseline model, loans and securities are chosen before shocks are realized. We first derive the revenue function of the bank in terms of assets, and then explicit its maximization problem to show that optimal spreads have a specification similar to the baseline's. We focus on the uniform-pricing case, but derivations for local pricing are analogous.

Given some assets A_j, the revenue function of bank j is given by:

$$Rev\left(A_j\right) = \max_{\{L_{ij}\},S_j} \mathbb{E}\left[\int_0^1 \left(R + z_j^L - \frac{1}{2}\alpha_i\alpha_j L_{ij}\right) L_{ij} d\Lambda_j(i) + \left(R + z_j^S - \frac{1}{2}\beta_j S_j\right) S_j\right], \quad \text{(C.11)}$$
$$\text{s.t. } A_j = \int_0^1 L_{ij} d\Lambda_j(i) + S_j.$$

The first order conditions with respect to S_j and L_{ij} are given by:

$$\mu_j = R + \mathbb{E}\left(z_j^S\right) - \beta_j S_j,$$
$$\mu_j = \left(R + \mathbb{E}\left(z_j^L\right)\right) - \alpha_i\alpha_j L_{ij},$$

where μ_j is the associated Lagrange multiplier. Combining these two expressions, and assuming $\mathbb{E}\left(z_j^L\right) = \mathbb{E}\left(z_j^S\right)$, we get:

$$L_{ij} = \frac{\beta_j}{\alpha_i\alpha_j} S_j. \quad \text{(C.12)}$$

Summing across all locations in which the bank operates:

$$L_j = \frac{\beta_j}{\alpha_j} S_j \int_0^1 \frac{1}{\alpha_i} d\Lambda_j(i),$$
$$= \frac{\beta_j}{\alpha_j} \varrho_j S_j, \quad \text{(C.13)}$$

where $\varrho_j \equiv \int_0^1 \frac{1}{\alpha_i} d\Lambda_j(i)$. Replacing equation (C.13) back in equation (C.12), we get L_{ij} as a function of L_j:

$$L_{ij} = \frac{1}{\alpha_i \varrho_j} L_j. \quad \text{(C.14)}$$

Then, using $L_j + S_j = A_j$ and equation (C.13), we get $L_j = \ell_j A_j$ and $S_j = (1-\ell_j)A_j$, where $\ell_j \equiv \frac{\varrho_j \beta_j}{\varrho_j \beta_j + \alpha_j}$. Substituting the solutions for L_{ij} and S_j back into the revenue function, and after combining terms, we obtain:

$$\begin{aligned} Rev\left(A_j\right) =& \mathbb{E}\left\{\left(R+z_j\right)\left(\int_0^1 \frac{1}{\alpha_i \varrho_j}\frac{\varrho_j\beta_j}{\varrho_j\beta_j+\alpha_j}\mathrm{d}\Lambda_j(i) + \frac{\alpha_j}{\varrho_j\beta_j+\alpha_j}\right)A_j\right\} + \\ & -\mathbb{E}\left\{\int_0^1 \frac{1}{2}\frac{\alpha_j}{\varrho_j}\frac{\varrho_j\beta_j}{\varrho_j\beta_j+\alpha_j}A_j\frac{1}{\alpha_i\varrho_j}\frac{\varrho_j\beta_j}{\varrho_j\beta_j+\alpha_j}A_j\mathrm{d}\Lambda_j(i) + \frac{1}{2}\beta_j\frac{\alpha_j}{\varrho_j\beta_j+\alpha_j}A_j\frac{\alpha_j}{\varrho_j\beta_j+\alpha_j}A_j\right\} \\ =& \mathbb{E}\left[\left(R+z_j\right)A_j - \frac{1}{2}\vartheta_j A_j^2\right], \end{aligned} \tag{C.15}$$

where we defined $\vartheta_j \equiv \frac{\alpha_j}{\varrho_j} l_j$ to simplify notation. Based on this revenue function, the problem of the bank is analogous to that of our baseline model. That is, each bank chooses deposit spreads, assets, and wholesale funding to solve:

$$\max_{\left\{R_j^D\right\},A_j,H_j} \mathbb{E}\left[\left(R+z_j-\frac{1}{2}\vartheta_j A_j\right)A_j - \int_0^1\left(R_j^D+k_{ij}\right)\mathcal{D}_{ij}d\Lambda_j(i) - \left(R+\frac{\nu_j}{2}H_j\right)H_j - \left(R+\frac{\chi_j}{2}B_j\right)B_j\right],$$

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

Following similar steps to the ones in Appendix C.3, we get that optimal spreads are given by

$$R - R_{ij}^D = \frac{\eta\left(1-s_j\right)+\theta s_j}{\eta\left(1-s_j\right)+\theta s_j - 1}\left[\kappa_j - \mathbb{E}\left(\tilde{z}_j\right) + \chi_j\mathbb{E}\left(D_j\right)\int_0^1 \omega_{kj}\frac{\rho_{ik}\sigma_i\sigma_k}{\mu_i\mu_k}d\Lambda_j(k)\right], \tag{C.16}$$

where $\mathbb{E}\left(\tilde{z}_j\right) \equiv \mathbb{E}\left(z_j\right) - \vartheta_j A_j$.

Mapping to the Data

We now describe how we solve for the vector $\{\alpha_i\}$. Summing Equation (C.14) across all locations and dividing by total lending $L \equiv \sum_i L_i$, we obtain:

$$\frac{L_i}{L}(\{\alpha_i\}) = \frac{1}{\alpha_i}\sum_{j\in i}\frac{1}{\varrho_j}\frac{L_j}{L}, \tag{C.17}$$

where ϱ_j denotes the bank-level term from the model.

We proxy location-level lending using county-level small business loan originations from the Community Reinvestment Act (CRA), denoted by $\mathcal{L}_i$.[57] Aggregating across counties gives us total loan flows, $\mathcal{L} = \sum_i \mathcal{L}_i$. We then solve for $\{\alpha_i\}$ to minimize the distance between model-implied and data-based loan shares, targeting the objective: $\sum_i \left|\left|\frac{\mathcal{L}_i}{\mathcal{L}} - \frac{L_i}{L}(\{\alpha_i\})\right|\right|$.[58] Specifically,

[57] Results are nearly identical when using mortgage originations.

[58] This implicitly assumes that the relative flows in the data, $\frac{\mathcal{L}_i}{\mathcal{L}}$, are proportional to relative loan stocks.

we solve:

$$\min_{\{\alpha_i\}} \sqrt{\sum_k \text{Loss}_k\left(\{\alpha_i\}\right)^2}, \tag{C.18}$$

$$\text{where} \quad \text{Loss}_k(\cdot) \equiv \frac{\mathcal{L}_k}{\mathcal{L}} - \frac{1}{\alpha_k} \sum_{j \in k} \left(\frac{1}{\sum_{i \in \mathcal{M}_j^S} \frac{1}{\alpha_i}} \cdot \frac{L_j}{L} \right).$$

This minimization problem recovers $\{\alpha_i\}$ up to a scaling constant. We normalize the vector so that $\sum_i \alpha_i = 1$.

Solving for $\{\alpha_i\}$ is non-trivial because changes in the curvature parameter for one location (say, i) indirectly affect other locations (e.g., k) through banks that operate in both. While in principle this problem can be solved at the county level, doing so is computationally burdensome given the roughly 3,000 counties in the data. To simplify, we solve for the vector $\{\alpha_i\}$ at the state level. Throughout our lending analysis, we assume that banks are allowed to lend in any state where they operate at least one branch.

