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

Deposits are the primary savings vehicle for households and the main source of funding for banks. As the largest retail financial market in the U.S., deposit markets exhibit substantial heterogeneity across local markets. In some locations, households are served mainly by small local banks; in others, they interact with large institutions operating nationwide branch networks. These differences shape both local competition and banks' funding-cost structure, generating systematic dispersion in deposit rates across banks and across locations. Understanding the aggregate implications of these patterns requires accounting for several intertwined forces, from market power and competition to differences in exposure to local funding shocks.

In this paper, we employ a structural approach to gain a deeper understanding of this heterogeneity and its implications. Building on spatial models in macro and trade, we formulate a general-equilibrium model with heterogeneous banks operating across multiple deposit markets. In the model, location-specific shocks create funding risk for banks, raising their effective cost of funds.[1] Our theory yields an intuitive pricing equation linking deposit rates to competition, operating costs, and geographic funding risk. We take this expression to the data and quantify the role of these forces.

We begin by documenting a number of salient facts about deposit rates in the cross-section. One basic pattern is that rates are higher, on average, in smaller counties. This pattern is not driven by higher concentration in small markets: if anything, market concentration *declines* with county size. Instead, it reflects systematic differences in the composition of banks across locations: smaller counties are served disproportionately by small institutions, which tend to offer higher deposit rates.

Next, we show that larger banks tend to have higher market shares, despite offering lower deposit rates. This suggests that the deposit services of large banks hold greater *appeal* for customers. In this sense, large banks offer higher *effective* (i.e. appeal-adjusted) rates. We argue that market power pushes in the opposite direction: in many models of imperfect competition (including the one in this paper), markups increase with market share, which would

[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). The model also allows for idiosyncratic risk in lending returns, but we find little interaction with deposit pricing, the key object of our interest.

lead larger banks to post lower effective rates.[2] The market share patterns instead point to a cost advantage: larger banks provide value to depositors at lower effective cost. We provide suggestive evidence that funding risk contributes to this advantage: expansions in geographic scope are associated with more stable deposit inflows and higher interest rates.

These facts are informative but do not, on their own, identify the relative importance of the forces shaping deposit rates. This motivates our approach: we calibrate a rich structural model to match these patterns and use it to quantify the drivers of deposit rates in the cross-section. We model deposit demand in an oligopolistic framework with imperfect substitution across banks and locations. Demand is subject to county-level shocks, creating idiosyncratic funding risk. Curvature in bank payoffs makes this risk costly. In the baseline specification, curvature arises from a combination of loan commitments and frictions in *ex-post* funding markets, though we show that our results hold even with other sources of curvature (e.g. diminishing returns to lending, risk aversion, and/or regulatory constraints).

How banks set deposit rates across markets is debated in the literature. A number of papers (Radecki, 1998; Heitfield and Prager, 2004; Granja and Paixao, 2021; Begenau and Stafford, 2025) 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. Rather than take a stand, our framework nests both uniform pricing—where banks post a common rate across locations—and local pricing—where rates vary by market. The key economic forces we highlight, and in particular the role of geographical funding risk in deposit pricing, operate similarly under both pricing protocols.

The key novel implication of our theory is that banks' effective marginal cost of providing deposits includes a risk premium. This premium depends on the volatility of deposit inflows across the locations in which a bank operates, which is shaped by the covariance structure of county-level shocks. Under uniform pricing, there is a single bank-level risk premium. *Ceteris paribus*, a less geographically diversified bank has a larger risk premium and therefore, charges a higher spread. Under local pricing, the risk premium is bank- and county-specific: the more positively a county's shock covaries with those of other counties in which the bank operates,

[2]The estimates from our structural analysis – consistent with the findings of (such as d'Avernas et al., 2023) – point to modestly higher markups for larger banks.

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 average deposit rates on time and saving deposits from bank financial statements. Our calibration strategy has two steps. First, we estimate deposit demand elasticities of substitution within and across markets and recover bank-level preference shifters and county-level demand shocks. Second, we use the covariance structure of these shocks, together with exogenous variation in banks' geographic exposure, to discipline the curvature in banks' payoffs—that is, the price of funding risk.

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 0.50 log points—equivalent to nearly a 60% 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 0.10 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 0.35 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.

We next analyze how the contributions of risk premia and markups to deposit spreads have evolved over time, focusing on the period from 1993 to 2019. We find that banks' geographic expansion has exerted substantial downward pressure on deposit spreads, particularly in the smallest and poorest counties. In these locations, spreads fell by almost 20 percent as funding risk declined, driven by diversification-induced reductions in risk premia operating through

extensive-margin expansion via entry of large out-of-state banks. In the aggregate, however, the decline in risk premia lowered deposit spreads by only 3 percent, because most deposits in larger counties are held at large banks that were already geographically diversified in the 1990s. Lastly, we show that, despite a rise in national concentration, changes in markups were more modest across all locations.

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.[3] 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: they decline under uniform pricing 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' 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

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

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. First, 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).[4] We differ from these papers in our explicit modeling of the market for deposits and by endogenizing how geographic diversification shapes banks' effective marginal cost of deposit funding through exposure to idiosyncratic risk, while taking location choices as given. In contrast to recent work emphasizing depositor preferences in explaining deposit pricing (e.g., d'Avernas et al. (2023)), we focus on a distinct cost-side channel and quantify the contribution of funding risk premia to deposit spreads in both the cross-section and over time.

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

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

deregulation induced large US banks to expand into markets that were relatively abundant in deposits relative to lending opportunities.[5] 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. (2016a), 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. (2022) 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, 2024), 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.

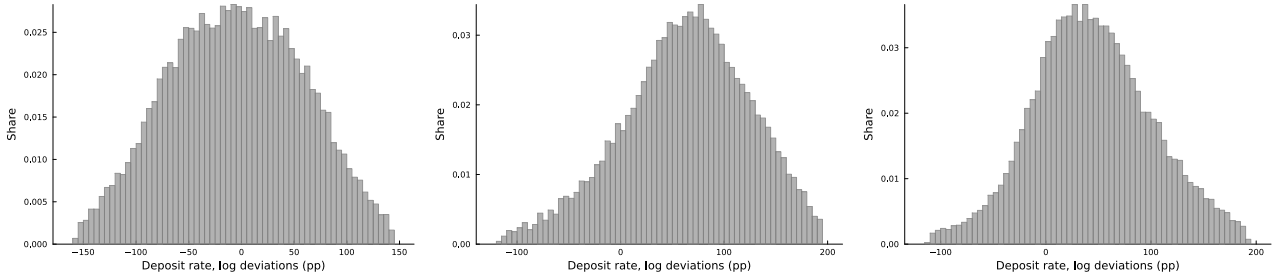
2 Motivating Facts

In this section, we present a number of facts that motivate the structural model and analysis. We begin by documenting dispersion in deposit rates across US markets. We focus on interest rates offered by banks on certificates of deposits (CDs) and money market accounts. We use two main sources. Data on deposit rates (at the branch level) come from RateWatch and on deposits from the Summary of Deposits provided by the FDIC. For each local market, defined as a county, we average rates across branches of a given bank to obtain rates at the bank-county level. These are then aggregated to the county level (using deposit shares of banks as weights) and bank level (again with deposits at the bank-county level as weights).

[5] 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. Dispersion in Deposit Rates

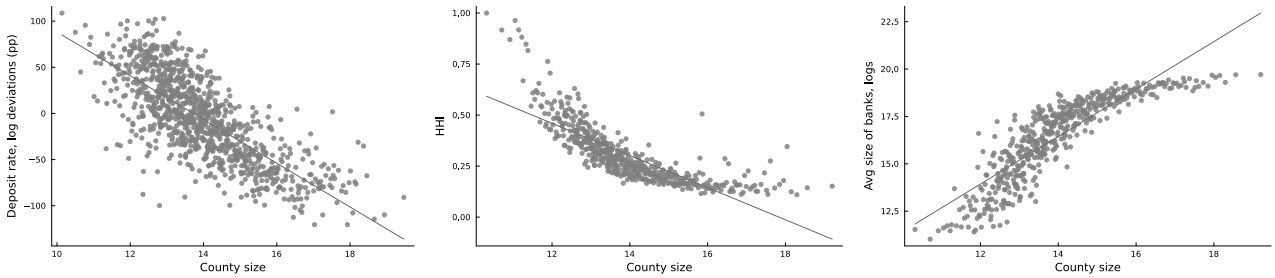
(A) Across counties (B) Across banks (C) Across banks, within county



Notes: The panels plot the histogram of deposit rates (in logs, net of a year fixed effect) across counties (Panel A), banks (Panel B) and banks within a county (Panel C). See main text and Appendix A for definitions and data sources.

FIGURE 2. Deposit Markets and County Size

(A) Deposit Rates (B) Concentration (C) Size of banks



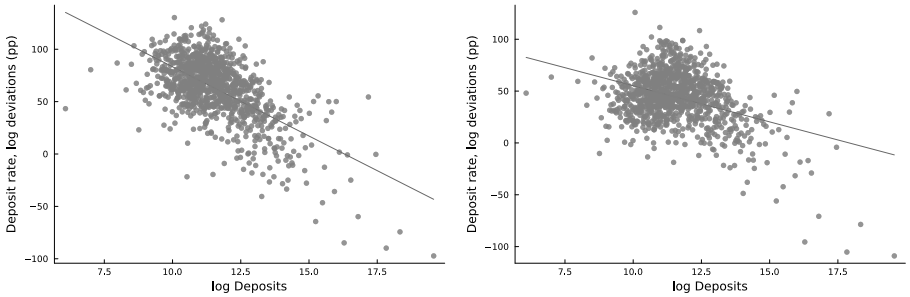
Notes: The panels show a bin-scatter plot of county size (log total income) versus log deposit rates (net of year fixed effects), concentration (measured by HHI) and average bank size (measured by total deposits in 2011).

Panel A of Figure 1 plots the histogram of these rates (residualized with year fixed effects) for 2011-2019. It shows considerable variation, with a standard deviation of 63 pp. The other two panels of Figure 1 plot the dispersion of deposit rates across banks, both overall (Panel B) and within county (Panel C), also showing considerable variation (63 pp and 61 pp standard deviation, respectively).

Next, we relate the variation in deposit rates to county- and bank- characteristics, starting with size. Panel (A) of Figure 2 depicts a bin scatter of deposit rates (in deviations) against county size (measured by total income in 2011). It shows a clear negative relationship, with a gap of almost 150 bps between the largest and smallest counties. Panel (B) suggests that this pattern is unlikely to be driven by lower competition: larger counties exhibit *lower* levels of market concentration (measured by the Herfindahl-Hirschman Index of deposits).

FIGURE 3. Deposit Rates and Bank Size

(A) Across banks (B) Across banks, within county



Notes: The left panel shows the relationship between bank size (measured by total deposits in 2011) and the average bank-level deposit rate (net of year fixed effects). The right panel shows the same relation but with a county-year fixed effect. Data are from RateWatch for 2011-2019 (see Appendix A for details).

Panel (C) highlights systematic differences between large and small counties in the types of banks operate that in them. In particular, larger counties tend be served by relatively bigger banks. To connect this to deposit rates, Figure 3 depicts the relationship between bank size (measured by total deposits) and deposit rates.[6] Panel (A) shows that larger banks tend to offer lower rates on average, a pattern which also holds within-county; see Panel (B).

Taken together, these facts paint a nuanced view of the US deposit market: smaller, poorer counties are disproportionately served by smaller banks, who tend to offer higher rates. In larger counties, big banks, who tend to pay lower rates on their deposits, have a more prominent role.

To capture relative preferences over banks, we formalize a notion of *relative appeal* at the bank-county level.[7] To measure appeal, we first define the deposit spread, $R_t - R^D_{ijt}$, where R_t is a benchmark rate of return (from an asset without liquidity benefits) and R^D_{ijt} the deposit rate offered by bank j in county i.[8] This spread is the effective 'price' of liquidity services from that bank and $(R_t - R^D_{ijt})D_{ijt}$ the associated 'spending'. Our appeal measure is given by:

$$\log(\text{Relative Appeal})_{ijt} = \frac{1}{\eta - 1}\log(\text{Relative Spending})_{ijt} + \log(\text{Relative Spread})_{ijt}, \qquad (1)$$

where $(\text{Relative Spending})_{ijt}$ and $(\text{Relative Spread})_{ijt}$ express spending and spreads of bank j in county i relative to the corresponding county averages and η is the elasticity of substitution.[9]

[6]The patterns are similar if size was measured by total assets instead.

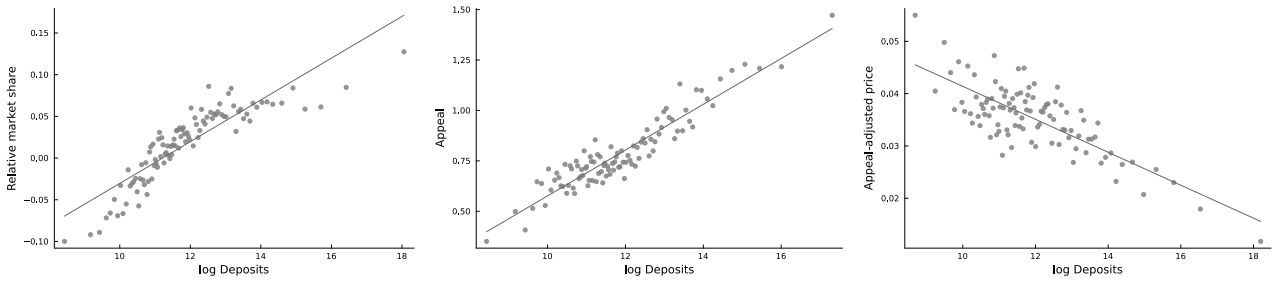
[7]Product appeal is an important source of heterogeneity in non-financial contexts (see, for instance, Hottman et al. (2016b) and He et al. (2025)). For banking, d'Avernas et al. (2023) provide evidence of heterogeneity in the preferences for liquidity services of banks of different sizes.

[8]We use the 5Y High Quality Market Corporate Bond Spot Rate as our measure of R_t; see Section 4 for details.

[9]This measure is based on the structural model in the following section and implicitly imposes a constant

FIGURE 4. Bank Size and Appeal

(A) Market Share (B) Relative Appeal (C) Appeal-adjusted Spreads



Notes: Panel (A) reports a bank-level, within-county measure of market share, defined as $\sum_{i \in \mathcal{M}_{jt}} \omega_{ijt} \frac{D_{ijt} - D_{it}}{D_{it}}$, where $\mathcal{M}_{jt}$ denotes the set of counties in which bank j operates at time t and ω_{ijt} is the fraction of bank j's total deposits accounted for by county i. Panel (B) displays our measure of relative appeal, defined in Equation (1), after aggregating to the bank level using ω_{ijt} weights. Panel (C) reports bank-level appeal-adjusted spreads, defined as $\sum_{i \in \mathcal{M}_{jt}} \omega_{ijt} \frac{R_t - R^D_{ijt}}{\text{Appeal}_{ijt}}$. All figures are based on 2019 data.

Equation (1) formalizes a simple intuition: for a given spread, higher spending indicates a relative preference for that bank. Conversely, for two banks with the same relative spending, the one with the higher relative spread holds higher appeal for depositors.

In the data, despite offering lower rates (i.e. higher spreads), large banks see *higher* relative spending, as shown in Panel (A) of Figure 4. This suggests that consumers have a strong relative preference for deposit services from larger banks—see Panel (B), which plots the implied relative appeal against size. This could stem from convenience, service quality, branch access, reliability, or overall customer experience. It may also reflect differences in perceived safety. For example, after the failure of Silicon Valley Bank in 2023, depositors demonstrated a clear preference for larger banks.

Panel (C) depicts appeal-adjusted spreads, defined as $\frac{R_t - R^D_{ijt}}{\text{Relative Appeal}_{ijt}}$, aggregated to the bank level and plotted against bank size. It reveals that the appeal advantage of larger banks more than offsets the increasing pattern of spreads shown in Figure 3: adjusting for appeal, spreads *decline* with bank size. In this sense, larger banks are more efficient at delivering deposit-related liquidity services to customers.

A central contribution of this paper is to explore one source of this efficiency: a cost advantage due to lower deposit flow variability. Larger banks operate in more locations and are thus more

elasticity of substitution. Formally $(\text{Relative Spread})_{ijt} \equiv \frac{R - R^D_{ijt}}{\frac{1}{N_i} \sum_{j'} R - R^D_{ij't}}$, where N_i is the number of banks operating in county i. The definition is analogous for $(\text{Relative Spending})_{ijt}$.

TABLE 1. Locations, Deposit Variability, and Spreads

	Deposit Volatility		**Deposit Spreads**	
	$\lvert\Delta \log D_{jt}\rvert$		$\log(R - R^D_{jt})$	
Num Locations	-0.137	-0.277	-0.078	-0.067
	(0.043)	(0.107)	(0.009)	(0.035)
Year FE	Yes	Yes	Yes	Yes
Bank FE	No	Yes	Yes	Yes
Observations	210,128	210,128	237,563	53,079
Period	1991-2019		1991–2019	2011-2019
Dataset	Call Reports		Call Reports	Ratewatch

Notes: The table reports the relationship between the number of locations and both deposit volatility and deposit spreads. We estimate $y_{jt} = \gamma_j + \gamma_t + \beta \widetilde{N}_{jt} + \epsilon_{jt}$, where $\widetilde{N}_{jt}$ denotes the bank's year-standardized number of locations, $\widetilde{N}_{jt} = \left(N_{jt} - \overline{N}_t\right)/\sigma_t$. The dependent variable y_{jt} in columns (1)–(2) is the absolute log change in bank-level deposits, and the dependent variable in columns (3)–(4) is the log deposit spread. Standard errors are clustered at the bank level.

diversified against idiosyncratic shocks to deposit supply. This stability reduces their overall costs, enabling them to offer more competitive rates.

Table 1 presents suggestive evidence in favor of this hypothesis. In the first two columns, we regress the absolute log change in bank-level deposits on the number of counties in which a bank operates, controlling for fixed effects. The coefficient is negative and statistically significant: banks with a wider geographical footprint experience more stable deposits. In particular, a bank with one-standard deviation more locations than the average bank in that year exhibits roughly 14% lower deposit volatility. This result is not driven by time-invariant cross-sectional differences in bank characteristics. Within a given bank, as it expands into more locations, its deposit volatility also declines. The last two columns provide complementary evidence that this lower volatility is priced: when a bank operates in one-standard deviation more locations than the average bank in that year, its deposit spreads are 6-8% lower.

3 The Model

We lay out an equilibrium model of heterogeneous banks (indexed by j) operating across multiple deposit markets (counties, indexed by $i \in [0, 1]$). Banks raise funds through deposits that provide liquidity services, as well as other illiquid liabilities (e.g., wholesale funding). These funds are invested in loans and securities. For simplicity, we treat all transactions as intra-period, which allows us to work with a static environment.

Each county is served by a finite number of banks, and each bank operates only in a finite subset of counties. Counties are subject to idiosyncratic shocks to deposit supply. Since a bank operates only in a subset of counties, it is exposed to idiosyncratic risk.

Formally, bank j operates in a finite set of counties $\mathcal{I}_j$. Let Λ_j denote the measure over counties, so that $\Lambda_j(i) = 1$ if $i \in \mathcal{I}_j$ and 0 otherwise. Throughout the paper, we take $\mathcal{I}_j$ as exogenous and given. In our quantitative analysis, this is taken directly from the data.

We assume that banks set interest rates for 'groups' of counties. Specifically, the set of counties bank j operates in, $\mathcal{I}_j$, is partitioned into disjoint subsets, indexed by $g = 1, 2, ...G_j$. The bank chooses an interest rate for each group, $\{R^D_{gj}\}_{g=1}^{G_j}$ with $R^D_{ij} = R^D_{gj}$ if i is in group g. Let Λ_{gj} denote the g-specific measure, so that $\Lambda_{gj}(i) = 1$ if i is in group g for bank j and 0 otherwise. This structure 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, 2025). As with the set $\mathcal{I}_j$, throughout our analysis, we take this partition as exogenous. In our quantitative analysis, we analyze two polar cases: local pricing (where the bank sets a distinct rate in each county) and uniform pricing (where it posts a single rate across all counties).