C.6. *Model Extensions: Multiple Assets*

This section provides details on the derivations for the model extension for multiple assets presented in Section 8.1. As mentioned, our baseline model can be extended to include other assets—beyond cash and deposits—that provide liquidity services. Consider the same composite goods X and X_i as defined in Equations (41) and (42), respectively. In what follows, we present the corresponding demand functions for this generalized setting, which nests the cash-only extension as a special case.

The household's optimality conditions for X_{li} and D_i yield the inverse demand functions for liquidity services from asset l and for deposits D_i in county i:

$$\frac{R - R_{li}}{R - R_i^X} = \zeta_l \left(\frac{X_{li}}{X_i} \right)^{-\frac{1}{\varepsilon}} \text{ and } \frac{R - R_i^D}{R - R_i^X} = \left(\frac{D_i}{X_i} \right)^{-\frac{1}{\varepsilon}}, \tag{C.19}$$

along with the county-level inverse demand function for liquidity services:

$$\frac{R - R_i^X}{R - R^X} = \phi_i \left(\frac{X_i}{X} \right)^{-\frac{1}{\theta}}. \tag{C.20}$$

From Equation (C.19), we obtain the ratio of county-level deposits to asset X_{li} as:

$$\frac{D_i}{X_{li}} = \zeta_l^{-\varepsilon} \left(\frac{R - R_i^D}{R - R_{li}} \right)^{-\varepsilon}. \tag{C.21}$$

The county-level ideal price index for liquidity services is derived by substituting Equation (C.19) into the definition of X_i, reproduced below for convenience:

$$\begin{aligned} X_i &= \left(\sum_l \zeta_l X_{li}^{\frac{\varepsilon-1}{\varepsilon}} + D_i^{\frac{\varepsilon-1}{\varepsilon}} \right)^{\frac{\varepsilon}{\varepsilon-1}} \\ &= \left[X_i^{\frac{\varepsilon-1}{\varepsilon}} (R - R_i^X)^{\varepsilon-1} \left(\sum_l \zeta_l^\varepsilon (R - R_{li})^{1-\varepsilon} + (R - R_i^D)^{1-\varepsilon} \right) \right]^{\frac{\varepsilon}{\varepsilon-1}} \\ &= X_i (R - R_i^X)^\varepsilon \left(\sum_l \zeta_l^\varepsilon (R - R_{li})^{1-\varepsilon} + (R - R_i^D)^{1-\varepsilon} \right)^{\frac{\varepsilon}{\varepsilon-1}} . \end{aligned}$$

Rearranging the last expression, we get:

$$R - R_i^X = \left(\sum_l \zeta_l^\varepsilon (R - R_{li})^{1-\varepsilon} + (R - R_i^D)^{1-\varepsilon} \right)^{\frac{1}{1-\varepsilon}} . \tag{C.22}$$

Similarly, substituting Equation (C.20) into the definition of X from Equation (41), we obtain the national-level ideal price index for liquidity services:

$$R - R^X = \left(\int \phi_i^\theta (R - R_i^X)^{1-\theta} \, di \right)^{\frac{1}{1-\theta}} . \tag{C.23}$$

Based on the demand for deposits D_{ij} in equation (46), we can compute the elasticity of deposit demand faced by bank j in market i as:

$$\begin{aligned} \frac{d \ln D_{ij}}{d \ln \left(R - R_{ij}^D \right)} = &- \eta \left[1 - \frac{d \ln \left(R - R_i^D \right)}{d \ln \left(R - R_{ij}^D \right)} \right] - \varepsilon \left[\frac{d \ln \left(R - R_i^D \right)}{d \ln \left(R - R_{ij}^D \right)} - \frac{d \ln \left(R - R_i^X \right)}{d \ln \left(R - R_{ij}^D \right)} \right] \\ &- \theta \left[\frac{d \ln \left(R - R_i^X \right)}{d \ln \left(R - R_{ij}^D \right)} \right] , \end{aligned} \tag{C.24}$$

making it clear that the elasticity of demand is now a weighted average of the three structural elasticity parameters η, ε, and θ. Further, using (C.22), we can compute:

$$\begin{aligned} \frac{d \ln (R - R_i^X)}{d \ln (R - R_{ij}^D)} &= \frac{d \ln (R - R_i^D)}{d \ln (R - R_{ij}^D)} \cdot \left[\frac{(R - R_i^D)^{1-\varepsilon}}{\sum_l \zeta_l^\varepsilon (R - R_{li})^{1-\varepsilon} + (R - R_i^D)^{1-\varepsilon}} \right] \\ &= \frac{d \ln (R - R_i^D)}{d \ln (R - R_{ij}^D)} \cdot \left(\frac{R - R_i^D}{R - R_i^X} \right)^{1-\varepsilon} . \end{aligned} \tag{C.25}$$

Substituting (C.25) into the elasticity of deposit demand expression from (C.24), and simplifying, we obtain:

$$\frac{d\ln D_{ij}}{d\ln(R-R_{ij}^D)} = -\left[(1-s_{ij})\eta + s_{ij}\hat{\theta}_i\right], \tag{C.26}$$

where we define $s_{ij} = \frac{d\ln(R-R_i^D)}{d\ln(R-R_{ij}^D)}$ and

$$\hat{\theta}_i \equiv \varepsilon + (\theta-\varepsilon)s_i^D, \quad \text{with} \quad s_i^D = \left(\frac{R-R_i^D}{R-R_i^X}\right)^{1-\varepsilon}, \tag{C.27}$$

as expressed in Section 8.1.

C.7. *Alternative Model Specifications*

Alternative Timing Assumption: Absence of Loan Commitments

We provide further derivations for the model in Section 8.2, which considers a lending technology with decreasing marginal returns and assumes that banks do not make ex-ante commitments to the loans they offer.

For the local-pricing case, each bank j chooses a deposit rate in each market it operates and its wholesale funding to maximize:

$$\max_{\left\{R_{ij}^D\right\}_{\forall i\in\mathcal{M}_j}, H_j} \mathbb{E}\Bigg\{\int_0^1 \left(R - R_{ij}^D + z_j - \kappa_{ij}\right)\mathcal{D}_{ij}\mathrm{d}\Lambda_j(i) - \frac{\chi_j}{2}\left(\int_0^1 \mathcal{D}_{ij}d\Lambda_j(i) + H_j + E_j\right)^2 +$$
$$+ \left(R + z_j\right)E_j - \left(\frac{\nu_j}{2}H_j\right)H_j\Bigg\}, \tag{C.28}$$

where we have already substituted bank loans with the banks' balance-sheet constraint $L_j = \int_0^1 D_{ij}\mathrm{d}\Lambda_j(i) + H_j + E_j$. After some algebra, we can express the first-order condition with respect to deposit spreads as:

$$R - R_{ij}^D + \frac{\mathbb{E}\left(\mathcal{D}_{ij}\right)}{\mathbb{E}\left(\mathcal{D}_{ij}'\right)} = k_{ij} - \mathbb{E}\left(z_j\right) - \frac{\mathbb{C}ov\left(z_j, \mathcal{D}_{ij}'\right)}{\mathbb{E}\left(\mathcal{D}_{ij}'\right)} + \chi_j\frac{\mathbb{E}\left[\left(\int_0^1 \mathcal{D}_{kj}\mathrm{d}\Lambda_j\left(k\right) + H_j + E_j\right)\mathcal{D}_{ij}'\right]}{\mathbb{E}\left(\mathcal{D}_{ij}'\right)}.$$