The bank acts as an oligopolist at the county level, internalizing its effect on county-level variables, but takes as given all economy-wide quantities. Demand is assumed to be subject to shocks, the source of idiosyncratic risk. It turns out to more useful to model demand as a function of deposit spreads, $R - R^D_{gj}$, where R denotes the return on an illiquid asset. This spread is the price paid by the depositor for liquidity services. We denote $\mathcal{D}_{ij}\left(R - R^D_{i,j}\right)$ to be the residual demand function faced by bank j in county i, with $\mathcal{D}'_{ij} < 0$.

Let $\Pi_j(D_j)$ denote the bank's profits as a function of realized total deposits $D_j \equiv \int_0^1 \mathcal{D}_{ij} d\Lambda_j(i)$. Note that Π_j denotes profits after accounting for the (potentially stochastic and heterogeneous) returns and costs associated with lending, wholesale funding, and interbank borrowing. At this stage, we make no assumptions about their structure.[10]

The bank's optimal deposit rate vector $\{R^D_{gj}\}_{g=1}^{G_j}$ solves

$$\max_{\{R-R^D_{gj}\}_{g=1}^{G_j}} \mathbb{E}\left[\Pi_j\left(\int_0^1 \mathcal{D}_{ij}\left(R - R^D_{ij}\right) d\Lambda_j(i)\right) - \int_0^1 \left(R^D_{ij} + \kappa_{ij}\right) \mathcal{D}_{ij}\left(R - R^D_{ij}\right) d\Lambda_j(i)\right], \quad (2)$$

[10]Expressing profits as a function of total deposits implicitly assumes that deposits are fungible at the bank-level, i.e. money raised through deposits can be moved across locations costlessly.

s.t. $R_{ij}^D = R_{gj}^D$ if i is in group g, and where κ_{ij} captures non-interest costs of raising deposits. The optimal spread is (see Appendix C.2):

$$R - R_{gj}^D = \frac{\vartheta_{gj}}{\vartheta_{gj} - 1} \left[\kappa_{gj} + R - \mathbb{E}\left(\Pi'_j\right) - \mathbb{C}ov\left(\Pi'_j \ , \ \frac{\mathcal{D}'_{gj}}{\mathbb{E}\left[\mathcal{D}'_{gj}\right]} \right) \right], \tag{3}$$

where $\mathcal{D}'_{gj} \equiv \int_0^1 \mathcal{D}'_{ij} \, d\Lambda_{gj}(i)$ and $\vartheta_{gj} \equiv -\left(R - R_{gj}^D\right) \frac{\mathbb{E}\left(\mathcal{D}'_{gj}\right)}{\mathbb{E}\left(\mathcal{D}_{gj}\right)}$ denote the slope and expected elasticity of the deposit demand at the group level.

Equation (3) expresses the optimal deposit spread as a markup times the effective marginal cost. The markup, $MKP_{gj} \equiv \frac{\vartheta_{gj}}{\vartheta_{gj}-1}$, decreases with the expected demand elasticity. The cost has three components. The first is the group-level average non-interest cost, $\kappa_{gj} \equiv \int_0^1 \omega_{igj}^s \, \kappa_{ij} \, d\Lambda_{gj}(i)$, where the weights depends on the expected slope of demand, $\omega_{igj}^s \equiv \frac{\mathbb{E}[\mathcal{D}'_{ij}]}{\mathbb{E}[\mathcal{D}'_{gj}]}$. The second component is the gap between R and the expected return, $\mathbb{E}\left(\Pi'_j\right)$. *Ceteris paribus*, the higher the expected marginal value for deposit funds relative to R, the lower are spreads.

The third component behind the effective cost of deposits captures deposit risk. This term is given by the covariance between the slope of group-level deposit demand and the marginal return on funds. Intuitively, if funds are more valuable when the group-level demand curve is relatively steep, then the group is an attractive funding source and the bank charges a smaller spread. This is a central insight: under uncertainty, deposit spreads fall when demand for deposits covaries positively with the marginal returns.

In the next section, we express Equation (3) in terms of observables and take it to the data. This will require imposing more structure on (i) deposit demand, (ii) other funding sources and lending returns, and (iii) the timing of banks' decisions.

3.1 Households, Deposit Demand and Markups

The economy has a representative household, endowed with $\overline{W}$ units of consumption goods. These funds can be invested in three assets: bank equity, 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 structure: The first level

aggregates D_{ij} to construct a county-level composite D_i while the second level then combines D_i into an economy-wide aggregate D. Formally:

$$D = \left(\int_0^1 \phi_i D_i^{\frac{\theta-1}{\theta}} di \right)^{\frac{\theta}{\theta-1}} \quad \text{and} \quad D_i = \left(\sum_{j \in \mathcal{J}_i} \psi_{ij} D_{ij}^{\frac{\eta-1}{\eta}} \right)^{\frac{\eta}{\eta-1}}, \tag{4}$$

where $\mathcal{I}_i$ denotes the finite set of banks operating in location i. The parameter $\theta > 1$ is the elasticity of substitution across county-level deposits, while $\eta > 1$ captures the substitutability across services provided by banks within a county.[11] We assume $\eta > \theta$, meaning that deposits at different banks within the same county are more substitutable than those across counties.[12] The variable ϕ_i is the household's relative preference for deposits in county i and captures factors that affect county-level demand for deposits (e.g. income, or economic conditions). Our empirical strategy, described in Section 4, recovers these preference shifters from the data. Lastly, ψ_{ij} denotes *appeal*: the relative preference for bank j within a given county.

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

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

where E denotes aggregate bank equity (exogenous), R_{ij}^D and R are as defined above and $\overline{\Pi}$ denotes aggregate bank profits. All non-deposit assets (i.e., wholesale funding and interbank lending) are assumed to earn an exogenous rate of return R. Optimality implies:

$$\frac{R - R_{ij}^D}{R - R_i^D} = \psi_{ij} \left(\frac{D_{ij}}{D_i} \right)^{-\frac{1}{\eta}} \quad \text{where} \quad R - R_i^D = \left(\sum_{j \in \mathcal{J}_i} \psi_{ij}^{\eta} \left(R - R_{ij}^D \right)^{1-\eta} \right)^{\frac{1}{1-\eta}}, \tag{5}$$

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

[11] These preferences can be micro-founded with a discrete choice problem where the value of bank deposits is drawn from a correlated Gumbel distribution with θ and η governing the similarity of draws across and within markets, respectively (Verboven, 1996; Berger et al., 2022). For details, see Appendix C.1.

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

From these equations, we have that the demand elasticity for bank j in county i is

$$\vartheta_{ij} \equiv -\left(R - R_{ij}^D\right) \frac{\mathbb{E}\left(\mathcal{D}'_{ij}\right)}{\mathbb{E}\left(\mathcal{D}_{ij}\right)} = \eta(1 - s_{ij}) + s_{ij}\theta, \qquad \text{where} \tag{7}$$

$$s_{ij} \equiv \frac{(R - R_{ij}^D)D_{ij}}{(R - R_i^D)D_i} = \psi_{ij}^{\eta} \frac{(R - R_{ij}^D)^{1-\eta}}{(R - R_i^D)^{1-\eta}} \in (0, 1) \tag{8}$$

denotes the market share (or, more precisely, the expenditure share) of bank j in county i. [13] This in turn implies that the group-level elasticities and markups are

$$\vartheta_{gj} = \eta\left(1 - s_{gj}\right) + \theta s_{gj} \qquad \text{and} \qquad MKP_{gj} = \frac{\eta\left(1 - s_{gj}\right) + \theta s_{gj}}{\eta\left(1 - s_{gj}\right) + \theta s_{gj} - 1}, \tag{9}$$

where $s_{gj} \equiv \int_0^1 \omega_{igj}^s s_{ij} d\Lambda_{gj}(i)$ is the bank's (weighted) average market share in the group.

The markup term is analogous to that of Atkeson and Burstein (2008): the elasticity of deposit demand is a weighted average of the within-county and across-county elasticity parameters (η and θ, respectively). The assumption $\eta > \theta > 1$ implies that markups are increasing in (group-level) market share, s_{gj}.[14]

3.2 Lending, Sources of Funding, and Timing of Choices

We next characterize the bank's profit function, $\Pi_j(\cdot)$. First, on the assets side we assume a linear lending technology with returns $R + z_j$, where z_j is a bank-specific stochastic spread. For instance, this is consistent with a large, economy-wide market for assets but with heterogeneity across banks in skill or information, resulting in a bank-specific spread. The linearity in returns makes the distinction between assets (e.g. loans vs securities) not relevant, so we economize on notation and refer to all assets as loans. In Section 7, we analyze a richer asset structure with securities and lending across local markets.

Second, on the liabilities side, banks have three sources of funding in addition to deposits. Wholesale funding, H_j, is available in a competitive economy-wide market where the household's supply of funds is perfectly elastic at R. Bank j faces issuance costs $\frac{\nu_j}{2} H_j^2$, so the marginal cost

[13] Re-arranging (8) and taking logs yields $\log \psi_{ij}^{\frac{\eta}{\eta-1}} = \frac{1}{\eta-1} \log s_{ij} + \log \frac{R - R_{ij}^D}{R - R_i^D}$. Expressed relative to the county-average is the theoretical foundation for the definition of relative appeal in Equation (1) in Section 2.

[14] When $s_{gj} > 0$, the bank has an effect on county-level aggregates, which changes the effective demand elasticity. As $s_{gj} \to 0$, the markup becomes $\frac{\eta}{\eta-1}$, the monopolistic competition limit.

of funds is $R + \nu_j H_j$. Bank j also receives equity financing, E_j, which we treat as exogenous—an innocuous choice given the absence of financial or agency frictions.[15] Lastly, there is a competitive lending market that opens after all the shocks have been realized. This can be interpreted as an interbank market, and is subject to costs $\frac{\chi_j}{2} B_j^2$ where B_j is borrowing by bank j.[16] For simplicity, we assume that the household also participates in this market with a supply curve that is perfectly elastic at R.[17] This implies that bank j's marginal cost of borrowing in this market is $R + \chi_j B_j$.

Finally, we describe the timing of various decisions. Banks first choose deposit rates $\{R_{gj}^D\}$ (or equivalently, spreads $\{R - R_{gj}^D\}$), 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 this stage (but their joint distribution is known). Shocks are then realized, and the household chooses $\{D_{ij}\}$. Banks cannot adjust their loans at this stage. Any funding mismatch is cleared through the interbank market, $B_j = L_j - E_j - H_j - \int_0^1 D_{ij} \mathrm{d}\Lambda_j(i)$.

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

$$\Pi_j(D_j) = (R + z_j) L_j^* - \left(R + \frac{\nu_j}{2} H_j^*\right) H_j^* - \left(R + \frac{\chi_j}{2} B_j\right) B_j, \tag{10}$$

$$\text{where} \qquad B_j = L_j^* - H_j^* - E_j - D_j,$$

and L_j^* and H_j^* denote the optimal (ex-ante) choices of loans and wholesale funding. We show in Appendix C that the marginal return is given by

$$\Pi_j'(D_j) = R + \mathbb{E}[z_j] - \chi_j (D_j - \mathbb{E}[D_j]), \tag{11}$$

that is, funds are less valuable when total deposits are high. Thus, the combination of loan commitments and costs of *ex-post* borrowing ($\chi_j > 0$) create curvature in bank payoffs and therefore, aversion to deposit risk. Intuitively, more uncertain deposit demand increases the expected activity in the costly *ex-post* market, which raises effective marginal costs.

[15] It is straightforward to endogenize equity subject to issuance costs. This has no effect on our results.

[16] 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 captures market frictions, such as credit risk and/or agency/information costs.

[17] This could reflect, for example, non-bank intermediaries, which have become increasingly important participants in interbank markets.

3.3 Optimal Deposit Pricing

Substituting Equations (9) and (11) into (3), we obtain the following expression for optimal deposit spreads (see Appendix C for the full derivation):

$$R - R^D_{gj} = \frac{\eta(1-s_{gj}) + \theta s_{gj}}{\eta(1-s_{gj}) + \theta s_{gj} - 1}\Big[\kappa_{gj} - \mathbb{E}\left(z_j\right) + \chi_j \mathbb{E}(D_j)\Gamma_{gj}\Big], \tag{12}$$

where Γ_{gj} denotes group-level exposure to geographic funding risk, defined as the weighted average of county-level risk, Γ_{ij}, across all locations whose deposits are priced at the rate R^D_{gj}.[18] That is:

$$\Gamma_{gj} = \int_0^1 \tilde{\omega}^g_{ij}\,\Gamma_{ij}\,d\Lambda_{gj}(i) \quad \text{with} \quad \Gamma_{ij} \equiv \int_0^1 \omega_{kj} Cov\left(\frac{\phi^\theta_i}{\mathbb{E}[\phi^\theta_k]}\,,\,\frac{\phi^\theta_k}{\mathbb{E}[\phi^\theta_k]}\right) d\Lambda_j(k). \tag{13}$$

The risk of county i, Γ_{ij}, is the average covariance of its deposit demand shocks with all the counties bank j operates in, weighted by deposit shares, $\omega_{kj} \equiv \frac{\mathbb{E}\left(D_{kj}\right)\Lambda_j(k)}{\int_0^1 \mathbb{E}(D_{ij})d\Lambda_j(i)}$. In other words, a county is risky for a bank if its deposit demand co-varies positively with the bank-level deposit demand—recall from (11) that the marginal return of funds declines with total deposits. Higher risk thus increases the overall cost of deposits from the county, pushing spreads for the corresponding group higher. The more geographically diversified a bank, the lower are risk exposures and, therefore, the overall costs of deposit funding and equilibrium spreads. In what follows, we define the (group-level) deposit risk premium $RP_{gj} \equiv \chi_j \mathbb{E}(\mathcal{D}_j)\Gamma_{gj}$ as the product of the quantity of risk, $\mathbb{E}(\mathcal{D}_j)\Gamma_{gj}$, and the price of risk, χ_j.

We conclude this section with two brief observations. The first relates to the robustness of Equation (12) and the second to implications of deposit risk beyond deposit spreads.

Alternative Sources of Curvature. The curvature in banks' profits in our baseline structure comes from *ex-ante* loan commitments and frictions in interbank lending markets. However, other sources of curvature also lead to optimal spreads that are very similar to those in Equation (12). We illustrate this using an alternative specification where curvature stems from diminishing returns in lending.[19] Suppose now that banks make loan decisions after shocks are

[18] The weight is given by : $\tilde{\omega}^g_{ij} \equiv \frac{\mathbb{E}(D_{ij})\,\vartheta_{ij}\Lambda_{gj}(i)}{\int_0^1 \mathbb{E}(D_{ij})\,\vartheta_{ij}\,d\Lambda_{gj}(i)}$ where $\vartheta_{ij} \equiv \eta(1-s_{ij}) + \theta s_{ij}$.

[19] Other sources of curvature, e.g. risk aversion (see Appendix C.4.2) and costly equity issuance or capital requirements, as in Bolton et al. (2020) also produce broadly similar results.

realized but with returns given by $R + z_j - \frac{\chi_j}{2} L_j$. The parameter $\chi_j > 0$ indexes the degree of diminishing returns. For simplicity, we abstract from *ex-post* borrowing and lending.[20]

The timing is as follows. First, banks choose R_{ij}^D and wholesale funding H_j. Second, shocks are realized, and households choose $\{D_{ij}\}$. Third, banks make and collect on loans L_j (which now depend on the realized shocks). The marginal profit on deposits is (see Appendix C.4):

$$\Pi_j'(D_j) = R + z_j - \chi_j(D_j - \mathbb{E}[D_j]) - \chi_j \mathbb{E}[L_j] \,. \tag{14}$$

Relative to equation (11), there are two differences. First, $\Pi_j'(\cdot)$ now depends on the realized loan return, z_j (instead of its expectation). Second, diminishing returns in lending introduce a size penalty, $\chi_j \mathbb{E}[L_j]$. The optimal deposit spread is given by (see Appendix C.4)

$$R - R_{gj}^D = \frac{\eta(1 - s_{gj}) + \theta s_{gj}}{\eta(1 - s_{gj}) + \theta s_{gj} - 1} \left[\kappa_{gj} - \mathbb{E}(z_j) + \chi_j \mathbb{E}(D_j)\Gamma_{gj} + \chi_j \mathbb{E}[L_j] - \Gamma_{gj}^z\right], \tag{15}$$

where $\Gamma_{gj}^z \equiv \int_0^1 \tilde{\omega}_{ij} \mathbb{C}ov\left(z_j, \frac{\phi_i^\theta}{\mathbb{E}[\phi_i^\theta]}\right) d\Lambda_{gj}(i)$ is the weighted average covariance between lending returns and deposit demand shocks. Equation (15) mirrors (12), but adds two terms. The first, $\chi_j \mathbb{E}[L_j]$, is the size penalty: as the bank grows, marginal returns fall, so it optimally offers a lower deposit rate. The second term, Γ_{gj}^z, reflects the effect of lending return risk. Intuitively, if deposit demand in a market tends to be high when returns are also high, the bank optimally sets a lower spread in that market.[21]

Implications for lending. While our focus in this paper is on the pricing of deposits, it is worth pointing out that funding risk premia do not just affect depositors. By raising the overall cost of funding, they also induce reductions in credit supply. Such reductions are particularly significant for smaller, less diversified banks who rely mostly on deposit financing. In Section 7, we use an extended version of the model with multiple assets (including 'local' loans and securities) to explore the effects of risk premia on lending across markets.

4 Mapping the Model to the Data

The model lends itself to a transparent empirical implementation. This section describes the data used and the estimation strategy for key parameters: elasticities of substitution, curvature, appeal ψ_{ij}, and demand shocks ϕ_i.

[20] Allowing for costly *ex-post* trading leads to a composite curvature parameter, a function of both diminishing returns in lending and *ex-post* costs, but otherwise does not change the main conclusions.

[21] As we will see, these new terms will turn to be quite modest quantitatively, so the spread decomposition in this version turns out to be almost identical to the baseline version.

4.1 Data Sources

For deposits, we use the annual Summary of Deposits (SOD) which lists deposits held at each branch as of June 30 for all FDIC-insured institutions. The SOD covers all U.S. states, encompassing over 86,000 branches as of 2019. For bank-level variables—including loans, deposits, total assets, and liabilities—we use Call Reports, which contain balance sheet information for the universe of US banks.

Deposit rates are obtained from two sources: RateWatch and Call Reports. RateWatch collects branch-level deposit rates through surveys covering a range of products, including savings accounts and time deposits. The data are available at weekly frequency for 2011-2019. Coverage is extensive for this period, with responding branches accounting for roughly 80% of domestic deposits.[22] We construct weighted average deposit rates across products (certificates of deposit and savings accounts) using bank-level deposit balances from Call Reports as weights.[23] We treat a county as the relevant local market and aggregate RateWatch rates to the bank–county–year level using branch-level deposits as weights.[24]

The second source is the Call Reports. We compute bank-level deposit rates as the ratio of interest expenses on savings and time deposits to the corresponding deposit balances. For both the RateWatch- and Call-Report-based measures, we use the 5-Year High Quality Market (HQM) Corporate Bond Spot Rate as our benchmark illiquid rate R.[25]

4.2 Empirical Strategy

Our empirical strategy proceeds in various steps. Though our model is static, we use a time subscript t to highlight parameters that are assumed to vary from year to year. We begin by estimating the elasticities of substitution within and across counties (η and θ), assumed to be constant throughout our sample. Given these elasticities, the model equations directly recover

[22]RateWatch data are available prior to 2011, but with substantially lower coverage. For example, in 2001 the survey covered only 16% of SOD branches (see Begenau and Stafford, 2025).

[23]Products include 12-, 24-, and 60-month certificates of deposits (12MCD10K, 24MCD10K, and 60MCD10K) and money market accounts (MM25K). Time-deposit rates are weighted using balances with remaining maturity below one year, one to three years, and above three years; money market rates are weighted using savings account balances.

[24]Appendix D.4 shows robustness to defining local markets at the MSA level, while Appendix D.5 shows robustness to excluding observations potentially affected by online banking or central booking practices.

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

the appeal shifters, $\{\psi_{ijt}\}$, and county-level shocks, $\{\phi_{it}\}$ for each $\{i, j, t\}$. The recovered shocks are used to estimate a covariance matrix, which then allows us to construct risk premia. Finally, we estimate the curvature parameters, $\{\chi_j\}$, and back out $\{\kappa_{ijt}, \mathbb{E}z_{jt}\}_{\forall\{i,j,t\}}$.