We now use the following results (obtained in the derivation of the local-pricing case for our baseline model): $\frac{\mathcal{D}_{ij}\prime}{\mathcal{D}_{ij}} = \frac{(\eta-\theta)s_{ij}-\eta}{R-R_{ij}^D}$ and $\frac{\mathbb{C}ov\left(\mathcal{D}_{kj}\Lambda_{kj}, \mathcal{D}_{ij}\Lambda_{ij}\right)}{\mathbb{E}(\mathcal{D}_{ij}\Lambda_{ij})} = \mathbb{E}\left(\mathcal{D}_{kj}\Lambda_{kj}\right)\frac{\rho_{ik}\sigma_i\sigma_k}{\mu_i\mu_k}$. Based on these results, the left-hand side of the previous expression is

$$R - R_{ij}^D + \frac{\mathbb{E}\left(\mathcal{D}_{ij}\right)}{\mathbb{E}\left(\mathcal{D}_{ij}'\right)} = \left(R - R_{ij}^D\right)\left[\frac{\left(\eta-\theta\right)s_{ij} - \eta + 1}{\left(\eta-\theta\right)s_{ij} - \eta}\right].$$

The last term on the right-hand side can also be re-written as:

$$\begin{aligned}
\chi_j \frac{\mathbb{E}\left[\left(\int_0^1 \mathcal{D}_{kj} \mathrm{d}\Lambda_j(k) + H_j + E_j\right)\mathcal{D}'_{ij}\right]}{\mathbb{E}\left(\mathcal{D}'_{ij}\right)} =& \chi_j (H_j + E_j) + \chi_j \frac{\mathbb{E}\left[\left(\int_0^1 \mathcal{D}_{kj} \mathrm{d}\Lambda_j(k)\right)\mathcal{D}'_{ij}\right]}{\mathbb{E}\left(\mathcal{D}'_{ij}\right)} \\
=& \chi_j \mathbb{E}(L_j) + \chi_j \frac{\mathbb{C}ov\left[\int_0^1 \mathcal{D}_{kj} \mathrm{d}\Lambda_j(k), \mathcal{D}'_{ij}\right]}{\mathbb{E}\left(\mathcal{D}'_{ij}\right)} \\
\equiv& \chi_j \mathbb{E}(L_j)\left(1 + \widetilde{\Gamma_{ij}}\right),
\end{aligned}$$

where $\widetilde{\Gamma_{ij}} \equiv \omega_j^D \int_0^1 \omega_{kj} \frac{\rho_{ik}\sigma_i\sigma_k}{\mu_i\mu_k} \mathrm{d}\Lambda_j(k)$. Lastly, we use the fact that $D_{ij} = \psi_{ij}^\eta \left(\frac{R-R_i^D}{R-R_{ij}^D}\right)^\eta D_i$ and $D_i = \phi_i^\theta \times \left(\frac{R-R^D}{R-R_i^D}\right)^\theta \times D$ to rewrite the $\frac{\mathbb{C}ov\left(z_j, \mathcal{D}'_{ij}\right)}{\mathbb{E}\left(\mathcal{D}'_{ij}\right)}$ as

$$\frac{\mathbb{C}ov\left(z_j, \mathcal{D}'_{ij}\right)}{\mathbb{E}\left(\mathcal{D}'_{ij}\right)} = \frac{\mathbb{C}ov\left(z_j, \mathcal{D}_{ij}\right)}{\mathbb{E}\left(\mathcal{D}_{ij}\right)} = \frac{\mathbb{C}ov\left(z_j, \psi_{ij}^\eta \left(\frac{R-R_i^D}{R-R_{ij}^D}\right)^\eta \phi_i^\theta \times \left(\frac{R-R^D}{R-R_i^D}\right)^\theta \times D\right)}{\mathbb{E}\left(\psi_{ij}^\eta \left(\frac{R-R_i^D}{R-R_{ij}^D}\right)^\eta \phi_i^\theta \times \left(\frac{R-R^D}{R-R_i^D}\right)^\theta \times D\right)} = \frac{\mathbb{C}ov\left(z_j, \phi_i^\theta\right)}{\mu_i}.$$

Combining all these expressions, we get a pricing equation for deposit spreads,

$$R - R_{ij}^D = \frac{\eta(1-s_{ij}) + \theta s_{ij}}{\eta(1-s_{ij}) + \theta s_{ij} - 1}\left[k_{ij} - \mathbb{E}(z_j) + \chi_j \mathbb{E}(L_j)\left(1 + \widetilde{\Gamma_{ij}}\right) - \frac{\mathbb{C}ov\left(z_j, \phi_i^\theta\right)}{\mu_i}\right],$$

which is Equation (49) in the main text.

Under uniform pricing, the bank's problem is analogous to that in Equation (C.28), with the additional condition that $R_{ij}^D = R_j^D$, for every location $i \in \mathcal{M}_j$. After some algebra, one can show that the first-order condition with respect to deposit spreads is:

$$\begin{aligned}
R - R_j^D + \frac{\mathbb{E}\left(\int_0^1 \mathcal{D}_{ij} \mathrm{d}\Lambda_j(i)\right)}{\mathbb{E}\left(\int_0^1 \mathcal{D}'_{ij} \mathrm{d}\Lambda_j(i)\right)} =& \kappa_j - \mathbb{E}(z_j) - \frac{\mathbb{C}ov\left(z_j, \int_0^1 \mathcal{D}'_{ij} \mathrm{d}\Lambda_j(i)\right)}{\mathbb{E}\left(\int_0^1 \mathcal{D}'_{ij} \mathrm{d}\Lambda_j(i)\right)} + \\
&+ \chi_j \frac{\mathbb{E}\left[\left(\int_0^1 \mathcal{D}_{\kappa_j} \mathrm{d}\Lambda_j(k) + H_j + E_j\right)\mathcal{D}'_{ij}\right]}{\mathbb{E}\left(\mathcal{D}'_{ij}\right)},
\end{aligned}$$

where $\kappa_j \equiv \int_0^1 \kappa_{ij} \frac{\mathbb{E}\left(\mathcal{D}'_{ij}\right)\mathrm{d}\Lambda_j(i)}{\int_0^1 \mathbb{E}\left(\mathcal{D}'_{ij}\right)\mathrm{d}\Lambda_j(i)}$. Following the same derivation as in our baseline model, the left-hand side of the previous equation is given by:

$$R - R_{ij}^D + \frac{\mathbb{E}\left(\int_0^1 \mathcal{D}_{ij} \mathrm{d}\Lambda_j(i)\right)}{\mathbb{E}\left(\int_0^1 \mathcal{D}'_{ij} \mathrm{d}\Lambda_j(i)\right)} = \left(R - R_{ij}^D\right)\left[\frac{\eta(1-s_j) + \theta s_j}{\eta(1-s_j) + \theta s_j - 1}\right].$$

Based also on an analogous derivation to our baseline uniform-pricing case, the last term on the right hand side can be expressed as:

$$\chi_j \frac{\mathbb{E}\left[\left(\int_0^1 \mathcal{D}_{kj} \mathrm{d}\Lambda_j(k) + H_j + E_j\right) \mathcal{D}'_{ij}\right]}{\mathbb{E}\left(\mathcal{D}'_{ij}\right)} \equiv \chi_j \mathbb{E}(L_j)\left(1 + \widetilde{\Gamma}_j\right),$$

where

$$\widetilde{\Gamma}_j \equiv \omega_j^D \int_{k\in\mathcal{M}_j} \tilde{\omega}_{kj} \int_{i\in\mathcal{M}_j} \omega_{ij} \frac{\rho_{ik}\sigma_i\sigma_k}{\mu_i\mu_k} di\, dk.$$

Lastly, working with the covariance term between loan returns and deposit demand:

$$\begin{aligned}
\frac{\mathbb{C}ov\left(z_j, \int_0^1 \mathcal{D}'_{ij}\mathrm{d}\Lambda_j(i)\right)}{\mathbb{E}\left(\int_0^1 \mathcal{D}'_{ij}\mathrm{d}\Lambda_j(i)\right)} &= \frac{\int_0^1 \mathbb{C}ov\left(z_j, \mathcal{D}'_{ij}\right)\mathrm{d}\Lambda_j(i)}{\int_0^1 \mathbb{E}\mathcal{D}'_{ij}\mathrm{d}\Lambda_j(i)} \\
&= \int_0^1 \frac{\left[(\eta-\theta)s_{ij} - \eta\right]\mathbb{E}(\mathcal{D}_{ij})}{\int_0^1 \left[(\eta-\theta)s_{ij}-\eta\right]\mathbb{E}(\mathcal{D}_{ij})\mathrm{d}\Lambda_j(i)} \frac{\mathbb{C}ov(z_j, \mathcal{D}_{ij})}{\mathbb{E}(\mathcal{D}_{ij})}\mathrm{d}\Lambda_j(i) \\
&= \int_0^1 \tilde{\omega}_{ij}\frac{\mathbb{C}ov(z_j, \mathcal{D}_{ij})}{\mathbb{E}(\mathcal{D}_{ij})}\mathrm{d}\Lambda_j(i) \\
&= \int_0^1 \tilde{\omega}_{ij}\frac{\mathbb{C}ov\left(z_j, \phi_i^\theta\right)}{\mu_i}\mathrm{d}\Lambda_j(i),
\end{aligned}$$

where $\tilde{\omega}_{ij} \equiv \frac{[(\eta-\theta)s_{ij}-\eta]\mathbb{E}(\mathcal{D}_{ij}\Lambda_j(i))}{\int_0^1\left[(\eta-\theta)s_{kj}-\eta\right]\mathbb{E}\left(\mathcal{D}_{kj}\Lambda_j(k)\right)}$. Combining all these results, the pricing equation under uniform pricing is then:

$$R - R_j^D = \frac{\eta(1-s_j)+\theta s_j}{\eta(1-s_j)+\theta s_j - 1}\left[\kappa_j - \mathbb{E}(z_j) + \chi_j\mathbb{E}(L_j)\left(1+\widetilde{\Gamma}_j\right) - \int_0^1 \tilde{\omega}_{kj}\frac{\mathbb{C}ov\left(z_j, \phi_k^\theta\right)}{\mu_k}\mathrm{d}\Lambda_j(k)\right],$$

which is Equation (50) in the main text.

Banks' Risk Aversion or Regulatory Constraints

Given the timing assumption of the previous subsection, one can obtain similar pricing equations without the need to assume diminishing marginal returns on lending. For instance, another mechanism that gives rise to risk premia is a case in which banks penalize the variance of deposits, due to their own preferences or some regulatory constraint. For ease of exposition, we assume bank j simply dislikes variability in deposits. Moreover, we assume that there are no equity, wholesale, or inter-bank lending markets. In this scenario, the problem of the bank can be expressed by the following maximization problem:

$$\max_{\left\{R-R_{ij}^D\right\}_{\forall i\in\mathcal{M}_j}} \mathbb{E}\int_0^1 \left(R + z_j - R_{ij}^D\right)\mathcal{D}_{ij}\,\mathrm{d}\Lambda_j(i) - \frac{\chi_j}{2}\mathbb{V}\left[\int_0^1 \mathcal{D}_{ij}\,\mathrm{d}\Lambda_j(i)\right].$$

Under this alternative problem, one can show that optimal spreads are given by

$$R-R_{ij}^{D}=\frac{\eta\left(1-s_{ij}\right)+\theta s_{ij}}{\eta\left(1-s_{ij}\right)+\theta s_{ij}-1}\left[\kappa_{ij}-z_{j}+\chi_{j}\mathbb{E}\left(D_{j}\right)\int_{k\in\mathcal{M}_{j}}\omega_{kj}\frac{\rho_{ik}\sigma_{i}\sigma_{k}}{\mu_{i}\mu_{k}}dk\right],$$

which analogous to the pricing equation of our baseline model.

C.8. *Solution Algorithm*

Below, we outline the algorithm developed to solve the model and conduct counterfactual analysis. The algorithm is iterative, designed to determine the equilibrium prices and allocations given the model parameters and a vector of $\{\phi_{it}\}$ shocks. We describe the algorithm specifically for the local-pricing case, but the methodology for the uniform-pricing scenario follows a similar structure and can be adapted accordingly.

(1) Guess spreads $\left(R-R_{ijt}^{D}\right)^{(0)}$ for each bank-county pair ij.

(2) Given these guesses, use the ideal price indexes to compute $R-R_{it}^{D}$ and $R-R_{t}^{D}$.

(3) Compute aggregate deposits D_t and, with that, county-level expected deposits:

$$\mathbb{E}\left[D_{i}\right]=\mu_{i}\left(\frac{R-R_{t}^{D}}{R-R_{it}^{D}}\right)^{\theta}D_{t}.$$

(4) Use the results from the previous step to compute bank-county expected deposits:

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

and

$$\mathbb{E}\left(D_{j}\right)=\sum_{i\in\mathcal{M}_{j}}\mathbb{E}\left[D_{ij}\right]$$

(5) Since in our main estimation we imposed that $\chi=\chi_j\mathbb{E}\left(D_j\right)$ for every bank j, we need to update the χ_j coefficient, given the newly updated value for $\mathbb{E}\left(D_j\right)$, computed in the previous step. That is, $\chi_j=\frac{\chi}{\mathbb{E}(D_j)}$.

(6) Back out the market shares $s_{ij}=\psi_{ij}^{\eta}\left(\frac{R-R_{ij}^{D}}{R-R_{i}^{D}}\right)^{1-\eta}$ and compute the markups

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

(7) Based on the estimated variance-covariance matrix for county-level shocks, compute the model-implied measure of risk

$$\Gamma_{ij} = \sum_{k \in \mathcal{M}_j} \omega_{kj}^{D} \frac{\rho_{ik}\sigma_i\sigma_k}{\mu_i\mu_k}.$$

(8) Use the risk-premium measure to update banks' marginal costs of providing deposits:

$$MC_{ij} = (k_{ij} - z_j) + \chi_j \, \mathbb{E}\left(D_j\right) \, \Gamma_{ij}.$$

(9) Based on the markups and the marginal costs computed in the previous step, update deposit spreads using the model's pricing equation:

$$\left(R - R_{ijt}^{D}\right)^{(1)} = MKP_{ij} \times MC_{ij}.$$

(10) The algorithm iterates, updating the spreads until convergence is achieved. Convergence is determined when the changes in the deposit spreads between iterations are sufficiently small.

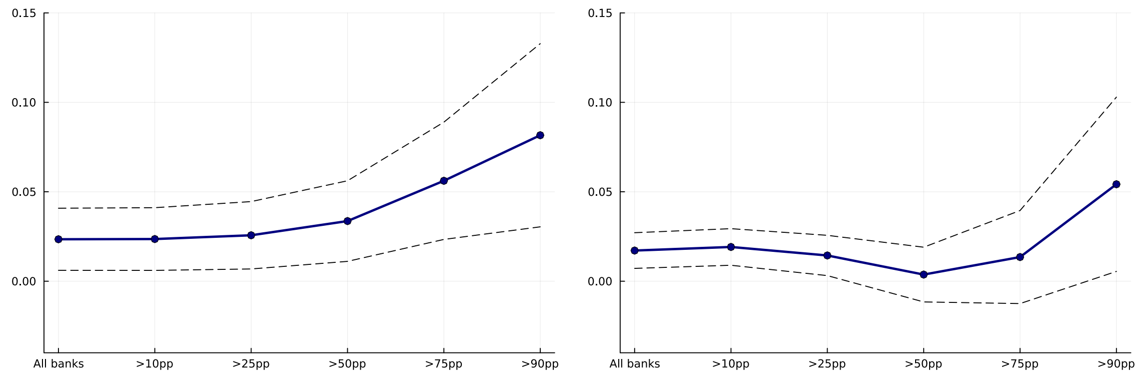
Appendix D. Additional Results

D.1. *Estimation of χ by Bank Group*

In the main text, we estimated a common χ parameter across all banks. Here, we relax that assumption and allow χ to vary with bank size. Specifically, we consider a more flexible specification in which banks are sorted into bins based on their total deposits, and χ is estimated separately for each group—using Equation (30) from the main text. Results are presented in Figure D.1. Overall, the magnitude of the estimates closely aligns with those in Table 5. If anything, we find that χ tends to increase modestly with bank size, particularly under the local pricing specification.