We present results under two assumptions about how banks partition counties while setting rates. In the first, termed *uniform pricing*, each bank posts a single rate across all its markets. Under *local pricing*, it sets a different rate for each market. Our main results are broadly similar under both protocols. Data on deposit rates indicate an intermediate case, but point to uniform pricing as a natural starting point. A bank-year fixed effect explains more than 90% of the variation in deposit spreads.[26] While not a direct test, this is consistent with a high degree of uniformity. The uniform pricing case also has better coverage: the bank-level Call Reports data (which maps naturally to the uniform pricing case) covers all banks and for a longer period (1990-2019) whereas bank-county level RateWatch data has much lower coverage prior to 2011.

Elasticities of Substitution

To estimate η, the within-county substitution elasticity, we take log differences of (5):

$$\Delta \log D_{ijt} = \Delta \log D_{it} + \eta \Delta \log \left(R_t - R_{it}^D\right) - \eta \Delta \log \left(R_t - R_{ijt}^D\right) + \eta \Delta \log \psi_{ijt}. \tag{16}$$

There are two identification challenges. First, equilibrium deposit spreads may co-move with unobserved appeal ψ_{ijt}. Second, under oligopoly, changes in spreads, even if induced by a bank-specific shock, will induce equilibrium responses in county-level spreads and quantities.[27] If these equilibrium responses are not correctly accounted for, even an otherwise valid instrument can deliver a biased reduced-form estimate of η (see Berger et al., 2022). Note that the market aggregates D_{it} and R_{it} depend on η, so controlling for them directly is not feasible.

Our approach addresses these concerns jointly. Equation (16) suggests the following regression specification:

$$\Delta \log D_{ijt} = \gamma_{it} - \eta \Delta \log \left(R_t - R_{ijt}^D\right) + \epsilon_{ijt}, \tag{17}$$

where γ_{it} are county-year fixed effects and the error term ϵ_{ijt} captures changes in ψ_{ijt}. We instrument $\Delta \log \left(R_t - R_{ijt}^D\right)$ with marginal cost shifters that are plausibly orthogonal to county–bank appeal. Following the literature on estimating deposit demand functions (Ho and Ishii, 2011;

[26] We restrict the sample to banks active in more than 100 counties to ensure this pattern is not driven by those operating in only a few markets.

[27] This includes both responses by competitors as the direct effect of the bank's spread on market averages.

Egan et al., 2017; Wang et al., 2022), we use the ratio of the sum of bank-level wage bill and non-interest expenses to fixed assets as our IV, denoted by $\mathcal{K}_{jt}$.

The county-year fixed effects play a key role: they absorb all county-level variation deposits and spreads, including shifts in county demand and competitors' equilibrium responses. Identification therefore comes from within-county changes across banks in a given year.[28]

Equations (18) and (19) describe our two-stage procedure. In the first stage, we regress changes in bank-county-level spreads on the cost IV. In the second stage, we regress changes in bank-county-level deposits on the instrumented changes in spreads. The identifying assumption is that changes in $\mathcal{K}_{jt}$ reflect shifts in the cost of providing deposit services (in particular, κ_{gjt}) but, after controlling for county-time fixed effects, they are orthogonal to variation in appeal.

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

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

The coefficient of interest is β^D, which maps directly into the within-county substitution elasticity (i.e., $\eta = -\beta^D$). Results are shown in columns (1)–(3) of Panel (A) in Table 2. Our preferred specifications in columns (2) and (3) yield a within-county elasticity of substitution close to 3. Column (1) omits county–time fixed effects. Without these fixed effects, the estimates are smaller in magnitude, since variation in relative spreads partly reflects county-level equilibrium movements—including competitors' responses—so the estimate captures not only within-county substitution across banks (η) but also substitution across counties (θ).

One concern with the strategy is that changes in $\mathcal{K}_{jt}$ may co-move with the appeal of a bank's deposit products—e.g., a bank might adjust its spending in response to changes in customer preferences or tastes – violating the identifying assumption. To address this concern, we repeat the analysis with an alternate IV: a Bartik-style average change in the relative wages of bank tellers across locations where a bank operates. This uses variation in local labor-market conditions rather than bank-level spending.[29] Working with *relative* teller wages—i.e., the (log) wages of bank tellers less the average wage across all occupations—removes the effect of county income. The identifying assumption is that changes in local tellers' wages shift a bank's cost

[28] Felix (2022) and Deb et al. (2024) also include market-time fixed effects to estimate substitution elasticities in labor markets. Berger et al. (2022) do not use fixed effects but use an indirect inference approach, relying on a structural model to recover η from reduced-form estimates.

[29] Dick (2008) follows a similar strategy but uses local wages across all occupations.

TABLE 2. Estimated Demand Elasticities

Panel A. Estimation of η

	(1)	(2)	(3)	(4)
$\widehat{\Delta \ln R_{ijt}}$	-3.05	-3.62	-3.70	-2.64
	(1.39)	(1.46)	(0.54)	(1.47)
Year FE	Yes	-	-	-
Bank-county FE	Yes	Yes	Yes	Yes
County-year FE	No	Yes	Yes	Yes
County Type	All	All	≥ 5 banks	≥ 5 banks
Observations	173,932	172,845	152,884	70,202
1st stage F-stat	270.10	186.23	186.23	21.56

Panel B. Estimation of θ

	(1)	(2)
$\widehat{\Delta \ln R_{it}}$	-1.86	-1.68
	(0.97)	(0.73)
Time FE	Yes	Yes
County FE	Yes	Yes
County Type	All	≥ 5 banks
Observations	21,850	15,077
1st stage F-stat	12.93	23.33

Notes: Panel A presents the estimates for the elasticity of substitution, η. Columns (1)-(3) are based on the $\mathcal{K}_{jt}$ instrument. In column (3), we condition on counties with more than five banks in a given year (the first stage regression is the same as in column 2). Column (4) shows the results for the $\mathcal{K}_{ijt}^{\text{Tellers}}$ instrument. Standard errors are clustered at the bank level. Panel B shows the estimates for θ, based on the $\mathcal{K}_{it}^{\text{Tellers}}$ instrument. Standard errors are clustered at the county level.

of providing deposit services but do not alter its appeal. To limit confounding effects from county-level changes, we use a leave-one-out approach: the IV for a given bank-county pair is constructed excluding the county itself, that is, a weighted average of the teller relative wage changes in all the other counties the bank operates in.[30] Formally,

$$\mathcal{K}_{ijt}^{\text{Tellers}} \equiv \sum_{k \in \mathcal{I}_{j0},\, k \neq i} \left(\Delta \ln \text{Wage}_{kt}^{\text{Tellers}} - \Delta \ln \text{Wage}_{kt}^{\text{All Occup}} \right) \times \frac{D_{kj0}}{D_{j0}}$$

where $\text{Wage}^{\text{Tellers}}$ denotes MSA-level wages for bank tellers, and $\text{Wage}^{\text{All Occup}}$ refers to the average wage across all occupations within the same MSA.[31] The results, shown in column (4) of Panel (A), are consistent with those previously reported, though slightly smaller.

To estimate the cross-county elasticity of substitution, θ, we follow a similar approach. We first use the estimated η to compute the county-level aggregates (see next section for details). We then construct a Bartik-style instrument that aggregates the $\mathcal{K}_{jt}$ cost shifters to the county level. For each county i we define $\mathcal{K}_{it} \equiv \sum_{j \in i} \tilde{s}_{ij0}\, \mathcal{K}_{jt}$, where $\tilde{s}_{ij0}$ denotes county-level market shares in the base year.[32] The identifying assumption is that the weighted exposure of county i to bank-level cost shocks is orthogonal to county-level demand shocks, ϕ_{it}. This is particularly plausible in counties where many large banks operate, as their costs are likely driven by

[30] We also have county-year fixed effects as an additional control for correlated shocks.

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

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

conditions outside the county. Equations (20)-(21) describe our two-stage regression.

$$\Delta \ln(R - R^D_{it}) = \gamma^R_i + \gamma^R_t + \alpha^R \mathcal{K}_{it} + \epsilon^R_{it}, \tag{20}$$

$$\Delta \ln D_{it} = \gamma^D_i + \gamma^D_t + \alpha^D \Delta \widehat{\ln(R - R^D_{it})} + \epsilon^D_{it}. \tag{21}$$

Under our CES demand system, the coefficient α^D maps directly into the cross-county elasticity, θ. The results, presented in Panel B of Table 2, yield an estimate for θ of approximately 2. This is consistent with the assumption that deposits are less substitutable across counties than across banks within a county.

Recovering Appeal and Demand Shocks

Given the estimated elasticities η and θ, we can use data on spreads and deposits to recover appeal $\{\psi_{ijt}\}_{\forall\{i,j,t\}}$ and the county-level shocks $\{\phi_{it}\}_{\forall\{i,t\}}$. Equation (5) can be re-arranged to obtain *relative* appeal for any two banks $\{j, j'\}$ operating in county i:

$$\frac{\psi_{ijt}}{\psi_{ij't}} = \frac{\left(R - R^D_{ijt}\right) D_{ijt}^{\frac{1}{\eta}}}{\left(R - R^D_{ij't}\right) D_{ij't}^{\frac{1}{\eta}}}. \tag{22}$$

Pinning down the ψ_{ijt} in absolute terms requires a normalization, so we assume $\sum_j \psi^\eta_{ijt} = 1$. This yields the following expression[33]

$$\psi^\eta_{ijt} = \frac{\left(R - R^D_{ijt}\right)^\eta D_{ijt}}{\sum_{j\in i}\left(R - R^D_{ijt}\right)^\eta D_{ijt}}. \tag{23}$$

Given $\{\psi_{ijt}\}$, equations (4)-(5) yield the county-level objects, $\left\{D_{it}, R - R^D_{it}\right\}_{\forall\{i,t\}}$. Then, using equations (4) and (6) we can recover county-level demand shocks $\{\phi_{it}\}_{\forall\{i,t\}}$:

$$\phi^\theta_{it} = \frac{\left(R - R^D_{it}\right)^\theta D_{it}}{\sum_i \left(R - R^D_{it}\right)^\theta D_{it}}. \tag{24}$$

As with appeal, this imposes a normalization, setting $\sum_i \phi^\theta_{it}\Lambda_i = 1$.[34] Table 3 summarizes the moments for $\{\psi_{ijt}\}$ and $\{\phi_{it}\}$.

[33]The normalization removes the effects of love for variety from the county-level $R - R^D_{it}$. For example, when all banks in the county offer the same spread, the normalization is an adjustment for the number of banks such that the county-level index equals the spread, regardless of the number of banks, i.e. $R - R^D_{it} = R - R^D_{ijt}$.

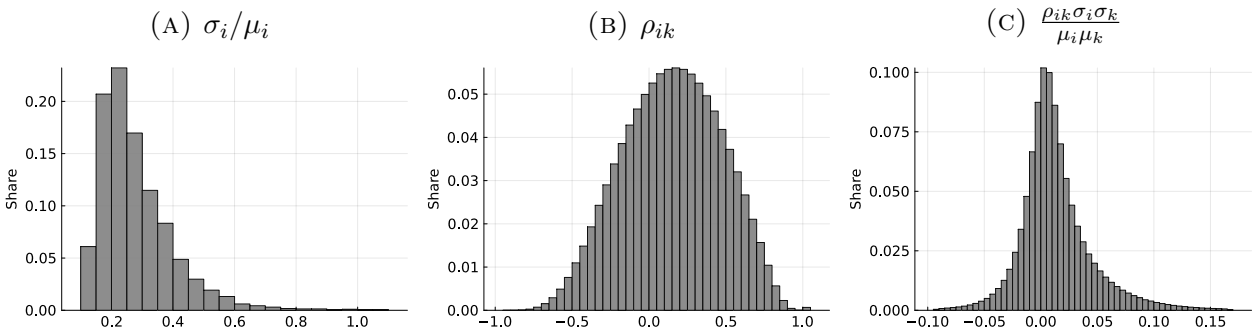
[34]Before imposing the normalization, we de-trend at the county level so that the estimated covariance matrix is not distorted by county-level trends. Using an aggregate trend produces similar results.

TABLE 3. Appeal and Demand Shocks: 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	0.98	0.70	-37.02
$k_{jt} - z_{jt}$ (pp)	Non-interest expenses (UP)	0.70	1.33	-24.21

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

FIGURE 5. Estimated Moments for the $\{\phi_{it}\}$ Distribution



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

We then estimate the covariance matrix using the recovered $\{\phi_{it}\}$. Let $\mu_i \equiv \mathbb{E}[\phi_i^\theta]$, $\sigma_i \equiv \text{StdDev}(\phi_i^\theta)$, and $\rho_{ik} \equiv \text{Corr}(\phi_i^\theta, \phi_k^\theta)$. It follows that $\text{Cov}\left(\frac{\phi_{it}^\theta}{\mu_i}, \frac{\phi_{kt}^\theta}{\mu_k}\right) = \frac{\rho_{ik}\sigma_i\sigma_k}{\mu_i\mu_k}$. Figure 5 summarizes these moments. Panel (A), which plots the distribution of the coefficient of variation, σ_i/μ_i, indicates a non-trivial amount of risk. The histogram of pairwise correlations in Panel (B) suggests an important role for geographical diversification.

Curvature in Payoffs

The final step of the calibration recovers the remaining parameters that govern effective marginal costs, namely $\{\chi_j\}_j$ and $\{\kappa_{ij}, \mathbb{E}z_{jt}\}_{i,j,t}$. In our baseline formulation, χ_j indexes frictions in the *ex-post* lending market, but as discussed earlier, it could also reflect diminishing returns in lending, risk aversion, or balance sheet frictions. [35] Rather than imposing a particular micro-foundation, we estimate χ_j by taking the model's optimal pricing equation to data on spreads. This approach has the advantage of being robust to different sources of curvature.

[35] See Appendix C for alternative micro-foundations that lead to the same expression for spreads as the baseline.

Under uniform pricing, where each bank posts a single rate across all its counties, equations (12)-(13) reduce to a single set of equations at the bank-level:

$$R_t - R_{jt}^D = \frac{\eta(1-s_{jt})+\theta s_{jt}}{\eta(1-s_{jt})+\theta s_j - 1}\left[\kappa_{jt} - \mathbb{E}\left(z_{jt}\right) + \chi_{jt}\mathbb{E}(D_{jt})\Gamma_{jt}\right], \tag{25}$$

$$\Gamma_{jt} \equiv \sum_{i\in\mathcal{I}_{jt}} \widetilde{\omega}_{ijt}\,\Gamma_{ijt} \quad \text{where} \quad \Gamma_{ijt} \equiv \sum_{k\in\mathcal{I}_{jt}} \omega_{kjt}\frac{\rho_{ik}\sigma_i\sigma_k}{\mu_i\mu_k}\ . \tag{26}$$

Equation (25) allows the curvature parameter to be time- and bank-specific. In practice, however, estimating χ_{jt} separately for every j and t is not feasible. Even at the bank level, the panel dimension of the data is thin.[36] We therefore need to impose some structure. Our baseline assumption is that χ_{jt} declines systematically with bank size, such that $\chi \equiv \chi_{jt}\mathbb{E}(D_{jt})$ is constant over time. [37] This assumption implies that differences across banks in the effect of risk on spreads are driven by differences in portfolio risk exposure (captured by Γ_{ijt}), rather than by heterogeneity in curvature.

Formally, for each bank in each year we construct an effective marginal cost, $MC_{jt} \equiv \frac{R-R_{jt}^D}{MKP_{jt}}$ where $MKP_{jt} = \frac{\eta(1-s_{jt})+\theta s_{jt}}{\eta(1-s_{jt})+\theta s_j - 1}$. From (25) above,

$$MC_{jt} = \kappa_{jt} - \mathbb{E}z_{jt} + \chi\,\Gamma_{jt}\ . \tag{27}$$

A challenge in directly estimating (27) is endogeneity: changes in the (unobserved) cost κ_{jt} can affect the deposit spreads and through that, the weights $\{\widetilde{\omega}_{ijt}, \omega_{ijt}\}_{i\in\mathcal{I}_{jt}}$ in Γ_{jt}. We therefore construct an instrument that captures variation in Γ_{jt} from changes in appeal ψ_{ijt}. Note that the deposit share weights ω_{ijt} can be written as:

$$\omega_{ijt} \equiv \frac{\mathbb{E}\left(\mathcal{D}_{ijt}\right)}{\sum_{k\in\mathcal{I}_{jt}}\mathbb{E}\left(\mathcal{D}_{kjt}\right)} = \frac{\psi_{ijt}^{\eta}\mathbb{E}\left(\mathcal{D}_{it}\right)\times\left(\frac{R-R_{it}^D}{R-R_{ijt}^D}\right)^{\eta}}{\sum_{k\in\mathcal{I}_{jt}}\psi_{kjt}^{\eta}\mathbb{E}\left(\mathcal{D}_{kt}\right)\times\left(\frac{R-R_{kt}^D}{R-R_{kjt}^D}\right)^{\eta}}. \tag{28}$$

The instrument is defined as follows for a bank's risk:

$$\Gamma_{ijt}^{IV} = \sum_{k\in\mathcal{I}_{j0}}\left(\frac{\psi_{kjt}^{\eta}\mathbb{E}\left(\mathcal{D}_{k0}\right)\left(\frac{R-R_{k0}^D}{R-R_{kj0}^D}\right)^{\eta}}{\sum_{k'\in\mathcal{I}_{j0}}\psi_{k'jt}^{\eta}\mathbb{E}\left(\mathcal{D}_{k'0}\right)\left(\frac{R-R_{k'0}^D}{R-R_{k'j0}^D}\right)^{\eta}}\right)\frac{\rho_{ik}\sigma_i\sigma_k}{\mu_i\mu_k}. \tag{29}$$

[36] Although the Call Reports span the whole sample, they contain only a short history for many banks due to entry, exit, and consolidation. The RateWatch data provide even less variation, with coverage beginning in 2011 and thus at most nine years for any bank–county pair.

[37] Appendix D.1 considers a more flexible specification that allows χ to vary across bank size bins. The results are broadly similar to the baseline.

Thus, the instrument is the relative risk exposure using contemporaneous demand shifters ψ_{ijt}, but the number of locations, spreads, and expected deposits are fixed at their base-year levels.[38] Since Γ_{ijt}^{IV} is a within-bank weighted average, it is unaffected by a common (i.e., bank-level) component in ψ_{kjt} drops out. To minimize the risk of endogeneity, we remove a county-year fixed effect. Our identifying assumption is that the residual variation is orthogonal to changes in costs.[39] We aggregate the residual to the bank level using base-period weights,

$$\Gamma_{jt}^{IV} \equiv \sum_{i \in \mathcal{I}_{j0}} \widetilde{\omega}_{ij0}\, \Gamma_{ijt}^{IV,Res}. \tag{30}$$

Using this instrument, we estimate χ via the following two-stage procedure:

$$\Delta\Gamma_{jt} = \gamma_j + \gamma_t + \zeta^{\Gamma}\, \Delta\Gamma_{jt}^{IV,Res} + \epsilon_{jt}^{\Gamma}, \tag{31}$$

$$\Delta MC_{jt} = \kappa_j + \kappa_t + \chi^{UP}\, \widehat{\Delta\Gamma_{jt}} + \epsilon_{jt}^{MC}. \tag{32}$$

Column (1) of Table 4 reports the baseline results. In Column (2), we residualize the instrument with a proxy of bank-level marginal costs constructed from accounting data with a trans-log estimation procedure following Berger et al. (2009) and Corbae and D'Erasmo (2022); see Appendix D.6 for details. This is particularly useful for banks operating in a relatively few number of locations or with a large fraction of their activity concentrated in a single county. The cost proxy helps remove correlated changes in costs and ψ_{ijt}. Across both specifications, we find a significant positive estimate of χ, consistent with banks pricing geographic volatility in their deposit portfolios.

We repeat the analysis under the assumption of local pricing. In this case, equations (12)–(13) apply at the bank–county level, so the group index g coincides with the county index i. The source of identification is similar to uniform pricing—changes in appeal at the bank-county level—but we can now directly use $\Gamma_{ijt}^{IV,Res}$ (without aggregating to bank–level). This allows us to exploit within bank–year variation and include bank–time fixed effects to absorb

[38] We restrict attention to banks operating in at least two counties.