Figure D.1. Estimated χ Coefficient, by Bank Group

(a) Local Pricing (b) Uniform Pricing

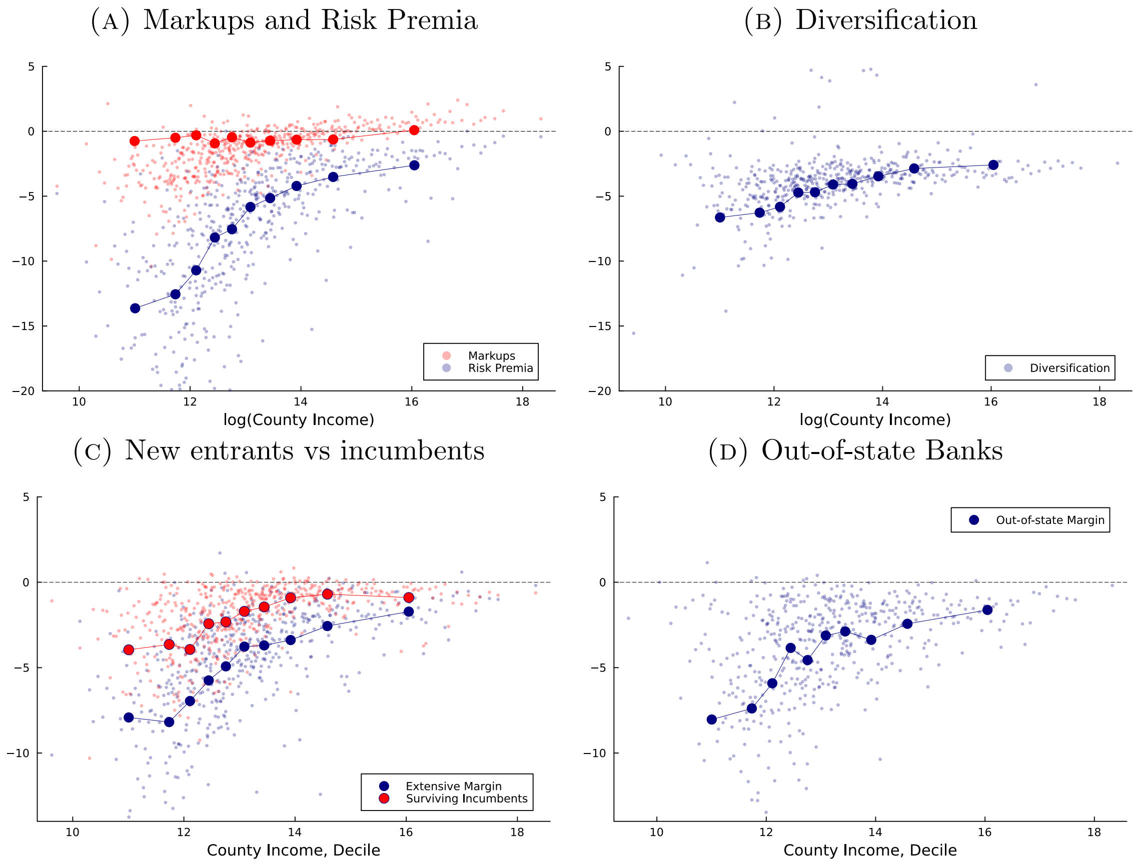


Notes: The figure displays estimates of χ across bank size bins, where size is defined by total loans. For example, the "$>$ 10pp" bin includes banks with total loans greater than the 10th percentile. Dashed lines show 90% confidence intervals. In the local-pricing specification, standard errors are clustered at the county-year level.

D.2. *Changes Across Time under Local Pricing*

In this section, we extend the analysis from Subsection 5.2 by examining changes in deposit spreads between 1993 and 2019 under local pricing. Figure D.2 shows that the results are broadly similar to those under uniform pricing: smaller counties experience larger declines in risk premia, primarily driven by greater diversification among banks. As in the uniform case, most of the reduction in risk stems from changes along the extensive margin—i.e., bank entry and exit—as shown in Panels C and D. Markups, in turn, exhibit only modest variation across the county distribution. Unlike the uniform-pricing case, however, markups for the smallest counties increase by as much as 5%.

FIGURE D.2. Changes in (log) Spreads, 1993-2019, by County - Local Pricing



Notes: Following the decomposition in Equation (32), Panel (A) shows changes in the markup and risk premium components of deposit spreads between 1993 and 2019 by county income decile, under the local-pricing specification. Blue dots represent changes in risk premia, while red dots indicate changes in markups. Panel (B) further decomposes the change in risk premia into contributions from diversification gains, as defined in Equation (33). Panel (C), based on Equation (34), separates the contributions of the extensive margin—i.e., bank entry and exit—from those of surviving incumbents. Panel (D) provides a more detailed breakdown of the extensive margin, isolating the roles of out-of-state entrants and exiters. Units are log points $\times 100$.

D.3. *Decomposition of Changes in Aggregate Spreads - Shares*

Table 6 in the main text presents an aggregate decomposition of the change in deposit spreads between 1993 and 2019, separating the contributions from changes in markups and risk premia. Appendix Table D.1 expresses these contributions as shares of the total observed change in spreads over the period. Since deposit spreads declined during this time, positive (negative) values indicate components that contributed to lowering (raising) spreads.