[39] Formally, let $\psi_{ijt} = \psi_{jt}\, \psi_{it}\, \varepsilon_{ijt}^{\psi}$. The IV is unaffected by the ψ_{jt}, the bank-level component while the county-year fixed effect removes ψ_{it}. The identifying assumption (under uniform pricing) is that $\varepsilon_{ijt}^{\psi} \perp \Delta\kappa_{jt}$.

all bank–level movements in funding and operating costs. The two–stage specification is:

$$\Delta\Gamma_{ijt} = \gamma_{ij} + \gamma_{it} + \gamma_{jt} + \chi^{LP}\Gamma_{ijt}^{IV,Res} + \epsilon_{ijt}^{\Gamma}, \tag{33}$$

$$\Delta MC_{ijt} = \kappa_{ij}^{MC} + \kappa_{it}^{MC} + \kappa_{jt}^{MC} + \chi^{LP}\,\widehat{\Delta\Gamma_{ijt}} + \epsilon_{ijt}^{MC}. \tag{34}$$

Column (3) of Table 4 reports the estimates under local pricing. They are broadly similar to those in columns (1)-(2) albeit with somewhat larger standard errors, perhaps due to the use of a narrower source of variation (within-bank). Ultimately, both the bank-level and within-bank variation lead to very similar estimates for the price of risk.

Finally, column (4) presents estimates under another specification for the local pricing case based on county-level variation. We begin by expressing bank-county appeal as $\psi_{ijt} = \mathcal{V}_{it}\frac{(R-R_{ijt}^D)D_{ijt}^{\frac{1}{\eta}}}{\sum_j (R-R_{ijt}^D)D_{ijt}^{\frac{1}{\eta}}}$, where $\mathcal{V}_{it}$ is the normalization factor, that can be interpreted as variety or the effective number of banks in the county (see discussion following equation (22)). Our final instrument is designed to isolate the variation in appeal from changes in this factor. Formally, we use $\widetilde{\psi}_{ijt} \equiv \mathcal{V}_{it}\frac{(R-R_{ij0}^D)D_{ij0}^{\frac{1}{\eta}}}{\sum_j (R-R_{ij0}^D)D_{ij0}^{\frac{1}{\eta}}}$ in place of ψ_{ijt} in (29):

$$\widetilde{\Gamma_{ijt}^{IV}} = \sum_{k\in\mathcal{I}_{j0}} \left(\frac{\widetilde{\psi}_{kt}^{\eta}\mathbb{E}\left(\mathcal{D}_{k0}\right)\left(\frac{R-R_{k0}^D}{R-R_{kj0}^D}\right)^{\eta}}{\sum_{k'\in\mathcal{I}_{j0}}\widetilde{\psi}_{k't}^{\eta}1\mathbb{E}\left(\mathcal{D}_{k'0}\right)\left(\frac{R-R_{k'0}^D}{R-R_{k'j0}^D}\right)^{\eta}} \right) \frac{\rho_{ik}\sigma_i\sigma_k}{\mu_i\mu_k}. \tag{35}$$

Since the variation is driven by a county-level object, this instrument is unaffected by unobserved correlation between the cost shifters κ_{ijt} and ψ_{ijt}. The curvature estimates, presented in column (4), are in line with those obtained under the other specifications.

We set $\chi = 0.03$ as our baseline value, which is in the middle of the range in Table 4. Given χ, we then use Equation (27) to back out $\{\kappa_{ijt} - \mathbb{E}z_{jt}\}_{\forall\{i,j,t\}}$. Table 3 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.[40] We use the following log-linear approximation of optimal spreads under uniform pricing – Equation (12) – around some reference marginal cost, for effective

[40] 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.

TABLE 4. Estimated Curvature, χ

	Uniform Pricing		Local Pricing	
	(1)	(2)	(3)	(4)
$\widehat{\Delta\Gamma}$	0.032	0.026	0.021	0.035
	(0.0117)	(0.0127)	(0.0139)	(0.0218)
Bank and year FE	Yes	Yes	-	-
Bank-year FE	-	-	Yes	Yes
County-year FE	-	-	Yes	Yes
Bank-county FE	-	-	Yes	Yes
Observations	17,387	12,282	98,082	98,048
First-stage F	236.3	126.5	1733.5	9.5

Notes: For uniform pricing, we restrict the sample to banks operating in at least two counties with at least five annual observations, and cluster standard errors at the bank level. For local pricing, we only retain counties with at least five banks and cluster standard errors at the county-year level.

marginal cost MC^*:

$$\ln\left(R - R^D_{jt}\right) \approx \ln MKP_{jt} + \frac{\chi}{MC^*}\Gamma_{jt} + \frac{\kappa_{jt} - \mathbb{E}z_{jt} + \chi}{MC^*} + \left(\ln MC^* - 1\right), \tag{36}$$

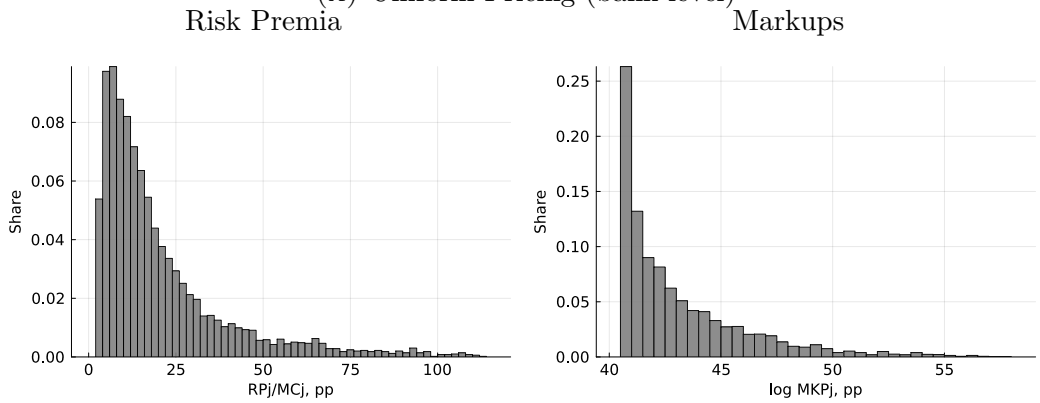
where the first two terms on the right hand side denote the markup and risk premium components of spreads, respectively. We use an analogous decomposition for the local pricing case.

5.1 Cross-sectional Patterns

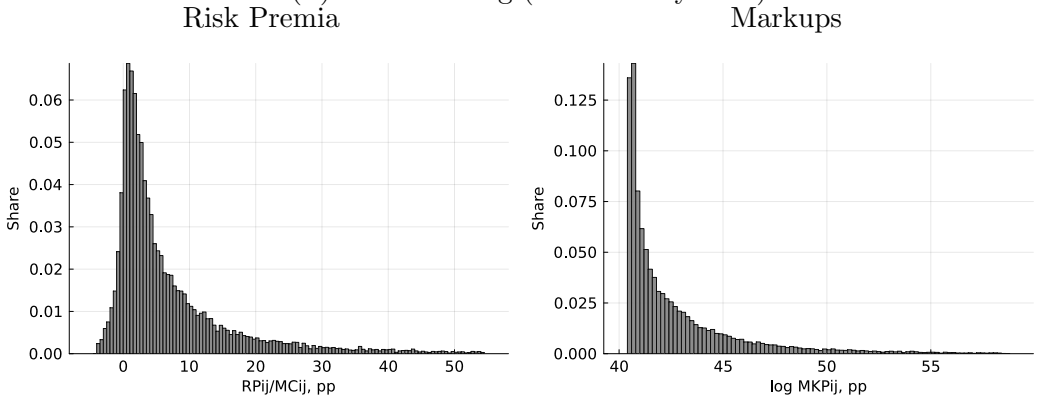
We start by analyzing cross-sectional pattern in markups and risk premia for 2019, the last year in our sample. Figure 6 shows the distributions of $\frac{\chi}{MC^*}\Gamma_{jt}$ and $\ln MKP_{jt}$, i.e., the contributions of risk premia (left panels) and markups (right panels) to (log) spreads (in percentage points). The top panels depict the bank-level distribution under uniform pricing, while the bottom panels show the bank-county-level distribution under local pricing. Both display considerable heterogeneity. For the median bank, the risk premium accounts for about 25% of its effective marginal cost and markups for over 40%. At the bank-county-level, the effects of risk premia are smaller, on average accounting for less than 10% of effective marginal costs. This is because large banks, which operate in many locations and tend to have lower risk premia, shift the bank-county risk distribution to the left. Even so, the histogram exhibits a long right tail, indicating that risk considerations play a sizable role for some bank-county pairs.

FIGURE 6. Contributions to (log) Spreads

(A) Uniform Pricing (bank level)



(B) Local Pricing (bank-county level)



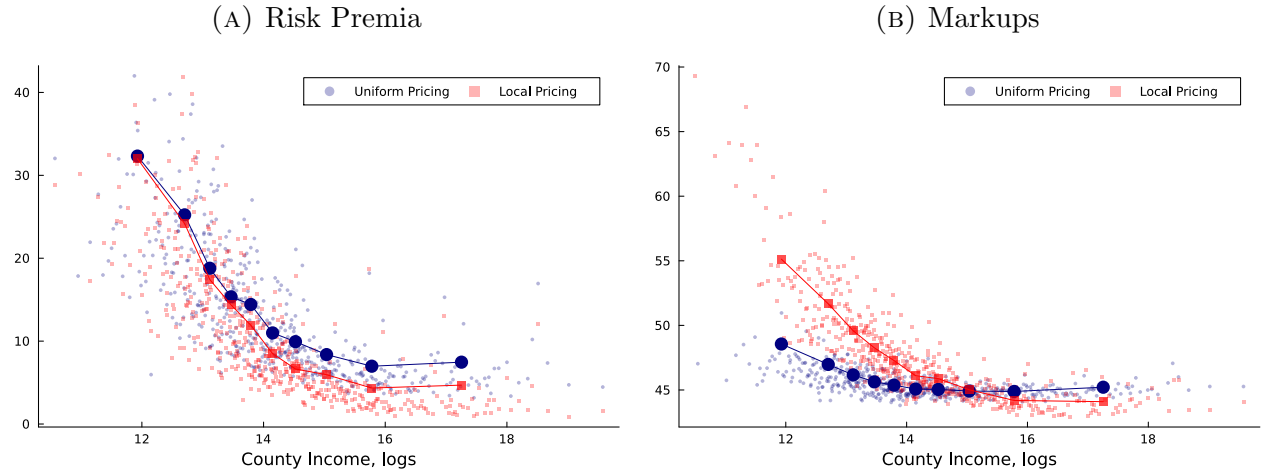
Notes: The figure presents histograms of the components of deposit spreads—risk premia and markups—based on the decomposition in Equation (36) for 2019. The top panel shows the results under the uniform-pricing scenario, while the bottom panel displays the outcomes under local pricing. Units are log points ×100.

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 effects, using shares s_{ij} as weights: e.g., under uniform pricing, the contribution of risk premia and markups to county-level spreads are, respectively, $\sum_{j\in\mathcal{J}_i} s_{ijt}\,\frac{\chi}{MC_i^*}\Gamma_{jt}$, and $\sum_{j\in\mathcal{J}_i} s_{ijt}\,\ln MKP_{jt}$.[41] The definitions are analogous under local pricing.

Panel (A) of Figure 7 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 0.35 log points. Panel

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

FIGURE 7. 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 (36). 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 ×100.

FIGURE 8. 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 (36). Blue dots represent results under uniform pricing, while red squares correspond to local pricing. Units are log points ×100.

(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 (36), 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., $\sum_{i\in\mathcal{I}_j}\omega^D_{ijt}\frac{\chi\Gamma_{ijt}}{MC^*_{jt}}$ and $\sum_{i\in\mathcal{I}_j}\omega^D_{ijt}\ln MKP_{ijt}$, respectively, and then apply the decomposition in Equation (36).[42]

Panel (A) of Figure 8 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 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 Over Time

Next, we decompose changes in deposit spreads over time, specifically to quantify the effects of changes in banks' geographical footprint 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.

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

$$\Delta\ln(R-R^D_{it})\approx\Delta\sum_{j\in\mathcal{J}_{it}}s_{ijt}\ln MKP_{jt}+\frac{\chi}{MC^*_i}\Delta\sum_{j\in\mathcal{J}_{it}}s_{ijt}\Gamma_{jt}+\frac{1}{MC^*_i}\Delta\sum_{j\in\mathcal{J}_{it}}s_{ijt}(\kappa_{jt}-\mathbb{E}z_{jt}),\quad(37)$$

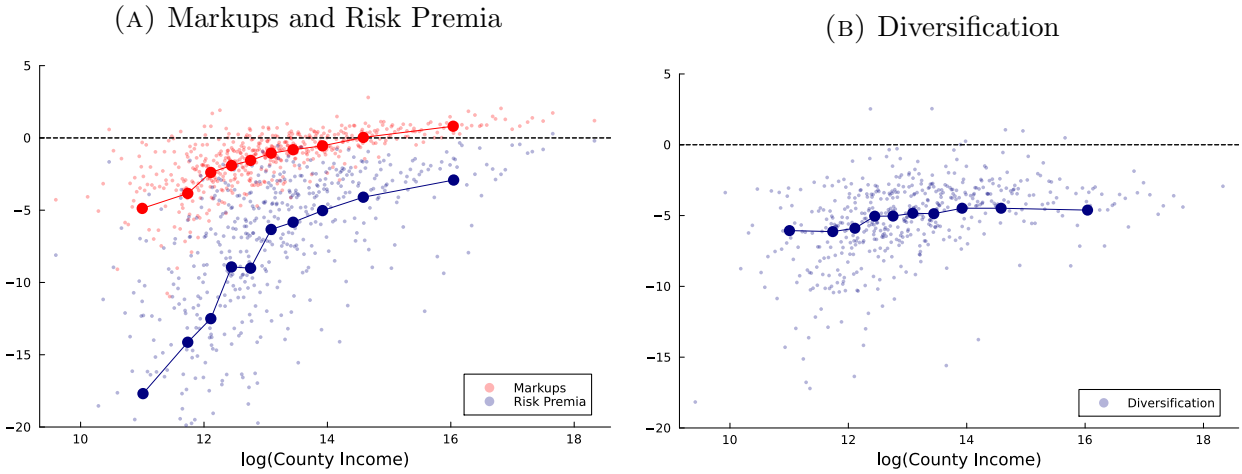
where the operator Δ defines changes across periods $t=1$ and $t=0$. The first two terms in the right hand side, $\Delta\sum_{j\in\mathcal{J}_{it}}s_{ijt}\ln MKP_{jt}$ and $\frac{\chi}{MC^*_i}\Delta\sum_{j\in\mathcal{J}_{it}}s_{ijt}\Gamma_{jt}$, capture county-level changes in deposits spreads driven by changes in markups and risk premia, respectively.[43]

Panel (A) of Figure 9 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.

[42] In this case, we approximate marginal costs around the bank-level average, $MC^*_j=\sum_{i\in\mathcal{I}_j}\omega^D_{ij}MC_j$.

[43] 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, by County



Notes: Using the decomposition in Equation (37), 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 (38). Units are log points $\times 100$.

Figure 10 shows a map of US counties 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). In larger/richer markets (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.

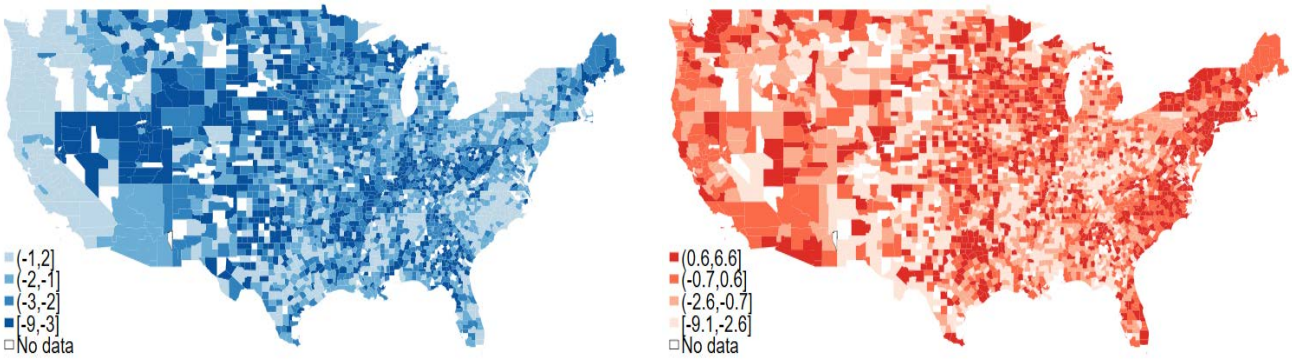
We can further decompose the changes in risk premia into variation in the extent of diversification and other movements in deposit risk (for instance, the composition of a bank's deposits shifting toward less volatile counties). For each bank j and date t, we define the following measure of diversification:

$$Diver_{jt} \equiv \Gamma_{jt} - \Gamma_{jt} \mid_{\rho=1} = \Gamma_{jt} - \int_{k \in \mathcal{I}_{jt}} \tilde{\omega}_{kjt} \left(\int_{i \in \mathcal{I}_j} \omega_{ijt} \frac{\sigma_i \sigma_k}{\mu_i \mu_k}, di \right) dk, \tag{38}$$

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 (37) to aggregate this measure to the county level using the bank market shares s_{ijt}

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

(A) Risk premia (B) Markups



Notes: Based on the decomposition in Equation (37), 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 $\times 100$.

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 9.

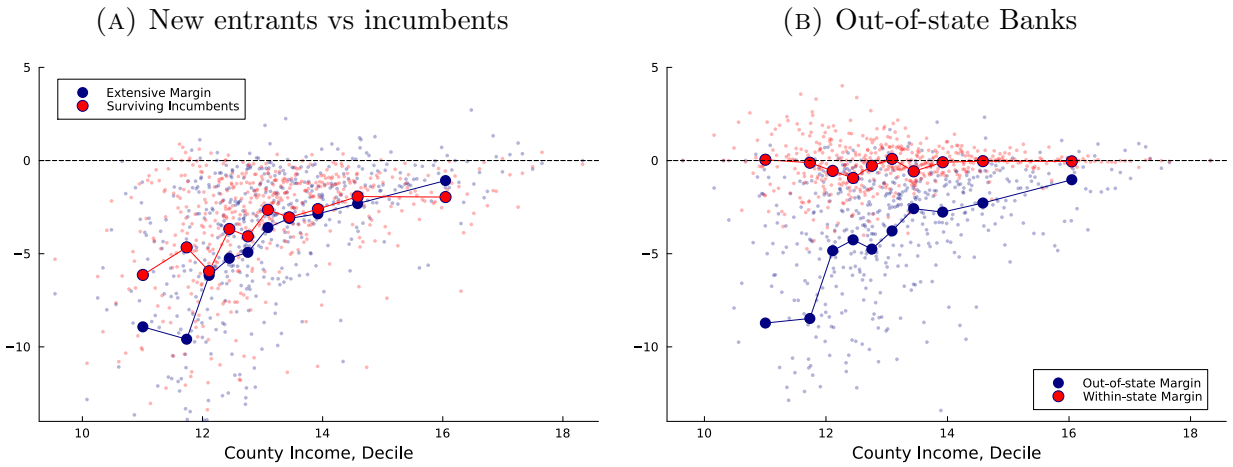
Next, we explore the role of the extensive margin in the observed time variation in risk premia. We do this by allocating county-level changes across surviving incumbents, entrants, and exiting banks. We define a *survivor* as a bank that operated in county i in both periods (1993 and 2019). An *entrant*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

$$\Delta\sum_{j\in\mathcal{J}_{it}} s_{ijt}\Gamma_{jt} = \underbrace{M_{i1}\Big(\sum_{j\in\{\tilde{J}_{i1}\}}\frac{s_{ij1}}{M_{i1}}\Gamma_{j1} - \sum_{j\in\{\hat{J}_i\}}\frac{s_{ij1}}{1-M_{i1}}\Gamma_{j1}\Big)}_{\text{Entrants vs. Survivors}} + \underbrace{M_{i0}\Big(\sum_{j\in\{\hat{J}_i\}}\frac{s_{ij0}}{1-M_{i0}}\Gamma_{j0} - \sum_{j\in\{\tilde{J}_{i0}\}}\frac{s_{ij0}}{M_{i0}}\Gamma_{j0}\Big)}_{\text{Survivors vs. Exiters}}$$
$$+ \underbrace{\sum_{j\in\{\hat{J}_i\}}\Big(\frac{s_{ij1}}{1-M_{i1}}\Gamma_{j1} - \frac{s_{ij0}}{1-M_{i0}}\Gamma_{j0}\Big)}_{\text{Within Survivors}}. \tag{39}$$

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.[44] We multiply this difference by the market share of entrants, M_{i1},

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

FIGURE 11. Changes in (log) Spreads, 1993-2019: Role of the Extensive Margin



Notes: Following the decomposition in Equation (39), 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 $\times 100$.

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 (37) to map the extensive-margin and surviving-incumbents components into changes in county-level spreads. Panel A of Figure 11 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.[45] 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.

[45]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.5 for further details on this decomposition.

TABLE 5. 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	-0.8	-4.7	1.5	0.7	-0.5	-4.3	1.7	1.1
Aggregate (fixed s_i shares)	-3.7	-4.4	0.8	-2.9	-4.3	-3.9	0.4	-3.9
By Group of Counties								
Small Counties (<p10)	-18.9	-6.3	-5.3	-24.2	-15.4	-7.8	-1.0	-16.4
Medium Counties	-6.9	-4.8	-1.3	-8.2	-6.0	-4.8	-0.6	-6.5
Large Counties (>p90)	-2.5	-4.5	0.9	-1.7	-3.2	-3.5	0.0	-3.1

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 (40). 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).

Aggregate Changes

Using a decomposition similar to Equation (37), we can decompose aggregate changes in deposit spreads as follows:

$$\Delta \ln(R - R_t^D) \approx \Delta \int_i s_{it} \left\{ \sum_{j \in \mathcal{J}_{it}} s_{ijt} \ln MKP_{jt} + \sum_{j \in \mathcal{J}_{it}} s_{ijt} \frac{\chi \Gamma_{jt}}{MC_i^*} + \sum_{j \in \mathcal{J}_{it}} s_{ijt} \frac{\kappa_{jt} - \mathbb{E} z_{jt}}{MC_i^*} \right\} \mathrm{d}i \,, \quad (40)$$

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 5 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 1-4 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 9). 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.

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.[46] 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 6 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 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

[46] 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 6. Counterfactuals

	Δ Deposit Spreads			Risk Premia			Markups		
	Small	Medium	Large	Small	Medium	Large	Small	Medium	Large
A. Higher curvature									
Increase χ_i	3.79	1.95	1.23	3.34	1.65	0.98	-0.06	-0.01	0.03
B. M&A, acquired banks operate in only 1 county									
Acquirer bank:									
B.1 Top local bank	2.54	0.50	-0.09	-0.90	0.25	0.23	0.76	0.43	0.06
B.2 Top regional bank	4.50	1.30	0.18	-10.12	-1.16	-0.10	-1.41	-0.00	0.07
B.3 Top national bank	5.72	2.08	0.38	-10.25	-1.22	-0.14	-0.93	0.24	0.11
C. M&A, acquired banks operate in at most 2 counties									
Acquirer bank:									
C.1 Top local bank	5.53	1.89	-0.18	-2.70	0.81	0.53	2.12	1.01	0.17
C.2 Top regional bank	11.43	3.19	0.40	-19.98	-2.50	-0.17	-2.39	-0.03	0.16
C.3 Top national bank	14.34	4.80	0.78	-20.60	-2.77	-0.27	-1.72	0.37	0.23
D. Changes in demographics									
D.1 Increase μ_i	-9.08	-3.98	0.19	-7.40	-2.84	0.22	0.01	-0.20	-0.06
D.2 Increase σ_i / μ_i	3.69	4.13	10.05	3.52	3.92	8.39	0.05	0.11	0.17

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.

counties.[47] 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.[48] Following a merger, the deposit demand for the acquirer bank j in county i is given by $\psi^{\eta}_{ijt} + \sum_k \psi^{\eta}_{ikt}$, where ψ_{ikt} denotes the demand shifters of the acquired banks.[49] For our uniform pricing case, we also assume that the merged entity inherits the acquirer's non-interest cost k_j.

Panel (B) of Table 6 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

[47]We omit banks with assets above the 95th national percentile to exclude acquisitions of very large, single-county banks (usually online banks).
[48]Under these definitions, our sample includes 4,758 local banks, 277 regional banks, and 20 national banks.
[49]Recall that the shifters are normalized so that $\sum_j \psi^{\eta}_{ijt} = 1$.

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 remain similar to those reported in Table 6, while markups increase slightly. 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.[50] 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 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

[50] 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.

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., $L_j = \int_{\mathcal{I}_j^{\mathcal{S}}} L_{ij} di$ where $\mathcal{I}_j^{\mathcal{S}}$ 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.[51] 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.6. In that appendix, we also consider a local-lending setup under the alternative source of curvature detailed in Appendix C.4.

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

$$Rev\left(A_j\right) \equiv \max_{\{L_{ij}\}_{\forall i \in \mathcal{I}_j^{\mathcal{S}}}, S_j} \mathbb{E} \int_{\mathcal{I}_j^{\mathcal{S}}} \left(R + z_j - \frac{1}{2}\alpha_i \alpha_j L_{ij}\right) L_{ij} di + \left(R + z_j - \frac{1}{2}\beta_j S_j\right) S_j, \tag{41}$$

$$\text{s.t. } A_j = \int_{\mathcal{I}_j^{\mathcal{S}}} L_{ij} di + S_j.$$

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

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

—$\alpha_i\alpha_j$. We define $\varrho_j \equiv \int_{i\in\mathcal{I}_j^S} \frac{1}{\alpha_i} di$, as the average curvature across all locations in which a bank operate. From Equation (41), 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

$$\ell_j \equiv \frac{\varrho_j \beta_j}{\varrho_j \beta_j + \alpha_j}. \tag{42}$$

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

$$L_{ij} = \frac{L_j}{\varrho_j \alpha_i}. \tag{43}$$

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 (41), we get that banks' interest income is given by:

$$Rev\left(A_j\right) = \left(R + z_j\right) A_j - \frac{1}{2}\vartheta_j A_j^2 \qquad \text{where} \qquad \vartheta_j \equiv \frac{\alpha_j}{\varrho_j} l_j. \tag{44}$$

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

$$R - R_{gj}^D = \frac{\eta(1-s_{gj}) + \theta s_{gj}}{\eta(1-s_{gj}) + \theta s_{gj} - 1} \left[\kappa_{gj} - \mathbb{E}\left(z_j\right) + \vartheta A_j + \chi_j \mathbb{E}(\mathcal{D}_j)\Gamma_{gj}\right], \tag{45}$$

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.[52] 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, and in particular the role of markups and risk premia, go through unchanged.

7.1 Effects on Local Lending

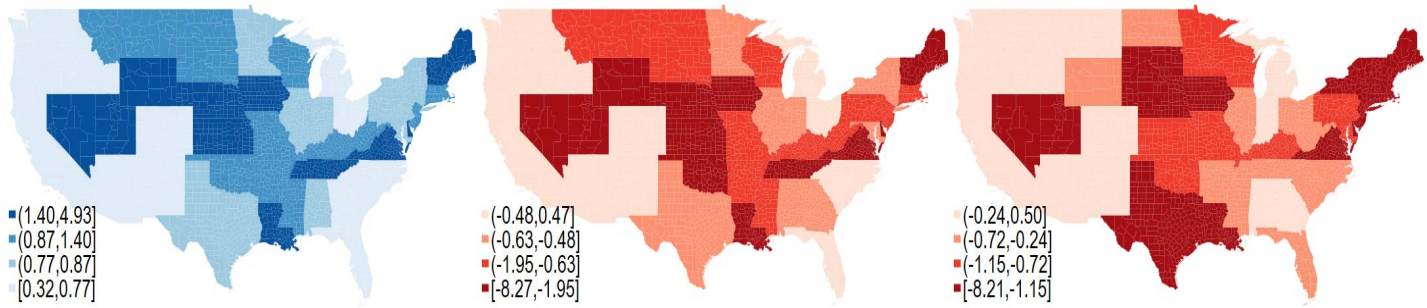
We next examine how industry structure affects lending at the local level. To this end, we first estimate the state-level parameters $\{\alpha_i\}$ using data on small business loan originations. Specifically, we choose $\{\alpha_i\}$ to minimize the distance between model-implied shares of loans by location ($\{L_i/L\}$) and their empirical counterparts (see Appendix C.6 for details).[53] To recover the bank-level parameters, we follow a similar strategy as in the baseline: assume ϑ_j is inversely

[52] It is easy to show that this robustness also obtains under local pricing.

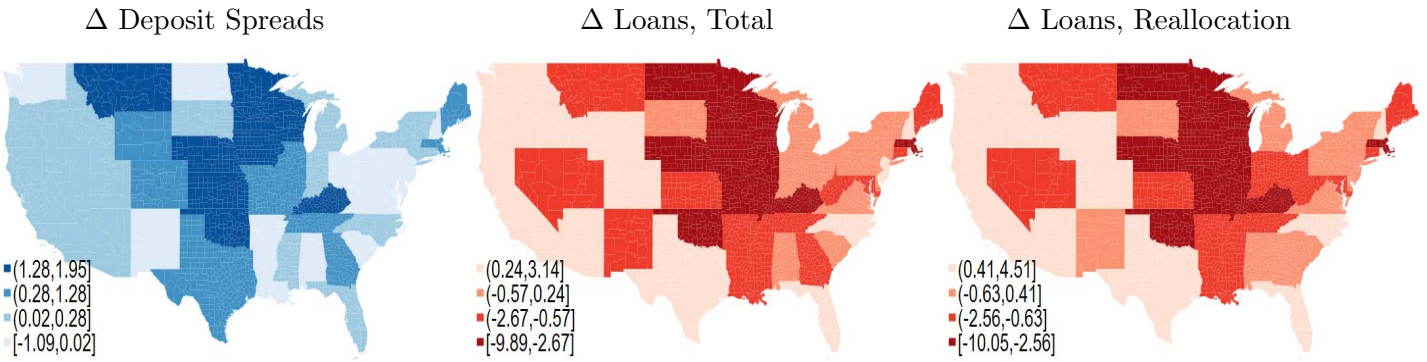
[53] This estimation is computationally demanding—even at the state level—since a change in a given α_i impacts all banks operating in that location.

FIGURE 12. 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 $\times 100$.

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.

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 12). 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 6. Panel B of Figure 12 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: $u(C, X) = C - \xi \log(X)$, where X denotes a liquidity composite defined by the following aggregator

$$X = \left(\int_0^1 \phi_i X_i^{\frac{\theta-1}{\theta}} di \right)^{\frac{\theta}{\theta-1}}, \tag{46}$$

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

$$X_i = \left(\sum_{l \in \mathcal{J}_i} \zeta_l X_{li}^{\frac{\varepsilon-1}{\varepsilon}} + D_i^{\frac{\varepsilon-1}{\varepsilon}} \right)^{\frac{\varepsilon}{\varepsilon-1}}. \tag{47}$$

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.7 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:

$$\frac{R-1}{R-R_i^X} = \zeta \left(\frac{M_i}{X_i} \right)^{-\frac{1}{\varepsilon}}, \qquad \frac{R-R_i^D}{R-R_i^X} = \left(\frac{D_i}{X_i} \right)^{-\frac{1}{\varepsilon}}, \qquad \frac{R-R_i^X}{R-R^X} = \phi_i \left(\frac{X_i}{X} \right)^{-\frac{1}{\theta}}, \tag{48}$$

with ideal spread indices defined as:

$$R - R_i^X = \left(\zeta^{\varepsilon} (R-1)^{1-\varepsilon} + \left(R - R_i^D \right)^{1-\varepsilon} \right)^{\frac{1}{1-\varepsilon}}, \tag{49}$$

$$R - R^X = \left(\int_0^1 \phi_i^{\theta} \left(R - R_i^X \right)^{1-\theta} di \right)^{\frac{1}{1-\theta}}. \tag{50}$$

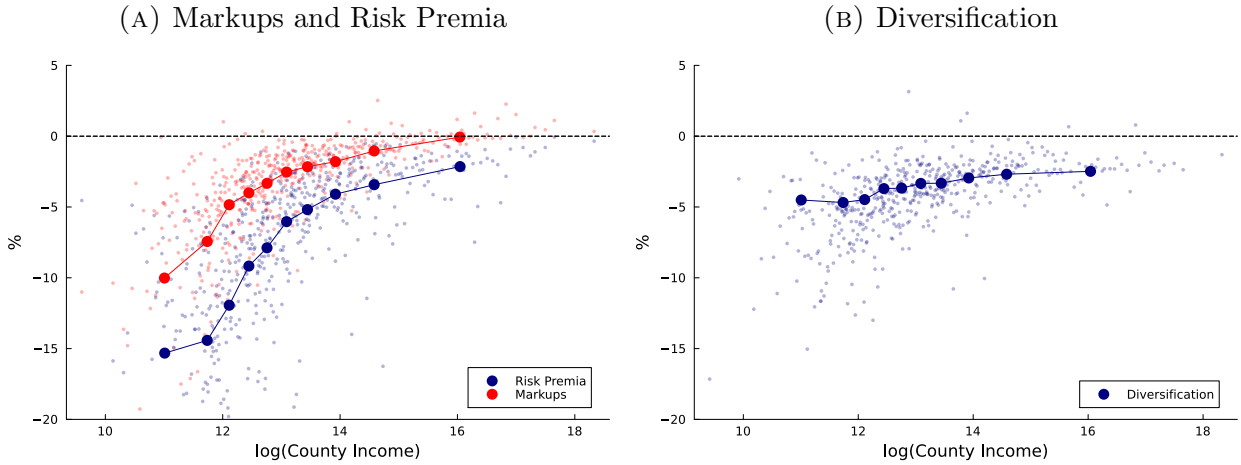
The individual bank's deposit demand in county i remains as in Equation (5). Combining this with Equation (48), we have:

$$D_{ij} = \psi_{ij}^{\eta} \left(\frac{R - R_{ij}^D}{R - R_i^D} \right)^{-\eta} \left(\frac{R - R_i^D}{R - R_i^X} \right)^{-\varepsilon} \phi_i^{\theta} \left(\frac{R - R_i^X}{R - R^X} \right)^{-\theta} X. \tag{51}$$

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:

$$\frac{d \ln D_{ij}}{d \ln \left(R - R_{ij}^D \right)} = - \left[(1 - s_{ij})\eta + s_{ij} \widehat{\theta}_i \right], \tag{52}$$

FIGURE 13. Changes in (log) Spreads, 1993-2019, by County — Cash Extension



Notes: Following the decomposition in Equation (37), 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 (38). Units are log points ×100.

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.8). 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.

Panel (A) of Figure 13 shows changes in risk premia and markups between 1993 and 2019.[54] The estimated reduction in risk premia remains similar to the baseline (see Figure 9), 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

[54]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.

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.

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.[55]

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.[56]

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

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

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

TABLE A.1. Average number of observations 1990-2010

	Average
Number of Banks	8278
Number of Counties	2982
Number of Bank-County Pairs	22670

Notes: This table shows the average frequency of banks, counties, and bank-county pairs per year for the period 1990-2010, from our SOD-Call Report combined dataset.

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 (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.[57] When this breakdown is missing, we fall back on the average interest rate across all domestic deposits.

Table A.1 shows the average number of banks, counties, and bank-county pairs per year in our sample for the period 1990-2010.

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.

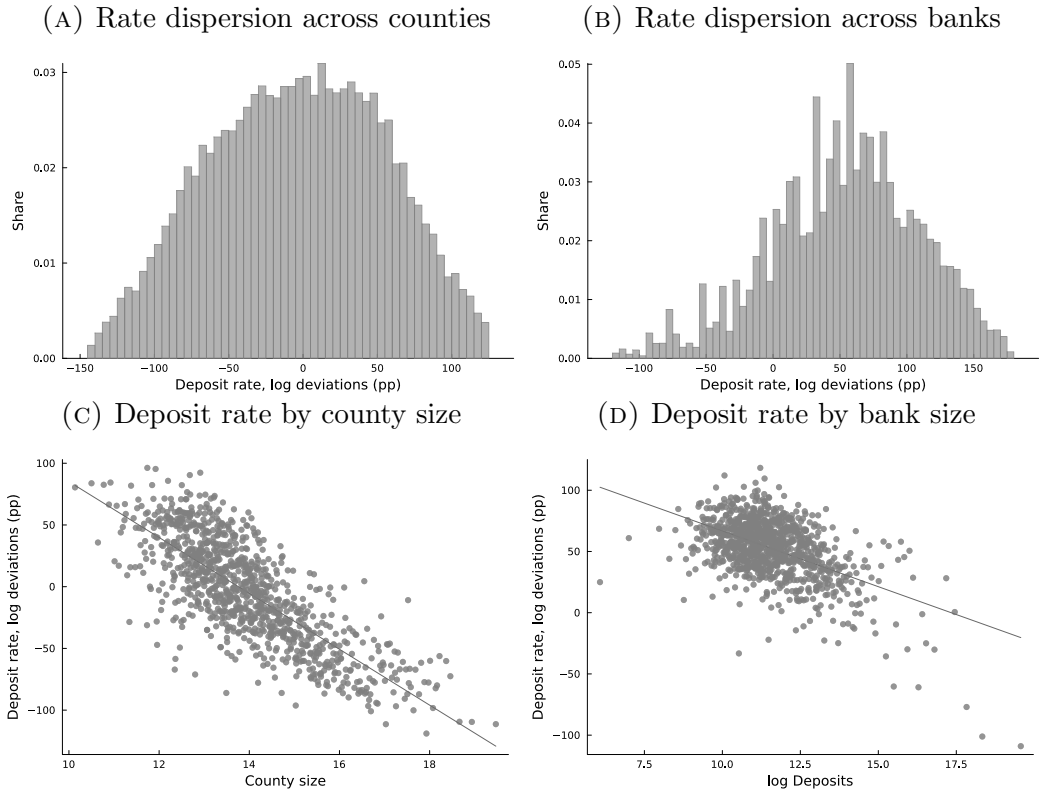
Appendix B Motivation: Additional Evidence

Alternative measure for deposit rates. We support our empirical motivation in Section **??** using an alternative measure of deposit rates based on 12-month certificates of deposit from RateWatch. Figure B.1 presents four panels similar to those in Figures 1-3 but using 12-month CDs instead of our main weighted average deposit rate. The results are qualitatively similar. Panels (A) and (B) show substantial dispersion in deposit rates across counties and banks, respectively. Panels (C) and (D) reveal that deposit rates are lower in larger counties and for larger banks.

In what follows, we provide further reduced-form evidence linking differences in county-level deposit rates to banks' geographical funding risk. First, we show that deposit flows are as volatile as loans. Second, we show that more than one-third of the variation in deposit growth

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

FIGURE B.1. Deposit Rates: 12-month Certificates of Deposit

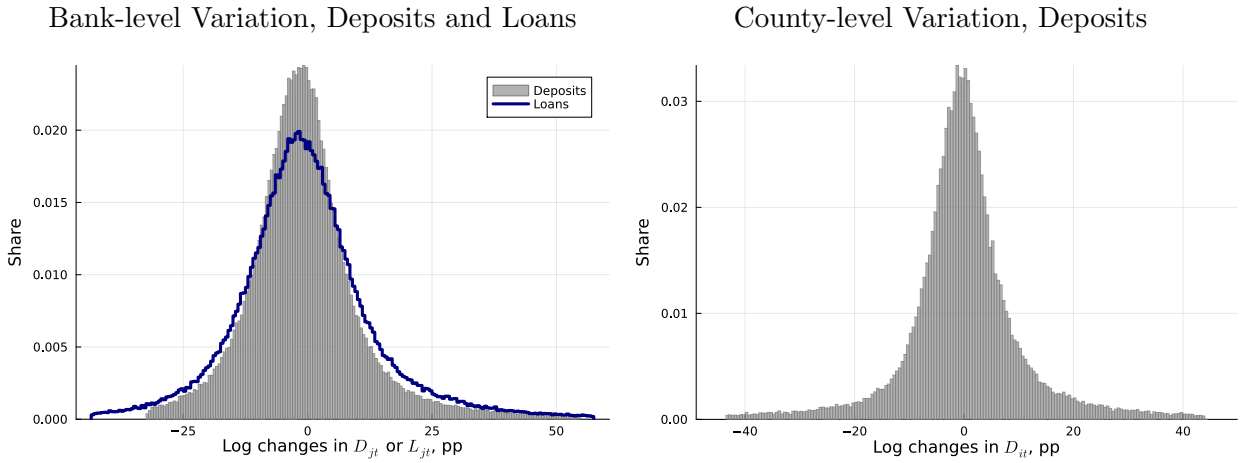


Notes: Panels (A) and (B) show dispersion in log deposit rates across counties and banks, respectively. Panel (C) shows the relationship between county size (log total income) and log deposit rates for the period 2011-2019, net of a year fixed effect. Panel (D) shows the relationship between bank size (measured by total deposits in 2011). The figure is based on 12-month certificate of deposit rates from RateWatch for the 2011-2019 period, residualized after extracting a year fixed effect component.

can be attributed to fluctuations in county-level deposits. Third, we show that banks that operate in more locations exhibit a lower volatility of deposit flows.