TABLE D.1. Share of Total Change in Spreads

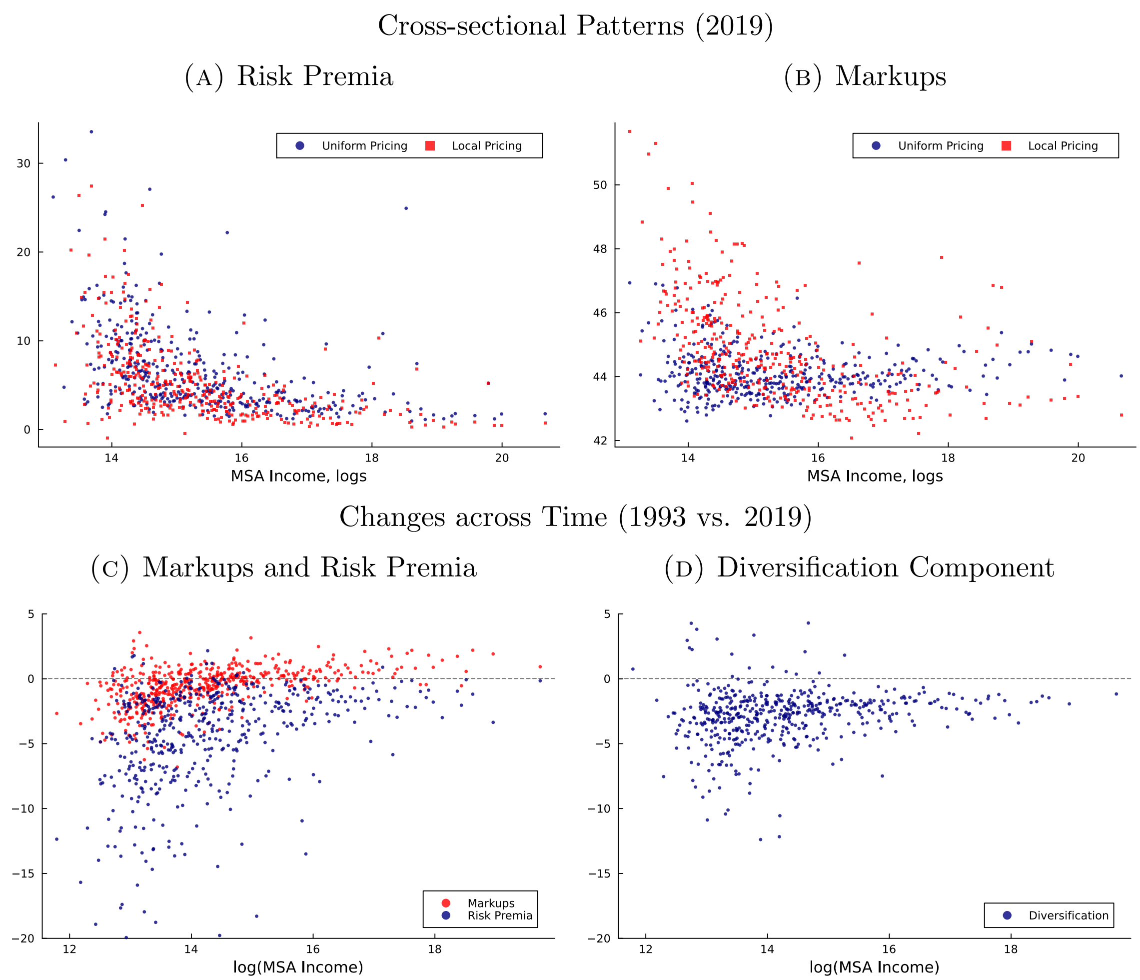
	Uniform pricing				**Local Pricing**			
	Risk Premium		Markup	Net	Risk Premium		Markup	Net
	Total	Diver			Total	Diver		
National Level								
Aggregate	6.9%	8.5%	-4.8%	2.1%	6.6%	7.4%	-5.5%	1.1%
Aggregate (fixed shares)	11.2%	9.0%	-2.4%	8.8%	11.6%	8.8%	-1.4%	10.2%
By Group of Counties								
Small Counties (<p10)	74.1%	19.3%	19.0%	93.0%	59.8%	26.1%	3.6%	63.4%
Medium Counties	32.3%	16.6%	6.2%	38.4%	29.1%	18.9%	2.5%	31.6%
Large Counties (>p90)	7.7%	9.1%	-3.2%	4.5%	8.6%	7.5%	-0.4%	8.2%

Notes: The table decomposes the change in log aggregate spreads, $\ln(R - R^D) \times 100$, from 1993 to 2019 into markup and risk premium components, using Equation (35). The row labeled 'fixed s_i shares' holds county weights fixed at their 1993 levels. The 'Diver' column reports the portion of the risk premium change attributable to diversification. The last three rows present results by county income groups: small (bottom 10th percentile), medium (45th-55th percentiles), and large (top 10th percentile). Each component is expressed as a share of the total change in spreads. Since spreads declined over this period, positive (negative) values indicate a contribution to reducing (increasing) spreads.

D.4. *Alternative Definition of Local Markets: MSA Regions*

In this section, we consider an alternative definition of a local market. While our baseline analysis defines markets at the county level, we now repeat the analysis using Metropolitan Statistical Areas (MSAs) as the unit of local markets. All baseline results remain robust under this alternative market definition. Panels A and B of Figure D.3 show cross-sectional patterns for risk premia and markups in 2019. Panels C and D show a decomposition of changes in deposit spreads between 1993 and 2019.

FIGURE D.3. Contributions of Risk Premia and Markups to (log) Spreads, MSA-level Analysis



Notes: Based on the decomposition in Equation (31), Panels (A) and (B) display the markup and risk premium components of deposit spreads by MSA income in 2019. Blue dots represent results under uniform pricing, while red squares correspond to the local-pricing case. Using Equation (32), Panel (C) shows changes in markups and risk premia between 1993 and 2019 across MSA income deciles under uniform pricing. Blue dots show model-implied changes in risk premia, while red dots indicate changes in markups. Panel (D) further decomposes the change in risk premia into contributions from diversification gains, as defined in Equation (33). Units are log points $\times 100$.

D.5. *On the Role of Online Banking and Central Booking*

In our baseline analysis, we include all banks reporting deposit holdings in the SOD dataset. However, some of these institutions may operate primarily online, making the geographic location of their branches less relevant for assessing regional risk and market concentration. For example, banks like Ally Bank serve customers nationwide despite having limited physical branch networks. Nonetheless, research covering our period of analysis indicates that, despite the growing relevance of online banking, households continued to rely heavily on physical branches. In the 2000s and 2010s, for instance, the number of branches declined only slightly (Amel et al., 2008; Anenberg et al., 2018; Sakong and Zentefis, 2023). A 2019 FDIC survey reported that approximately 83% of banked households had visited a bank branch in the past 12 months, and that local banking—i.e., through tellers or ATMs—remained the primary access point during 2015-2019.[59]

A second concern is that some banks may not report deposit holdings at the branch level consistently, instead aggregating all deposits under a single branch—a practice known as *central booking*. This can distort the measurement of local deposit concentration and geographic risk exposure.

In this section, we refine our sample to exclude banks likely to fall into these categories. First, we exclude counties where the ratio of deposits to total income is more than 10 times the 99th percentile. Second, within the top 1% of banks by total deposits, we exclude those that report over 99% of their deposits in a single county. In 2019, approximately 15% of total deposits meet either of these criteria. In contrast, this share was less than 5% in the early 1990s, pointing to a growing prevalence of either online banking or central booking over time.

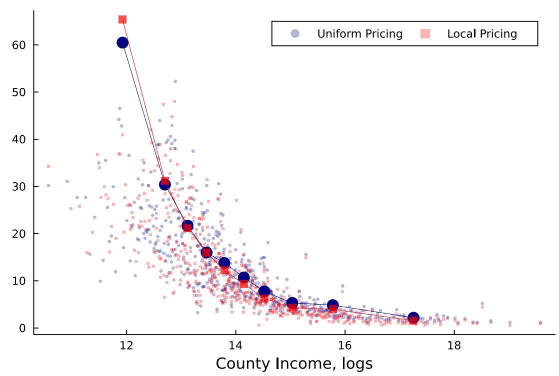
Figure D.4 presents a decomposition of deposit spreads after excluding banks that appear to rely on online operations or central booking. Our baseline findings remain robust to these adjustments.

[59]See https://www.fdic.gov/analysis/household-survey/2019/index.html.