Deposit Risk and Geographical Diversification. Figure B.2 compares the distribution of residualized growth in deposits and loans at the bank level (left panel) with residualized deposit growth at the county level (right panel). Bank-level residuals come from regressions of $\Delta \log x_{jt}$ on bank and year fixed effects; county-level residuals come from regressions of $\Delta \log D_{it}$ on county and year fixed effects. Two facts stand out. First, bank-level deposit growth is about as volatile as loan growth. Second, county-level deposit growth also displays sizable dispersion, even after accounting for county and year fixed effects. These patterns are consistent with prior work documenting substantial volatility in deposits, particularly at the branch level (see, for

FIGURE B.2. Bank- and County-level Variation: Deposits vs. Loans



Notes: The left panel shows the volatility of bank-level deposit and loan growth, based on the residuals from the regression $\Delta \log x_{jt} = \gamma_j + \gamma_t + \epsilon^x_{jt}$, where x_{jt} denotes deposits or loans. The right panel shows the volatility of county-level deposit growth, based on the residuals from $\Delta \log D_{it} = \gamma_i + \gamma_t + \epsilon_{it}$. All residuals are expressed in percentage points.

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.

Role of Local shocks. We next 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. To isolate variation driven by changes in the set of counties in which a bank operates, 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, $\omega^0_{ij} = \frac{D_{ij,t(0)}}{\sum_{i \in \mathcal{M}_j} D_{ij,t(0)}}$. [58]

We then combine these weights with county-level deposits (net of year fixed effects) to predict bank-level deposits, $\log \widehat{D}_{jt}$.[59] Table B.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.

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

[59] 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 $\widehat{D_{jt}} = \sum_{i \in \mathcal{M}_{j,t}} \omega^0_{ij} \widehat{D_{it}}$ where ω^0_{ij} are the base-year county exposures of the bank.

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

	Within R^2			
FEs	All banks	≥ 5 counties	≥ 10 counties	≥ 25 counties
Bank	0.48	0.67	0.73	0.78
Year	0.54	0.62	0.60	0.55
Bank and Year	0.29	0.30	0.33	0.36

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..

Number of Locations and Deposit Volatility. The following analysis complements the main-text results on the link between the number of locations and deposit variability (Table 1). In that analysis, we relate the (observed) volatility of bank-level deposits to the number of locations in which a bank operates. Here, we focus instead on deposit volatility that is driven solely by county-level changes. To this end, we construct a panel of bank-level deposit changes by combining county-level deposit growth with a vector of deposit weights that captures each bank's exposure to the counties in which it operates.

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, 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

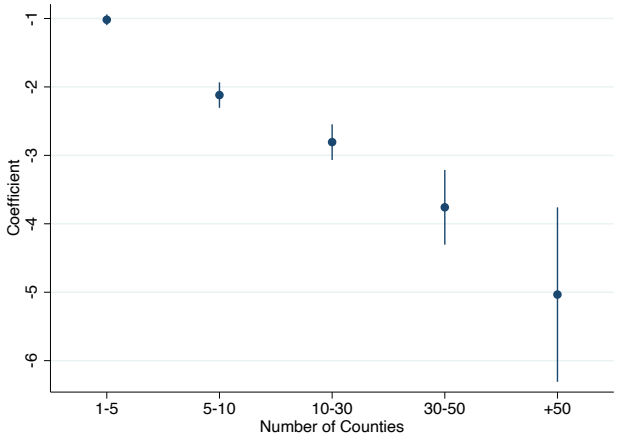
$$\sigma_j^{\tau} = \sqrt{\frac{1}{T} \sum_t \left(\Delta \ln D_{jt}^{\tau} - \overline{\Delta \ln D_{jt}^{\tau}} \right)^2}. \tag{B.1}$$

We use the yearly panel σ_j^{τ} 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.3 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.3. Banks' Exposure to Deposit Fluctuation Risk



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

in more than 50 counties having 4 pp lower deposit volatility than banks operating in 1-5 counties.[60] Similar results hold when sorting by bank size (not shown).

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

[60] 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.

that solves:

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

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 Derivation of the Pricing Equation under the General Problem

We derive here the optimal deposit spreads when bank j sets a common rate for groups of counties. Recall that $\mathcal{I}_j$ denotes the (finite) set of counties in which bank j operates and that $\{\mathcal{G}_{gj}\}_{g=1}^{G_j}$ is a measurable partition of $\mathcal{I}_j$ into G_j disjoint groups. Counties in group $\mathcal{G}_{gj}$ are assigned the same deposit rate R^D_{gj}, so that $R^D_{ij} = R^D_{gj}$ for all $i \in \mathcal{G}_{gj}$. Conditional on this assignment, deposit demand in county i is denoted by $\mathcal{D}_{ij}(R^D_{gj})$ for $i \in \mathcal{G}_{gj}$, and the bank's

profit function is $\Pi_j\big(\{\mathcal{D}_{ij}\}_{i\in\mathcal{I}_j}\big)$, defined net of all financing costs except those associated with deposits.

The bank chooses the vector of deposit rates $\mathbf{R}_j^D = \{R_{gj}^D\}_{g=1}^{G_j}$ by solving

$$\max_{\mathbf{R}_j^D} \mathbb{E}\left[\Pi_j\left(\{\mathcal{D}_{ij}(R^D_{\alpha_j(i),j})\}_{i\in\mathcal{I}_j}\right) - \int_0^1 \left(R^D_{\alpha_j(i),j} + \kappa_{ij}\right)\mathcal{D}_{ij}\left(R^D_{\alpha_j(i),j}\right) d\Lambda_j(i)\right], \tag{C.1}$$

where $\alpha_j(i) \in \{1,\ldots,G_j\}$ indicates the group to which county i is assigned and $\Lambda_j(\cdot)$ denotes the measure over $\mathcal{I}_j$. It is convenient to rewrite the problem in terms of deposit spreads $R - R_{gj}^D$. Rewriting (C.1) yields

$$\max_{\{R-R_{gj}^D\}_{g=1}^{G_j}} \mathbb{E}\Bigg[\Pi_j\left(\{\mathcal{D}_{ij}(R - R^D_{\alpha_j(i),j})\}_{i\in\mathcal{I}_j}\right) + \int_{i\in\mathcal{I}_j}\left(R - R^D_{\alpha_j(i),j}\right)\mathcal{D}_{ij}\left(R - R^D_{\alpha_j(i),j}\right) di$$
$$- \int_{i\in\mathcal{I}_j}\left(R+\kappa_{ij}\right)\mathcal{D}_{ij}\left(R - R^D_{\alpha_j(i),j}\right) di\Bigg].$$

For each group $\mathcal{G}_{gj}$, only counties $i \in \mathcal{G}_{gj}$ are affected by a change in the spread $R - R_{gj}^D$. Define

$$\mathcal{D}'_{ij} \equiv \frac{\partial \mathcal{D}_{ij}}{\partial(R - R_{gj}^D)}, \qquad \Pi'_{ij} \equiv \frac{\partial \Pi_j}{\partial \mathcal{D}_{ij}}, \quad \text{for } i \in \mathcal{G}_{gj}. \tag{C.2}$$

The first-order condition with respect to $R - R_{gj}^D$ is

$$\mathbb{E}\left[\int_{i\in\mathcal{G}_{gj}} \Pi'_{ij}\mathcal{D}'_{ij}\, di + \int_{i\in\mathcal{G}_{gj}} \mathcal{D}_{ij}\, di + (R - R_{gj}^D)\int_{i\in\mathcal{G}_{gj}} \mathcal{D}'_{ij}\, di - \int_{i\in\mathcal{G}_{gj}} (R+\kappa_{ij})\mathcal{D}'_{ij}\, di\right] = 0. \tag{C.3}$$

Define the group-level demand and slope as

$$\mathcal{D}_{gj} \equiv \int_{i\in\mathcal{G}_{gj}} \mathcal{D}_{ij}\, di, \qquad \mathcal{D}'_{gj} \equiv \int_{i\in\mathcal{G}_{gj}} \mathcal{D}'_{ij}\, di. \tag{C.4}$$

Dividing the FOC by $\mathbb{E}(\mathcal{D}'_{gj})$ and rearranging gives

$$(-)\frac{\mathbb{E}\left(\int_{i\in\mathcal{G}_{gj}} \Pi'_{ij}\mathcal{D}'_{ij} di\right)}{\mathbb{E}(\mathcal{D}'_{gj})} - \frac{\mathbb{E}(\mathcal{D}_{gj})}{\mathbb{E}(\mathcal{D}'_{gj})} - \left(R - R_{gj}^D\right) + \frac{\int_{i\in\mathcal{G}_{gj}}(R+\kappa_{ij})\mathbb{E}(\mathcal{D}'_{ij})di}{\mathbb{E}(\mathcal{D}'_{gj})} = 0. \tag{C.5}$$

The final term of this equation can be re-written as:

$$\frac{\int_{i\in\mathcal{G}_{gj}}(R+\kappa_{ij})\mathbb{E}(\mathcal{D}'_{ij})di}{\mathbb{E}(\mathcal{D}'_{gj})} = R + \kappa_{gj},$$

where $\kappa_{gj} \equiv \int_{i\in\mathcal{G}_{gj}} \kappa_{ij}\, \omega_{ij}^{\prime(g)} di$ is a weighted-average of operating costs in each location, where the weights are given by $\omega_{ij}^{\prime(g)} \equiv \frac{\mathbb{E}(\mathcal{D}'_{ij})}{\int_{i\in\mathcal{G}_{gj}} \mathbb{E}(\mathcal{D}'_{ij}) di}$. Solving for spreads in equation (C.5) gives

$$R - R^D_{gj} = \frac{\vartheta_{gj}}{\vartheta_{gj}+1}\left[R + \kappa_{gj} - \frac{\mathbb{E}\left(\int_{i\in\mathcal{G}_{gj}} \Pi'_{ij} D'_{ij} di\right)}{\mathbb{E}(\mathcal{D}'_{gj})}\right], \tag{C.6}$$

where $\vartheta_{gj} \equiv (R - R^D_{gj})\frac{\mathbb{E}(\mathcal{D}'_{gj})}{\mathbb{E}(\mathcal{D}_{gj})}$ and $\frac{\vartheta_{gj}}{\vartheta_{gj}+1}$ denotes the markup term—a function of the demand elasticity across all the locations in the g-group. Next, we define the group-level expected marginal benefit $\mathbb{E}(\Pi'_{gj}) \equiv \int_{i\in\mathcal{G}_{gj}} \mathbb{E}(\Pi'_{ij})\, \omega_{ij}^{\prime(g)} di$, and rewrite the last term of equation (C.6) as

$$\frac{\mathbb{E}\left(\int_{i\in\mathcal{G}_{gj}} \Pi'_{ij} D'_{ij} di\right)}{\mathbb{E}(\mathcal{D}'_{gj})} = \frac{\int_{i\in\mathcal{G}_{gj}} \mathbb{C}ov\left(\Pi'_{ij}, \mathcal{D}'_{ij}\right) di}{\mathbb{E}(\mathcal{D}'_{gj})} + \mathbb{E}\left(\Pi'_{gj}\right). \tag{C.7}$$

Replacing back in equation (C.6), the final pricing kernel is

$$R - R^D_{gj} = \frac{\vartheta_{gj}}{\vartheta_{gj}+1}\left[R + \kappa_{gj} - \mathbb{E}\left(\Pi'_{gj}\right) - \frac{\int_{i\in\mathcal{G}_{gj}} \mathbb{C}ov\left(\Pi'_{ij}, \mathcal{D}'_{ij}\right) di}{\mathbb{E}(\mathcal{D}'_{gj})}\right], \tag{C.8}$$

which coincides with equation (3) in the main text. Notice that, under local pricing (i.e., an scenario in which the bank sets a different rate in each of its locations) the previous expressions collapses to

$$R - R^D_{ij} = \frac{\vartheta_{ij}}{\vartheta_{ij}+1}\left[R + \kappa_{ij} - \mathbb{E}(\Pi'_{ij}) - \frac{\mathbb{C}ov\left(\Pi'_{ij}, \mathcal{D}'_{ij}\right)}{\mathbb{E}(\mathcal{D}'_{ij})}\right]. \tag{C.9}$$

C.3 Pricing Equation under the Baseline Structural Assumptions

In this subsection, we provide additional derivations for optimal deposit spreads. As described in the main text, for a given equity E_j, each bank chooses deposit spreads $R - R^D_{gj}$ for each group $\mathcal{G}_{gj}$, loans L_j, and wholesale funding H_j to solve the problem in Equation (**??**). After replacing B_j with the bank's balance sheet equation, the problem can be written as follows:

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

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

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

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

$$\begin{aligned}\mathbb{E}\Bigg[&\int_{i\in\mathcal{G}_{gj}}\mathcal{D}_{ij}di+\int_{i\in\mathcal{G}_{gj}}(R-R^D_{gj}-\kappa_{ij})\mathcal{D}'_{ij}di+\\&+\chi_j\left(L_j-\int_0^1\mathcal{D}_{ij}\Lambda_j\left(i\right)-H_j-E_j\right)\int_{i\in\mathcal{G}_{gj}}\mathcal{D}'_{ij}di\Bigg]=0.\end{aligned}$$

Dividing by $\mathbb{E}\left(\int_{i\in\mathcal{G}_{gj}}\mathcal{D}'_{ij}di\right)$ and after rearranging terms, we get:

$$R-R^D_{gj}=-\frac{\int_{i\in\mathcal{G}_{gj}}\mathbb{E}\mathcal{D}_{ij}di}{\int_{i\in\mathcal{G}_{gj}}\mathbb{E}\mathcal{D}'_{ij}di}+\kappa_{gj}-\chi_j\frac{\mathbb{E}\left[\int_{i\in\mathcal{G}_{gj}}\mathcal{D}'_{ij}di\times\left(L_j-\int_{i\in\mathcal{I}_j}\mathcal{D}_{ij}di-H_j-E_j\right)\right]}{\int_{i\in\mathcal{G}_{gj}}\mathbb{E}\mathcal{D}'_{ij}di},$$

with $\kappa_{gj}\equiv\int_{i\in\mathcal{G}_{gj}}\kappa_{ij}\frac{\mathbb{E}\mathcal{D}'_{ij}}{\int_{i\in\mathcal{G}_{gj}}\mathbb{E}\mathcal{D}'_{ij}di}di$. Replacing with the first-order condition for L_j, we can rewrite the last term of the previous expression as follows:

$$\frac{\mathbb{E}\left[\int_{i\in\mathcal{G}_{gj}}\mathcal{D}'_{ij}di\times\left(L_j-\int_{i\in\mathcal{I}_j}\mathcal{D}_{ij}di-H_j-E_j\right)\right]}{\int_{i\in\mathcal{G}_{gj}}\mathbb{E}\mathcal{D}'_{ij}di}=-\chi_j\mathbb{C}ov\left[\int_{i\in\mathcal{G}_{gj}}\mathcal{D}'_{ij}di\,,\int_{i\in\mathcal{I}_j}\mathcal{D}_{ij}di\right]+\mathbb{E}\left(z_j\right).$$

Replacing back in the first-order condition, we get:

$$R-R^D_{gj}=-\frac{\int_{i\in\mathcal{G}_{gj}}\mathbb{E}\mathcal{D}_{ij}di}{\int_{i\in\mathcal{G}_{gj}}\mathbb{E}\mathcal{D}'_{ij}di}+(\kappa_{gj}-\mathbb{E}z_j)+\chi_j\frac{\mathbb{C}ov\left[\int_{i\in\mathcal{G}_{gj}}\mathcal{D}'_{ij}di\,,\int_{i\in\mathcal{I}_j}\mathcal{D}_{ij}di\right]}{\int_{i\in\mathcal{G}_{gj}}\mathbb{E}\mathcal{D}'_{ij}di}.\tag{C.10}$$

From the household's optimality conditions —Equations (5) and (6) in the main text— we can directly get an expression for $\mathcal{D}'_{ij}$:

$$\mathcal{D}'_{ij}=\mathcal{D}_{ij}\frac{1}{R-R^D_{gj}}\left[\frac{\theta-\eta}{\theta}\frac{d\ln D_i}{d\ln R-R^D_{gj}}-\eta\right].\tag{C.11}$$

Combining Equations (**??**) and (6) and after taking logs, we get

$$\ln D_i=\theta\ln\phi_i+\theta\ln\left(R-R^D\right)+\frac{\theta}{\eta-1}\ln\left(\sum_{j\in\mathcal{J}_i}\psi_{ij}^{\eta}\left(R-R^D_{ij}\right)^{1-\eta}\right)+\ln D,$$

which implies that $\frac{d\ln D_i}{d\ln R - R_{ij}^D} = -\theta \frac{\psi_{ij}^{\eta}\left(R-R_{ij}^D\right)^{1-\eta}}{\sum_{j\in\mathcal{J}_i}\psi_{ij}^{\eta}\left(R-R_{ij}^D\right)^{1-\eta}}$. Substituting this last expression into equation (C.11):

$$\begin{aligned}\mathcal{D}'_{ij} =& \mathcal{D}_{ij}\frac{1}{R-R_{gj}^D}\left[(\eta-\theta)\frac{\psi_{ij}^{\eta}\left(R-R_{gj}^D\right)^{1-\eta}}{\sum_{j\in\mathcal{J}_i}\psi_{ij}^{\eta}\left(R-R_{gj}^D\right)^{1-\eta}}-\eta\right]\\ =& \mathcal{D}_{ij}\frac{1}{R-R_{gj}^D}\left[(\eta-\theta)\,s_{ij}-\eta\right],\end{aligned} \tag{C.12}$$

where in the second equality we make use of our definition for county-level market shares, s_{ij}.

Using (C.12), we can rewrite the first term in the right-hand side of equation (C.10) as:

$$-\frac{\int_{i\in\mathcal{G}_{gj}}\mathbb{E}\mathcal{D}_{ij}di}{\int_{i\in\mathcal{G}_{gj}}\mathbb{E}\mathcal{D}'_{ij}di} = -\frac{R-R_{gj}^D}{(\eta-\theta)\,s_{gj}-\eta},$$

where $s_{gj}\equiv\int_{i\in\mathcal{G}_{gj}}\omega_{ij}^{(g)}s_{ij}di$ is a deposit-weighted average of the bank's effective market share across all counties governed by the group-g rate, where the weights are $\omega_{ij}^{(g)}\equiv\frac{\mathbb{E}\mathcal{D}_{ij}}{\int_{k\in C_{gj}}\mathbb{E}\mathcal{D}_{kj}\,dk}$.

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

$$\frac{Cov\left(\mathcal{D}_{ij}\,,\,\mathcal{D}_{kj}\right)}{\mathbb{E}\left(\mathcal{D}_{ij}\right)} = \mathbb{E}\left(\mathcal{D}_{kj}\right)\frac{\mathbb{C}ov\left(\phi_i^{\theta}\phi_k^{\theta}\right)}{\mathbb{E}\left(\phi_i^{\theta}\right)\mathbb{E}\left(\phi_k^{\theta}\right)} \equiv \mathbb{E}\left(\mathcal{D}_{kj}\right)\frac{\rho_{ik}\sigma_i\sigma_k}{\mu_i\mu_k}. \tag{C.13}$$

Using (C.12) and (C.13), the covariance term in equation (C.10) can be expressed as:

$$\frac{\mathbb{C}ov\left[\int_{i\in\mathcal{G}_{gj}}\mathcal{D}'_{ij}di\,,\,\int_{i\in\mathcal{I}_j}\mathcal{D}_{ij}di\right]}{\int_{i\in\mathcal{G}_{gj}}\mathbb{E}\mathcal{D}'_{ij}di} = \mathbb{E}\left(\mathcal{D}_j\right)\int_{i\in\mathcal{G}_{gj}}\tilde{\omega}_{ij}\left(\int_{k\in\mathcal{I}_j}\omega_{kj}\frac{\rho_{ik}\sigma_i\sigma_k}{\mu_i\mu_k}dk\right)di,$$

where $\tilde{\omega}_{ij}\equiv\frac{\mathbb{E}(\mathcal{D}_{ij})(\eta(1-s_{ij})+\theta s_{ij})}{\int_{k\in\mathcal{G}_{gj}}\mathbb{E}\left(\mathcal{D}_{kj}\right)\left(\eta(1-s_{kj})+\theta s_{kj}\right)dk}$ is a weighted-average elasticity of substitution.