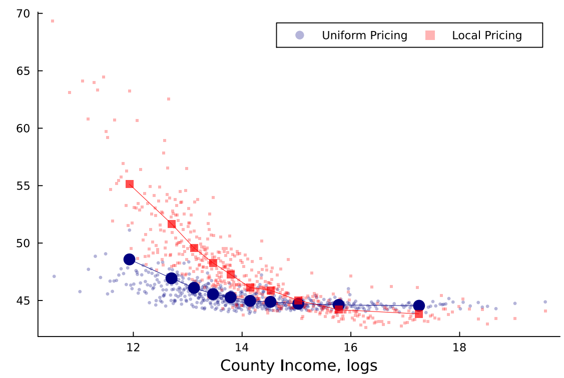
Figure D.4. Contributions of Risk Premia and Markups to (log) Spreads, Excluding Online Banks and Banks with Central Booking Practice

Cross-sectional Patterns (2019)

(A) Risk Premia

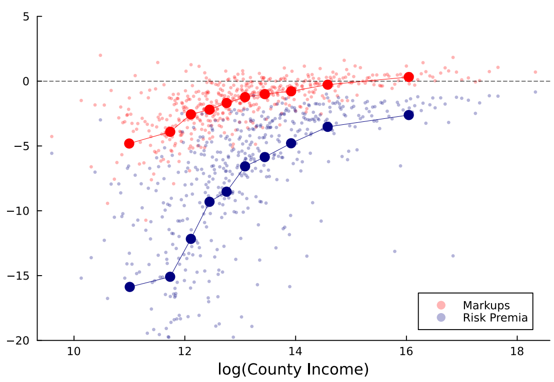


(B) Markups

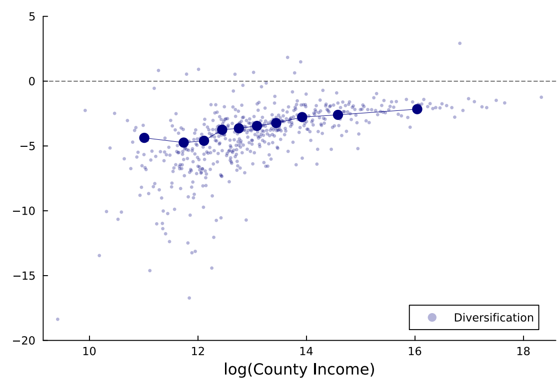


Changes across Time (1993 vs. 2019)

(C) Markups and Risk Premia



(D) Diversification Component



Notes: Panels (A) and (B) display the markup and risk premium components of deposit spreads by county income in 2019. Blue dots represent results under uniform pricing, while red squares correspond to the local-pricing case. Using Equation (32), Panel (C) shows changes in markups and risk premia between 1993 and 2019 across county income deciles under uniform pricing. Blue (red) dots show changes in risk premia (markups). Panel (D) further decomposes the change in risk premia into contributions from diversification gains, as defined in Equation (33). Data is adjusted to exclude online banks and banks employing central booking practices. Units are log points ×100.

D.6. *Additional Figures and Tables for the Counterfactual Analysis*

In this section, we provide additional results for our counterfactual analysis. We start by considering additional exercises for the uniform pricing case. Then, we show how the counterfactuals reported in the main text change under local pricing.

Under a uniform-pricing assumption, in Table D.2, we examine the impact of a 1 pp increase in k_j for local, regional, and national banks. We find that when local banks experience higher costs, small counties see a notable reduction in risk premia, as market shares shift toward more diversified regional and national banks. In contrast, higher costs for larger banks lead to increased risk premia, amplifying the initial cost shock. Second, we study how changes in households' relative preferences across bank types affect deposit spreads and risk premia by reducing the relative demand shifter (ψ_{ij}) for each bank type separately. In all cases, we re-normalize ψ_{ij} so that $\sum_j \psi_{ijt}^{\eta} = 1$. When households' preferences shift away from local banks, regional and national banks gain market share, resulting in lower risk premia, particularly in small and medium-sized counties.

Table D.2. Additional Counterfactuals: Cost and Demand Shocks

	Δ Deposit Spreads			Risk Premia			Markups		
	Small	Medium	Large	Small	Medium	Large	Small	Medium	Large
A. Increase in k_{ij}									
A.1 Local banks	57.23	26.00	6.84	-23.12	-5.57	-0.61	0.10	0.03	0.52
A.2 Regional banks	14.86	17.24	9.00	2.37	1.11	-0.05	0.60	0.42	0.51
A.3 National banks	9.14	15.84	39.34	5.49	4.13	1.51	0.16	0.44	-0.51
B. Decrease in ψ_{ij}									
B.1 Local banks	1.72	3.01	1.65	-4.24	-4.15	-0.58	0.82	0.28	0.67
B.2 Regional banks	2.00	1.85	1.95	4.44	2.73	0.06	0.94	0.80	0.74
B.3 National banks	0.84	0.78	-1.71	1.58	3.85	3.78	0.21	0.67	-0.57

Notes: The table reports log changes in deposit spreads, risk premia, and markups under uniform pricing for two additional counterfactuals, relative to the baseline results for 2019. Columns present average changes across three county groups—small, medium, and large—classified by total income. Panel A considers an increase in the cost parameter k_j, applied separately to local, regional, and national banks. Panel B varies the bank-county demand shifter ψ_{ij} by bank type to reflect changes in households' relative preferences. Units are log points $\times 100$.

Table D.3 presents the same set of counterfactuals as in the main text, but under the local-pricing specification. In this case, and specifically for the M&A counterfactuals, we take a different approach by assuming that the acquiring bank inherits the non-interest cost structure of the acquired branch (i.e., its k_{ij}), rather than holding fixed the acquirer's cost parameter k_j as under uniform pricing. As a result, we observe a *decline* in deposit spreads following M&A exercises where the acquiring bank is either a top regional or top national institution. Aside from this difference, the risk premia channel—the key object of our study—remains similar in magnitude to that described in the main text.

Table D.3. Counterfactuals under Local Pricing

	Δ Deposit Spreads			Risk Premia			Markups		
	Small	Medium	Large	Small	Medium	Large	Small	Medium	Large
A. Higher curvature									
Increase χ_i	3.45	1.28	0.33	3.93	1.49	0.36	-0.00	-0.01	0.00
B. M&A, acquired bank: 1-location bank									
Acquirer bank:									
B.1 Top local bank	2.81	0.81	-0.04	-1.17	0.08	0.08	1.17	0.44	0.04
B.2 Top regional bank	-5.24	-1.16	-0.03	-4.29	-0.38	0.02	0.82	0.43	0.02
B.3 Top national bank	-12.37	-2.95	0.28	-14.18	-1.81	0.09	1.93	0.68	0.07
C. M&A, acquired bank: 2-location bank									
Acquirer bank:									
C.1 Top local bank	6.74	2.47	0.02	-2.56	0.46	0.23	3.12	1.20	0.13
C.2 Top regional bank	-5.62	-1.12	0.12	-6.98	-0.23	0.18	2.00	1.26	0.11
C.3 Top national bank	-25.10	-5.37	0.34	-36.07	-4.22	-0.07	4.09	1.93	0.20
D. Changes in demographics									
D.1 Increase μ_i	-9.30	-3.36	-0.00	-9.03	-3.18	-0.04	0.04	0.02	-0.00
D.2 Increase σ_i / μ_i	0.84	0.49	3.51	0.84	0.48	2.85	-0.00	-0.00	0.02

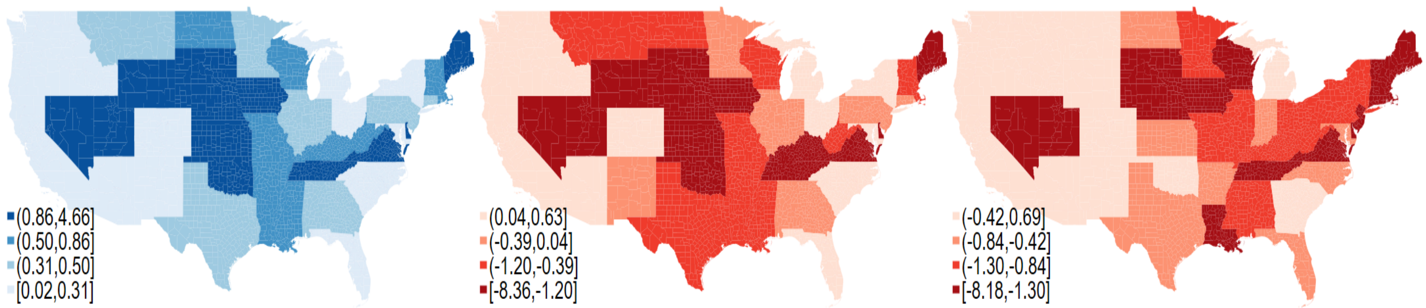
Notes: The table reports log changes in deposit spreads, risk premia, and markups relative to the 2019 baseline. Columns display average changes for three groups of counties—small, medium, and large—classified by total income. Panel A shows the effect of increasing the curvature parameter χ in banks' profit functions. Panels B and C report outcomes under different merger and acquisition scenarios (see main text for details). Panel D examines the impact of demographic shifts. All results correspond to the local-pricing specification. Units are log points $\times 100$.