Replacing these last expressions in Equation (C.10), we get our optimal pricing equation:

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

where $\Gamma_{gj}\equiv\int_{i\in\mathcal{G}_{gj}}\tilde{\omega}_{ij}\left(\int_{k\in\mathcal{I}_j}\omega_{kj}\frac{\rho_{ik}\sigma_i\sigma_k}{\mu_i\mu_k}dk\right)di$ represents bank j' g-level weighted risk term.

C.4 Pricing Equation under Alternative Model Specifications

C.4.1 Absence of Loan Commitments and Diminishing Lending Returns

We provide further derivations for our alternative model specification, in which banks' curvature arises from a lending technology with decreasing marginal returns and assumes that banks do not make ex-ante commitments to the loans they offer.

In this setup, the bank problem can be written as follows:

$$\max_{\substack{\{R-R^D_{gj}\}\\ H_j}} \mathbb{E}\Bigg\{ \int_{i\in\mathcal{I}_j} \left(R - R^D_{gj} + z_j - \kappa_{ij}\right) \mathcal{D}_{ij}\, di - \frac{\chi_j}{2}\Big(\int_{i\in\mathcal{I}_j} \mathcal{D}_{ij} di + H_j + E_j\Big)^2 + (R+z_j)E_j - \frac{\nu_j}{2}H_j^2 \Bigg\}.$$

The first-order condition with respect to $R - R^D_{gj}$ is

$$\mathbb{E}\Bigg[\int_{i\in\mathcal{G}_{gj}} \mathcal{D}_{ij}\, di + \int_{i\in\mathcal{G}_{gj}} \left(R - R^D_{gj} + z_j - \kappa_{ij}\right) \mathcal{D}'_{ij}\, di - \chi_j \left(\int_0^1 \mathcal{D}_{ij} d\Lambda_j(i) + H_j + E_j \right) \int_{i\in\mathcal{G}_{gj}} \mathcal{D}'_{ij}\, di \Bigg] = 0.$$

Dividing by $\mathbb{E}\left(\int_{i\in\mathcal{G}_{gj}} \mathcal{D}'_{ij} di\right)$ and after rearranging terms, we get:

$$R - R^D_{gj} = -\frac{\int_{i\in\mathcal{G}_{gj}} \mathbb{E}\mathcal{D}_{ij} di}{\int_{i\in\mathcal{G}_{gj}} \mathbb{E}\mathcal{D}'_{ij} di} + \kappa_{gj} - \frac{\mathbb{E}\left(z_j \int_{i\in\mathcal{G}_{gh}} \mathcal{D}'_{ij} di\right)}{\int_{i\in\mathcal{G}_{gj}} \mathbb{E}\mathcal{D}'_{ij} di} + \chi_j \frac{\mathbb{E}\left[\int_{i\in\mathcal{G}_{gj}} \mathcal{D}'_{ij} di \times \left(\int_{i\in\mathcal{I}_j} \mathcal{D}_{ij} di + H_j + E_j\right)\right]}{\int_{i\in\mathcal{G}_{gj}} \mathbb{E}\mathcal{D}'_{ij} di},$$

Notice that one can rewrite the last term of the previous expression as follows:

$$\frac{\mathbb{E}\left[\int_{i\in\mathcal{G}_{gj}} \mathcal{D}'_{ij} di \times \left(\int_{i\in\mathcal{I}_j} \mathcal{D}_{ij} di + H_j + E_j\right)\right]}{\int_{i\in\mathcal{G}_{gj}} \mathbb{E}\mathcal{D}'_{ij} di} = \frac{\mathbb{C}ov\left[\int_{i\in\mathcal{G}_{gj}} \mathcal{D}'_{ij} di\,,\, \int_{i\in\mathcal{I}_j} \mathcal{D}_{ij} di\right]}{\mathbb{E}\mathcal{D}'_{gj}} + \mathbb{E}\left(L_j\right).$$

Replacing back in the first-order condition, we get:

$$R - R^D_{gj} = -\frac{\int_{i\in\mathcal{G}_{gj}} \mathbb{E}\mathcal{D}_{ij} di}{\int_{i\in\mathcal{G}_{gj}} \mathbb{E}\mathcal{D}'_{ij} di} + \left(\kappa_{gj} - \mathbb{E}z_j\right) + \chi_j \left[\mathbb{E}\left(L_j\right) + \frac{\mathbb{C}ov\left[\int_{i\in\mathcal{G}_{gj}} \mathcal{D}'_{ij} di\,,\, \int_{i\in\mathcal{I}_j} \mathcal{D}_{ij} di\right]}{\int_{i\in\mathcal{G}_{gj}} \mathbb{E}\mathcal{D}'_{ij} di} \right].$$

Following the same steps as in our baseline problem—in particular exploiting the CES structure of the demand—we can then rewrite this pricing equation as

$$R - R^D_{gj} = \frac{\eta(1-s_{gj}) + \theta s_{gj}}{\eta(1-s_{gj}) + \theta s_{gj} - 1} \left[\kappa_{gj} - \frac{\mathbb{E}\left(z_j \int_{i\in\mathcal{G}_{gh}} \mathcal{D}'_{ij} di\right)}{\int_{i\in\mathcal{G}_{gj}} \mathbb{E}\mathcal{D}'_{ij} di} + \chi_j \mathbb{E}\left(L_j\right) \left(1 + \frac{\mathbb{E}(\mathcal{D}_j)}{\mathbb{E}\left(L_j\right)} \Gamma_{gj}\right) \right].$$

To conclude, we can work with the $\frac{\mathbb{E}\left(z_j \int_{i\in\mathcal{G}_{gh}} \mathcal{D}'_{ij} di\right)}{\int_{i\in\mathcal{G}_{gj}} \mathbb{E}\mathcal{D}'_{ij} di}$ term. Using Equation (C.12), we get:

$$\frac{\mathbb{C}ov\left(z_j, \int_{i\in C_{ij}} \mathcal{D}'_{ij} di\right)}{\mathbb{E}\left(\int_{i\in C_{ij}} \mathcal{D}'_{ij} di\right)} = \int_{i\in C_{ij}} \frac{\left[(\eta-\theta)\, s_{ij} - \eta\right] \mathbb{E}\left(\mathcal{D}_{ij}\right)}{\int_{i\in C_{ij}} \left[(\eta-\theta)\, s_{ij} - \eta\right] \mathbb{E}\left(\mathcal{D}_{ij}\right) di} \frac{\mathbb{C}ov\left(z_j, \mathcal{D}_{ij}\right)}{\mathbb{E}\left(\mathcal{D}_{ij}\right)} di$$

$$= \int_{i\in C_{ij}} \tilde{\omega}_{ij} \frac{\mathbb{C}ov\left(z_j, \mathcal{D}_{ij}\right)}{\mathbb{E}\left(\mathcal{D}_{ij}\right)} di = \int_{i\in C_{ij}} \tilde{\omega}_{ij} \frac{\mathbb{C}ov\left(z_j, \phi_i^\theta\right)}{\mu_i} di.$$

where the last step follows from the fact that:

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

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

Combining all tese expressions, we get the pricing equation of the main text:

$$R - R_{gj}^D = \frac{\eta(1-s_{gj}) + \theta s_{gj}}{\eta(1-s_{gj}) + \theta s_{gj} - 1} \left[\kappa_{gj} - \mathbb{E}\left(z_j\right) + \chi_j \mathbb{E}\left(L_j\right) \left(1 + \frac{\mathbb{E}(\mathcal{D}_j)}{\mathbb{E}\left(L_j\right)} \Gamma_{gj}\right) - \int_{i\in C_{ij}} \tilde{\omega}_{ij} \frac{\mathbb{C}ov\left(z_j, \phi_i^\theta\right)}{\mu_i} di\right].$$

This equation mirrors the baseline pricing equation but adds two elements: a bank-size penalty from lending curvature and a covariance term linking lending returns to deposit demand shocks. 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.[61]

C.4.2 Risk Aversion or Regulatory Constraints

Given the same timing assumption of the previous subsection, one can obtain a similar pricing equation without the need to assume diminishing marginal returns on lending. For instance,

[61] 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.

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:

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

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

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

which is analogous to the pricing equation of our baseline model.

C.5 Extensive Margin Decomposition

In the main text, we decomposed county-level changes in risk premia to analyze the role of entrants and exiters. In particular, Equation (39), which we rewrite below, shows that county-level changes in risk can be written as follows:

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

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:

$$\begin{aligned}
\Delta \sum_{j\in\mathcal{J}_{it}} s_{ijt}\Gamma_{jt} = {} & \underbrace{\alpha_i^1 M_i^1 \left(\sum_{\{\tilde{j}_1\}_i} \frac{s_{ij}^1}{\alpha_i^1 M_i^1}\Gamma_{ij}^1 - \sum_{\{\hat{j}\}_i} \frac{s_{ij}^1}{1-M_i^1}\Gamma_{ij}^1 \right)}_{\text{Out-of-state Entrants vs. Survivors}} - \underbrace{\alpha_i^0 M_0^0 \left(\sum_{\{\tilde{j}_0\}_i} \frac{s_{ij}^0}{\alpha_i^0 M_i^0}\Gamma_{ij}^0 - \sum_{\{\hat{j}\}_i} \frac{s_{ij}^0}{1-M_i^0}\Gamma_{ij}^0 \right)}_{\text{Survivors vs Out-of-state Exiters}} \\
& + \underbrace{\left(1-\alpha_i^1\right) M_i^1 \left(\sum_{\{\tilde{j}_1^\star\}_i} \frac{s_{ij}^1}{\left(1-\alpha_i^1\right) M_i^1}\Gamma_{ij}^1 - \sum_{\{\hat{j}\}_i} \frac{s_{ij}^1}{1-M_i^1}\Gamma_{ij}^1 \right)}_{\text{Within-state Entrants vs. Survivors}} \\
& - \underbrace{\left(1-\alpha_i^0\right) M_i^0 \left(\sum_{\{\tilde{j}_0^\star\}_i} \frac{s_{ij}^0}{\left(1-\alpha_i^0\right) M_i^0}\Gamma_{ij}^0 - \sum_{\{\hat{j}\}_i} \frac{s_{ij}^0}{1-M_i^0}\Gamma_{ij}^0 \right)}_{\text{Survivors vs. Within-state Exiters}} \\
& + \underbrace{\sum_{\{\hat{j}\}_i} \frac{s_{ij}^1}{1-M_i^1}\Gamma_{ij}^1 - \sum_{\{\hat{j}\}_i} \frac{s_{ij}^0}{1-M_i^0}\Gamma_{ij}^0}_{\text{Within Survivors}}
\end{aligned} \tag{C.14}$$

The sum of the first two terms on the right-hand-side of Equation (C.14) 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 11 of the main text, we show that more than half of the extensive-margin is explained by out-of-state entrants and exiters.

C.6 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, $L_j = \int_{\mathcal{I}_j^S} L_{ij} di$, 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:

$$Rev\left(A_j\right) = \max_{\{L_{ij}\},S_j} \mathbb{E}\left[\int_0^1 \left(R + z_j^L - \frac{1}{2}\alpha_i\alpha_j L_{ij}\right) L_{ij} d\Lambda_j(i) + \left(R + z_j^S - \frac{1}{2}\beta_j S_j\right) S_j\right], \quad \text{(C.15)}$$

$$\text{s.t. } A_j = \int_0^1 L_{ij} d\Lambda_j(i) + S_j.$$

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:

$$L_{ij} = \frac{\beta_j}{\alpha_i\alpha_j} S_j. \quad \text{(C.16)}$$

Summing across all locations in which the bank operates:

$$L_j = \frac{\beta_j}{\alpha_j} S_j \int_0^1 \frac{1}{\alpha_i} d\Lambda_j(i),$$
$$= \frac{\beta_j}{\alpha_j} \varrho_j S_j, \quad \text{(C.17)}$$

where $\varrho_j \equiv \int_0^1 \frac{1}{\alpha_i} d\Lambda_j(i)$. Replacing equation (C.17) back in equation (C.16), we get L_{ij} as a function of L_j:

$$L_{ij} = \frac{1}{\alpha_i \varrho_j} L_j. \quad \text{(C.18)}$$

Then, using $L_j + S_j = A_j$ and equation (C.17), 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:

$$\begin{aligned} Rev\left(A_j\right) =& \mathbb{E}\left\{\left(R + z_j\right)\left(\int_0^1 \frac{1}{\alpha_i\varrho_j}\frac{\varrho_j\beta_j}{\varrho_j\beta_j + \alpha_j} \mathrm{d}\Lambda_j(i) + \frac{\alpha_j}{\varrho_j\beta_j + \alpha_j}\right) A_j\right\} + \\ & -\mathbb{E}\left\{\int_0^1 \frac{1}{2}\frac{\alpha_j}{\varrho_j}\frac{\varrho_j\beta_j}{\varrho_j\beta_j + \alpha_j} A_j \frac{1}{\alpha_i\varrho_j}\frac{\varrho_j\beta_j}{\varrho_j\beta_j + \alpha_j} A_j \mathrm{d}\Lambda_j(i) + \frac{1}{2}\beta_j \frac{\alpha_j}{\varrho_j\beta_j + \alpha_j} A_j \frac{\alpha_j}{\varrho_j\beta_j + \alpha_j} A_j\right\} \\ =& \mathbb{E}\left[\left(R + z_j\right) A_j - \frac{1}{2}\vartheta_j A_j^2\right], \end{aligned} \quad \text{(C.19)}$$

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:

$$\max_{\{R_{gj}^D\}A_j,H_j} \mathbb{E}\left[\left(R+z_j-\frac{1}{2}\vartheta_j A_j\right)A_j-\int_{i\in\mathcal{G}_j}\left(R_{gj}^D+\kappa_{ij}\right)\mathcal{D}_{ij}di-\left(R+\frac{\nu_j}{2}H_j\right)H_j-\left(R+\frac{\chi_j}{2}B_j\right)B_j\right],$$

$$\text{s.t. } A_j=\int_{i\in\mathcal{M}_j}\mathcal{D}_{ij}di+H_j+B_j+E_j.$$

This problem is thus identical to our baseline problem, with the only expection that the marginal expected return from an additional unit of deposit is $\mathbb{E}\left(\tilde{z}_j\right)\equiv\mathbb{E}\left(z_j\right)-\vartheta_j A_j$. Following identical steps to those in Appendix C.2, we get the following pricing equation:

$$R-R_{gj}^D=\frac{\eta(1-s_{gj})+\theta s_{gj}}{\eta(1-s_{gj})+\theta s_{gj}-1}\left[\kappa_{gj}-\mathbb{E}\left(z_j\right)+\vartheta A_j+\chi_j\mathbb{E}(\mathcal{D}_j)\Gamma_{gj}\right]. \tag{C.20}$$

C.6.1 Mapping to the Data

We now describe how we solve for the vector $\{\alpha_i\}$. Summing Equation (C.18) across all locations and dividing by total lending $L\equiv\sum_i L_i$, we obtain:

$$\frac{L_i}{L}(\{\alpha_i\})=\frac{1}{\alpha_i}\sum_{j\in\mathcal{J}_i}\frac{1}{\varrho_j}\frac{L_j}{L}, \tag{C.21}$$

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 $\mathcal{L}_i$.[62] 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: $\sum_i\left|\left|\frac{\mathcal{L}_i}{\mathcal{L}}-\frac{L_i}{L}(\{\alpha_i\})\right|\right|$.[63] Specifically, we solve:

$$\min_{\{\alpha_i\}}\sqrt{\sum_k \text{Loss}_k\left(\{\alpha_i\}\right)^2}, \tag{C.22}$$

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

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

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

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

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.6.2 Alternative Timing and Source of Curvature

We can also extend the alternative model specification described in Section **??** and Appendix C.4.1 to allow for local lending. In this case, it is straightforward to show that the resulting pricing equation is identical to the one in the main text, Equation (**??**).

The timing assumption remains the same as in Section **??**. To introduce a local lending dimension, we assume that the bank can lend only in the locations in which it operates. For a given total lending amount L_j, the bank allocates loans across its locations without frictions. The bank's profit, conditional on a vector of deposit inflows and optimal choices for loans and wholesale borrowing, can be written as:[64]

$$\Pi_j\left(\{\mathcal{D}_{ij}\}_{\forall i\in\mathcal{I}_j}\right)=\int_{i\in\mathcal{I}_j}\left(R+z_j-\frac{\chi_j}{2}L_{ij}^{\star}\right)L_{ij}^{\star}di-\left(R+\frac{\nu_j}{2}H_j^{*}\right)H_j^{*}. \tag{C.23}$$

Thus, once shocks have been realized and conditional on L_j, the bank chooses $\{L_{ij}\}_{i\in\mathcal{I}_j}$ to solve

$$\begin{aligned} Rev_j(L_j)&=\max_{\{L_{ij}\}}\int_{i\in\mathcal{I}_j}\left(R+z_j-\frac{\chi_j}{2}L_{ij}\right)L_{ij}\,di, \\ \text{subject to}\qquad L_j&=\int_{i\in\mathcal{I}_j}L_{ij}\,di, \end{aligned} \tag{C.24}$$

where $Rev_j(L_j)$ denotes the bank's total revenue from optimally allocating L_j across locations. It is easy to show that the optimal allocation takes the form

$$L_{ij}^{*}(L_j)=\frac{L_j}{\int_{i\in\mathcal{I}_j}di}, \tag{C.25}$$

[64]For easiness of exposure, we consider a bank-level χ_j curvature, instead of $\chi_i\chi_j$ as in the baseline model.

Substituting this allocation into the objective yields

$$Rev_j(L_j) = \left(R + z_j - \frac{\widetilde{\chi}_j}{2} L_j\right) L_j, \qquad \text{with } \widetilde{\chi}_j \equiv \frac{\chi_j}{\int_{k \in \mathcal{I}_j} dk}. \tag{C.26}$$

Substituting this expression into the ex post return function gives

$$\Pi_j(\{D_{ij}\}) = \left(R + z_j - \frac{\widetilde{\chi}_j}{2} L_j\right) L_j - \left(R + \frac{\nu_j}{2} H_j^*\right) H_j^*, \tag{C.27}$$

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

This return function has the same structure as Equation (**??**). The only difference is that $\widetilde{\chi}_j$ now summarizes the average diminishing returns to lending across the markets in which bank j operates. As a result, the pricing equation for deposit spreads is unchanged.