We also examine changes in local lending under local pricing. We begin with the counterfactual scenario in which banks' curvature parameter χ increases (Panel A of Figure D.5). Despite the different pricing protocol, the effects are broadly consistent with those in the main text. Next, we consider the M&A counterfactual in which local banks—defined as those operating in a single county—are acquired by the largest regional banks (Panel B of Figure D.5). The overall patterns closely mirror those observed under uniform pricing.

Figure D.5. Changes in Lending and Deposit Spreads under Local Pricing

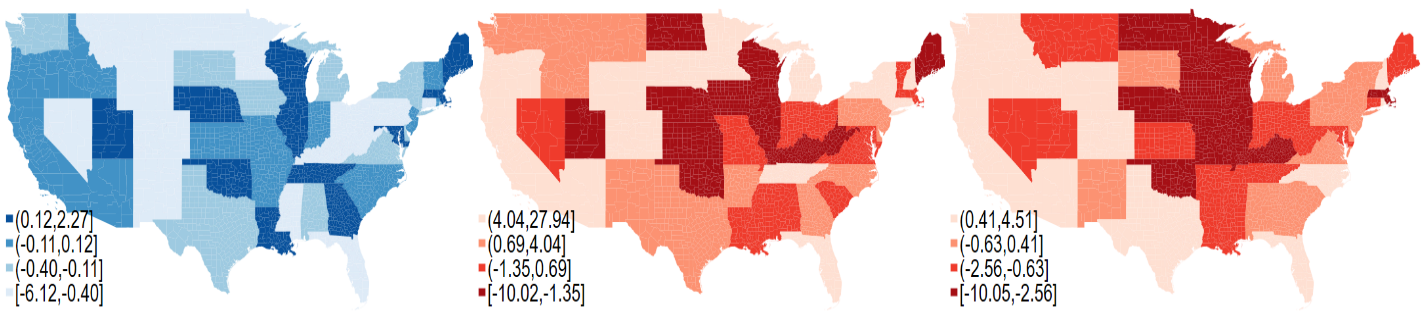
(A) Higher Bank Curvature

Δ Deposit Spreads Δ Deposits Δ Loans



(B) Mergers and Acquisition

Δ Deposit Spreads Δ Loans, Total Δ Loans, Reallocation



Notes: The maps display state-level changes in deposit spreads (under local pricing) and lending for two counterfactual experiments. Panel (A) shows the effects of an increase in the curvature parameter χ. The left panel shows changes in deposit spreads, the middle panel shows change in expected deposits, and the right panel shows changes in loans. Panel (B) presents results from an M&A scenario in which top regional banks acquire banks operating in a single market. The left panel displays changes in deposit spreads following the mergers, the middle panel shows the total change in lending, and the right panel isolates the portion attributable to the "reallocation channel." Units are log points $\times 100$.

D.7. *Estimating Elasticity of Substitution with Cash*

This section provides details on the procedure used to estimate the reduced-form elasticity of the cash-to-deposits ratio, M_t/D_t, with respect to the net rate of return, $R_t - 1$. This elasticity is used in Section 8.1 as a target to calibrate the structural elasticity parameter ε. To estimate the reduced-form elasticity, we run an IV regression of $\Delta \ln(M_t/D_t)$ onto $\Delta \ln(R_t - 1)$, using monetary policy shocks as an instrument for the latter.

Data on households' holdings of cash and deposits are obtained from the Board of Governors' Financial Accounts of the United States (Z.1). We define cash as "Checkable deposits and currency" (FL153020005), and deposits as "Total time and savings deposits" (FL153030005),

Table D.4. Elasticity of Cash-to-deposits with Respect to R_t

	(1)	(2)	(3)	(4)
$\Delta \ln\widehat{(R_t - 1)}$	-1.38^{***}	-1.08^{***}	-1.66^{**}	-1.59^{**}
	(0.27)	(0.30)	(0.71)	(0.73)
Shock	JK	PC1	JK	PC1
Exclude GFC	Yes	Yes	No	No
Controls	Yes	Yes	Yes	Yes
F-stat (1st stage)	15.44	11.64	13.73	8.88
Observations	24	24	30	30

Notes: The table reports estimates of the elasticity of the cash-to-deposits ratio with respect to R_t, using annual data from 1990 to 2019. Columns 1 and 2 exclude the 2008-2013 period. "PC1" refers to the first principal component of surprises in interest rate derivatives with maturities from 1 month to 1 year (MP1, FF4, ED2, ED3, ED4). "JK" denotes the monetary policy shock series adjusted to exclude news components around FOMC announcements, as in Jarociński and Karadi (2020). Standard errors are robust to heteroskedasticity.

both from the "Households and nonprofit organizations" sector.[60] We consider two measures of the monetary policy shock FF_t, both constructed by Jarociński and Karadi (2020).[61] The first measure ("PC1") is the first principal component of surprises in interest rate derivatives with maturities ranging from 1 month to 1 year (MP1, FF4, ED2, ED3, ED4). The second measure ("JK") adjusts the surprise to remove any *news* component present during FOMC announcements. All data are aggregated to yearly frequency.

The exclusion restriction is that changes in $R_t - 1$ induced by these shocks are not systematically related to households' preferences for cash relative to deposits (i.e., to the share parameter ζ). The two-stage IV regression is:

$$\Delta \ln(R_t - 1) = \beta_0^R + \beta_1^R FF_{t-k} + \boldsymbol{\beta}'\mathbf{X}_t + \epsilon_t^R, \tag{D.1}$$

$$\Delta \ln\left(\frac{M_t}{D_t}\right) = \gamma_0^M + \gamma_1^M \Delta \ln\widehat{(R_t - 1)} + \boldsymbol{\gamma}'\mathbf{X}_t + u_t^M. \tag{D.2}$$

where FF_{t-k} is the monetary policy shock and X_t is a vector of controls (specifically, the lagged values of both dependent variables). The coefficient of interest is γ_1^M, which captures how instrumented changes in $\ln(R_t - 1)$ translate into changes in $\ln(M_t/D_t)$.

Table D.4 reports the estimates for γ_1^M across various specifications for the period 1990-2019. The first two columns exclude the Great Financial Crisis period (2008-2013), while the last two use the full sample. The point estimates are both economically and statistically significant

[60]Note that this aggregate is not the same as the model-implie aggregate D_t. Accordingly, for the purposes of calibration, we construct the same object in the model by summing up deposits.
[61]Data source: https://github.com/marekjarocinski/jkshocks_update_fed.

across all specifications, ranging from -1.1 to -1.6. Standard errors are heteroskedasticity-robust, and F-statistics confirm the relevance of the instruments. While not shown, the first-stage estimates for β_1^R are also positive and statistically significant. We adopt a target reduced-form elasticity of -1.3, approximately the midpoint of the range of estimates in the table.