C.7 Multiple Liquid 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 (46) and (47), 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:

$$\frac{R - R_{li}}{R - R_i^X} = \zeta_l \left(\frac{X_{li}}{X_i}\right)^{-\frac{1}{\varepsilon}} \text{ and } \quad \frac{R - R_i^D}{R - R_i^X} = \left(\frac{D_i}{X_i}\right)^{-\frac{1}{\varepsilon}}, \tag{C.28}$$

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

$$\frac{R - R_i^X}{R - R^X} = \phi_i \left(\frac{X_i}{X}\right)^{-\frac{1}{\theta}}. \tag{C.29}$$

From Equation (C.28), we obtain the ratio of county-level deposits to asset X_{li} as:

$$\frac{D_i}{X_{li}} = \zeta_l^{-\varepsilon} \left(\frac{R - R_i^D}{R - R_{li}}\right)^{-\varepsilon}. \tag{C.30}$$

The county-level ideal price index for liquidity services is derived by substituting Equation (C.28) 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:

$$R - R_i^X = \left(\sum_l \zeta_l^\varepsilon (R - R_{li})^{1-\varepsilon} + (R - R_i^D)^{1-\varepsilon} \right)^{\frac{1}{1-\varepsilon}}. \tag{C.31}$$

Similarly, substituting Equation (C.29) into the definition of X from Equation (46), we obtain the national-level ideal price index for liquidity services:

$$R - R^X = \left(\int \phi_i^\theta (R - R_i^X)^{1-\theta} \, di \right)^{\frac{1}{1-\theta}}. \tag{C.32}$$

Based on the demand for deposits D_{ij} in equation (51), we can compute the elasticity of deposit demand faced by bank j in market i as:

$$\begin{aligned} \frac{d \ln D_{ij}}{d \ln \left(R - R_{ij}^D\right)} = &- \eta \left[1 - \frac{d \ln \left(R - R_i^D\right)}{d \ln \left(R - R_{ij}^D\right)} \right] - \varepsilon \left[\frac{d \ln \left(R - R_i^D\right)}{d \ln \left(R - R_{ij}^D\right)} - \frac{d \ln \left(R - R_i^X\right)}{d \ln \left(R - R_{ij}^D\right)} \right] \\ &- \theta \left[\frac{d \ln \left(R - R_i^X\right)}{d \ln \left(R - R_{ij}^D\right)} \right], \end{aligned} \tag{C.33}$$

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.31), we can compute:

$$\begin{aligned} \frac{d \ln (R - R_i^X)}{d \ln (R - R_{ij}^D)} &= \frac{d \ln (R - R_i^D)}{d \ln (R - R_{ij}^D)} \cdot \left[\frac{(R - R_i^D)^{1-\varepsilon}}{\sum_l \zeta_l^\varepsilon (R - R_{li})^{1-\varepsilon} + (R - R_i^D)^{1-\varepsilon}} \right] \\ &= \frac{d \ln (R - R_i^D)}{d \ln (R - R_{ij}^D)} \cdot \left(\frac{R - R_i^D}{R - R_i^X} \right)^{1-\varepsilon}. \end{aligned} \tag{C.34}$$

Substituting (C.34) into the elasticity of deposit demand expression from (C.33), and simplifying, we obtain:

$$\frac{d\ln D_{ij}}{d\ln(R-R_{ij}^D)} = -\left[(1-s_{ij})\eta + s_{ij}\hat{\theta}_i\right], \tag{C.35}$$

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

$$\hat{\theta}_i \equiv \varepsilon + (\theta-\varepsilon)s_i^D, \quad \text{with} \quad s_i^D = \left(\frac{R-R_i^D}{R-R_i^X}\right)^{1-\varepsilon}, \tag{C.36}$$

as expressed in Section 8.1.

C.8 Solution Algorithm for Model Counterfactuals

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

$$\mathbb{E}\left(D_j\right) = \sum_{i\in\mathcal{I}_j}\mathbb{E}\left[D_{ij}\right]$$

(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

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

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

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

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

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

(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.

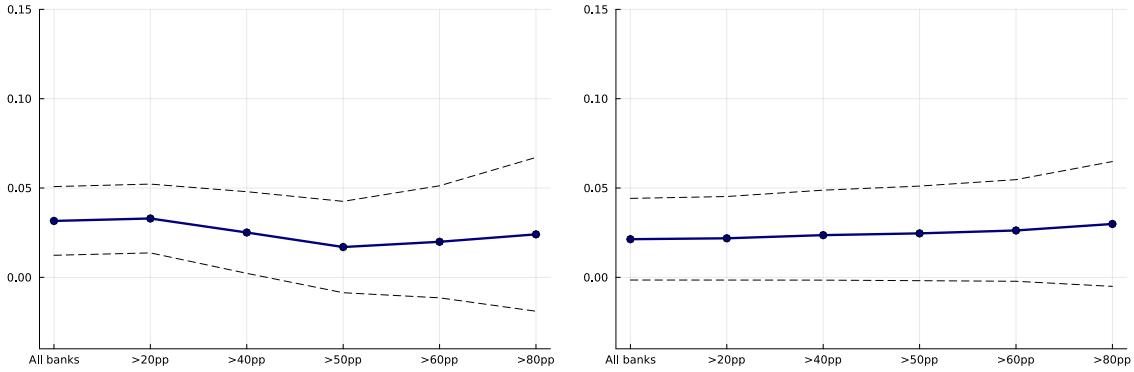
Appendix D Additional Results

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 (32) from the main text. Results are presented in Figure D.1. Overall, the magnitude of the estimates closely aligns with those in Table 4. 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) Uniform Pricing (B) Local Pricing

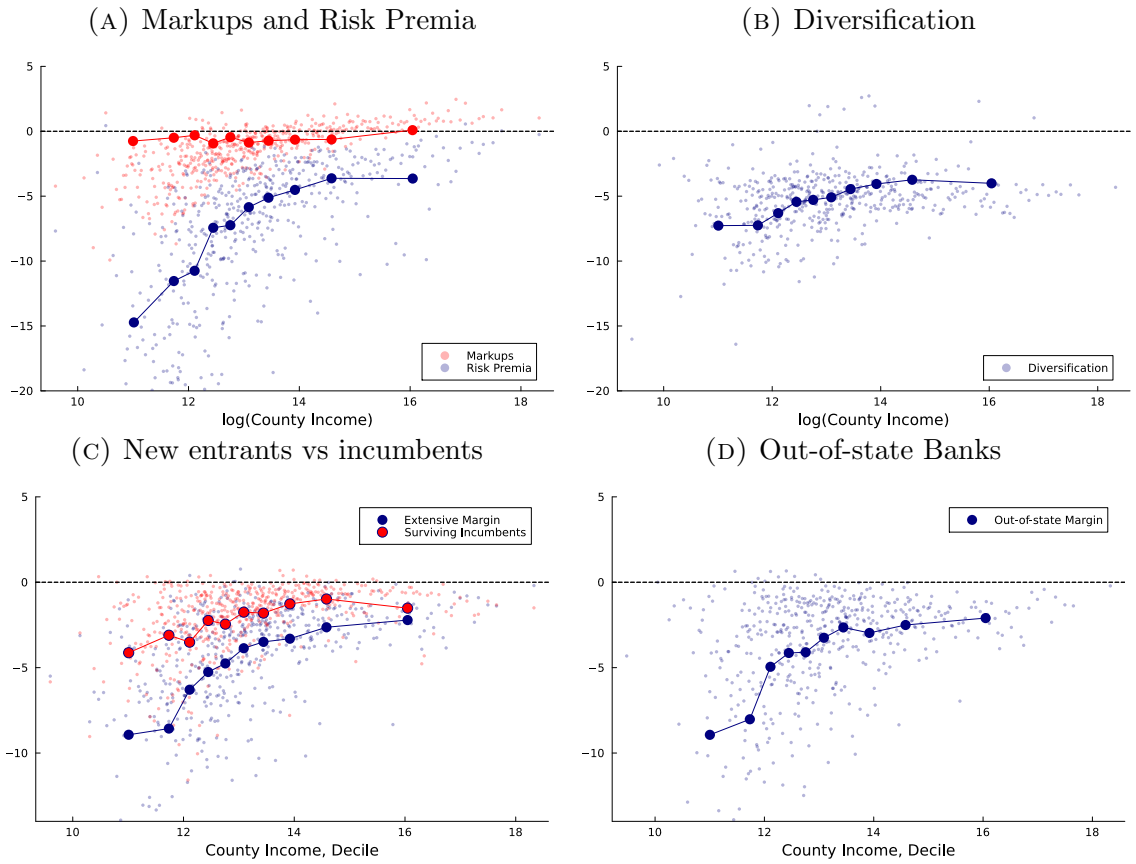


Notes: The figure displays estimates of χ across bank size bins, where size is defined by total loans. For example, the "> 50pp" bin includes banks with total loans greater than the 50th percentile. Dashed lines show 90% confidence intervals. For the uniform-pricing case, standard errors are clustered at the bank level. In the local-pricing specification, standard errors are clustered at the bank-county 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 (37), 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 (38). Panel (C), based on Equation (39), 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 ×100.

D.3 Decomposition of Changes in Aggregate Spreads - Shares

Table 5 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

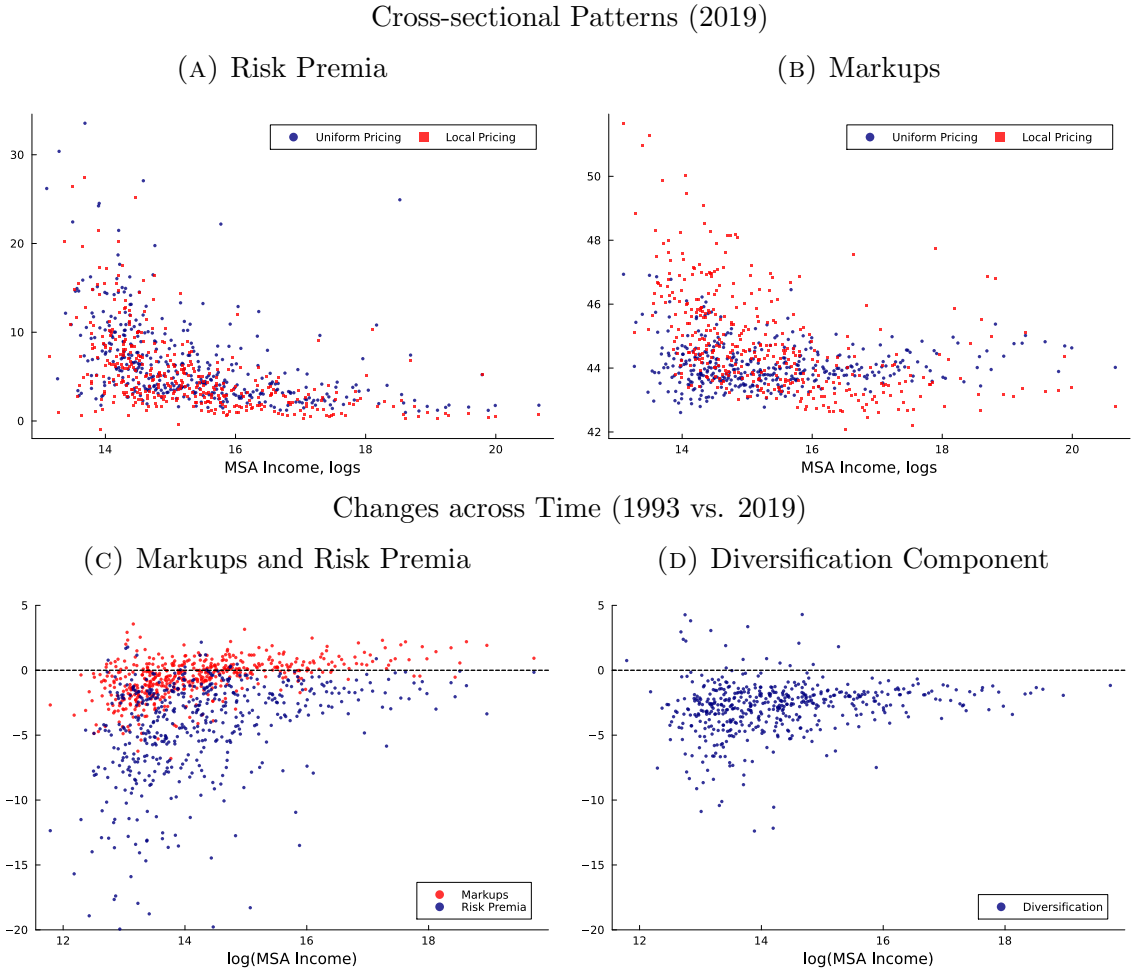
	Uniform pricing				Local Pricing			
	Risk Premium		Markup	Net	Risk Premium		Markup	Net
	Total	Diver			Total	Diver		
National Level								
Aggregate	2.7%	15.6%	-5.0%	-2.3%	1.8%	14.2%	-5.5%	-3.8%
Aggregate (fixed shares)	12.3%	14.7%	-2.6%	9.7%	14.2%	13.0%	-1.4%	12.8%
By Group of Counties								
Small Counties (<p10)	72.9%	23.7%	19.1%	92.0%	58.7%	29.2%	3.6%	62.3%
Medium Counties	32.9%	22.7%	6.1%	39.0%	28.9%	22.3%	2.5%	31.4%
Large Counties (>p90)	9.4%	16.0%	-3.4%	6.0%	12.1%	12.6%	-0.4%	11.7%

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 (40). 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 (36), 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 (37), 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 (38). 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.[65]

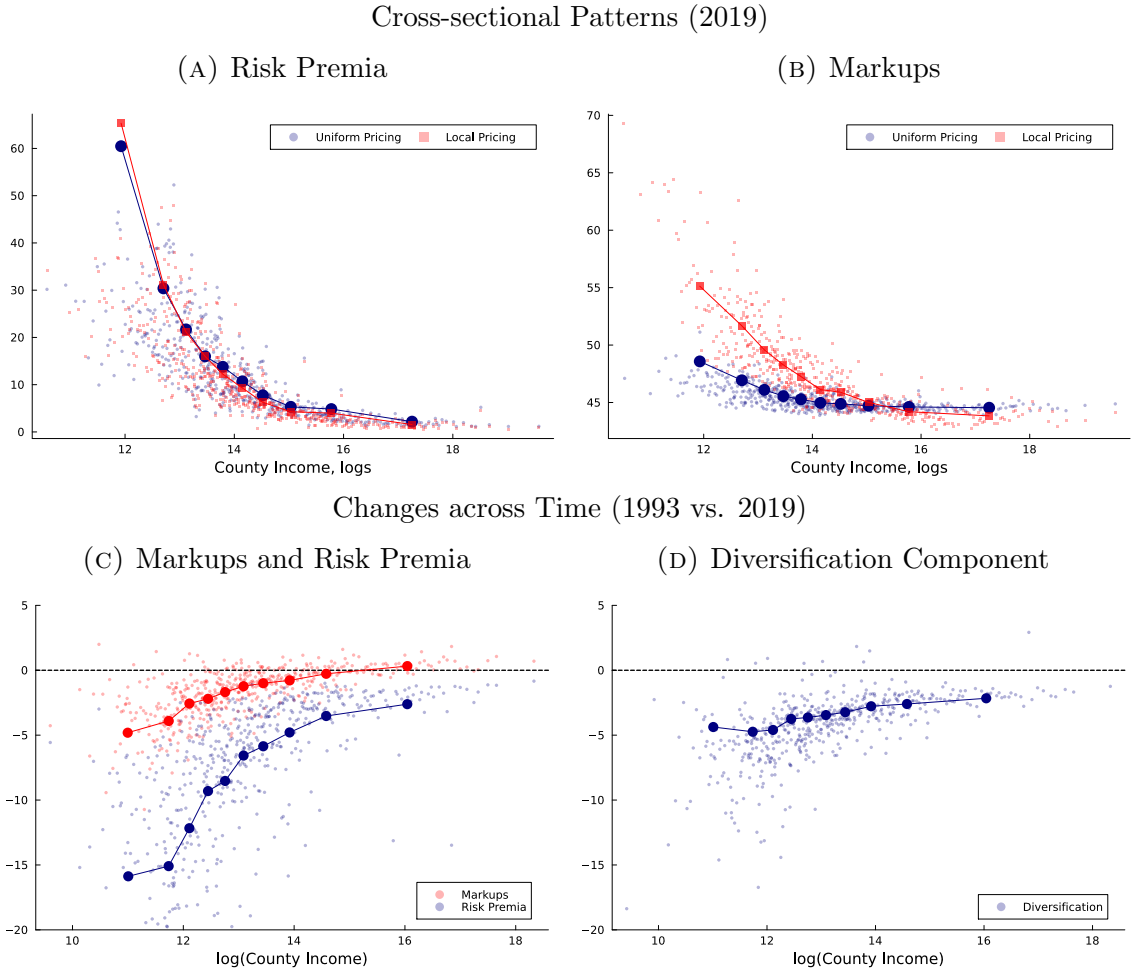
A second concern is that some banks may not report deposit holdings at the branch level consistently, instead aggregating all deposits under a single branch—a practice known as *central booking*. This can distort the measurement of local deposit concentration and geographic risk exposure.

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.

[65] 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



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 (37), 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 (38). Data is adjusted to exclude online banks and banks employing central booking practices. Units are log points $\times 100$.

D.6 Empirical Proxy for Non-interest Marginal Costs

In this subsection, we provide an empirical measure of non-interest marginal costs, $(k-z)_{jt}$, that does not depend on the model structure. We follow Berger et al. (2009) and Corbae and D'Erasmo (2022) to compute marginal non-interest expenses—an empirical proxy for k_{jt}, hereafter labeled $\tilde{k}_{jt}$—based on the estimation of a translog cost function. In particular, using

yearly data from Call Reports over the period 1990-2019, we estimate

$$\begin{aligned}\log NIE_{jt} = {} & \alpha_t + \alpha_j + \beta_{0Q}\log Q_{jt} + \beta_{0S}\log S_{jt} + \beta_{0W}\log\left(W_{jt}\right) \\ & + \beta_{1Q}(\log Q_{jt})^2 + \beta_{1S}(\log S_{jt})^2 + \beta_{1W}(\log W_{jt})^2 \\ & + \gamma_1 \log Q_{jt}\log S_{jt} + \gamma_2 \log Q_{jt}\log W_{jt} + \gamma_3 \log S_{jt}\log W_{jt} + \sum_{k=1}^{2}\gamma_{4,k}t^k + \epsilon_{jt},\end{aligned} \tag{D.1}$$

where S_{jt} are safe securities (i.e., Treasuries and agency-backed securities), and W_{jt} is salaries over total assets.[66] With the estimated coefficients at hand, we compute marginal NIE as

$$\tilde{k}_{jt} = \frac{\widehat{\partial NIE_{jt}}}{\partial Q_{jt}} = \frac{NIE_{jt}}{Q_{jt}} \times \left(\hat{\beta}_0 + 2\hat{\beta}_1 \log Q_{jt} + \sum_k \hat{\gamma}_k x_{k,jt}\log Q_{jt}\right), \tag{D.2}$$

where each $x_{k,jt}$ denotes one of the variables interacted with $\log Q_{jt}$ and $\hat{\gamma}_k$ the estimated coefficient for the interaction. We then compute a proxy for marginal non-interest costs, $\widetilde{(k-z)}_{jt}$, as

$$\widehat{(k-z)}_{jt} = \tilde{k}_{jt} - \left(\frac{IIL_{jt}}{TL_{jt}} - R_t\right), \tag{D.3}$$

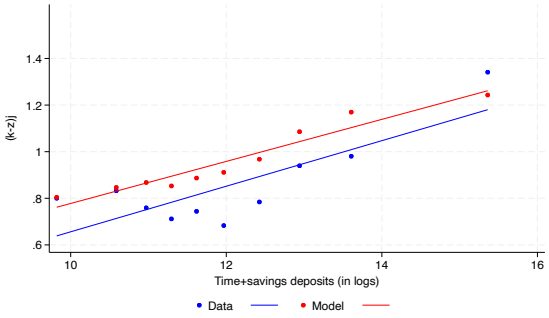
where IIL_{jt} are total interest income, TL_{jt} are loans and securities, and R_t is the illiquid rate of return.

Figure D.5 compares the model's $(k-z)_{jt}$ with the empirical proxy, as of 2019, sorted by bank size (pane (A)) and number of counties in which the bank operates (panel (B)). Overall, we find that the two measures provide similar patterns and magnitudes across banks, thus serving as a source of external validation for our model.

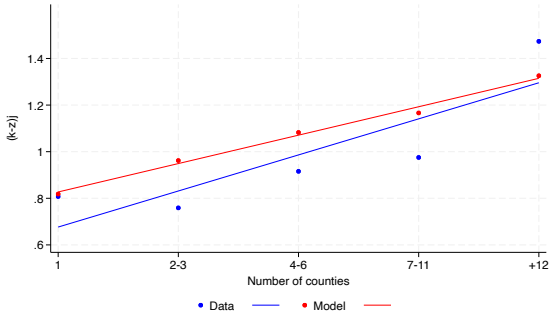
[66] As in Corbae and D'Erasmo (2022), we constructed NIE as total expenses net of interest exepenses on deposits, interest expenses on federal funds and repo agreements, and noninterest expenses on premises.

FIGURE D.5. Estimates for $(k-z)_j$ as of 2019

(A) By bank size



(B) By number of counties



D.7 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	60.02	26.41	6.81	-19.27	-4.41	-0.72	0.07	0.04	0.52
A.2 Regional banks	14.76	17.11	9.08	1.91	0.66	0.11	0.61	0.42	0.52
A.3 National banks	9.15	15.62	39.49	5.54	3.80	1.15	0.16	0.44	-0.54
B. Decrease in ψ_{ij}									
B.1 Local banks	1.70	3.23	1.54	-3.71	-2.89	-0.70	0.79	0.29	0.66
B.2 Regional banks	2.15	1.65	1.87	4.25	2.15	0.17	0.96	0.81	0.75
B.3 National banks	2.07	1.29	-0.52	2.57	3.79	4.41	0.23	0.68	-0.59

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

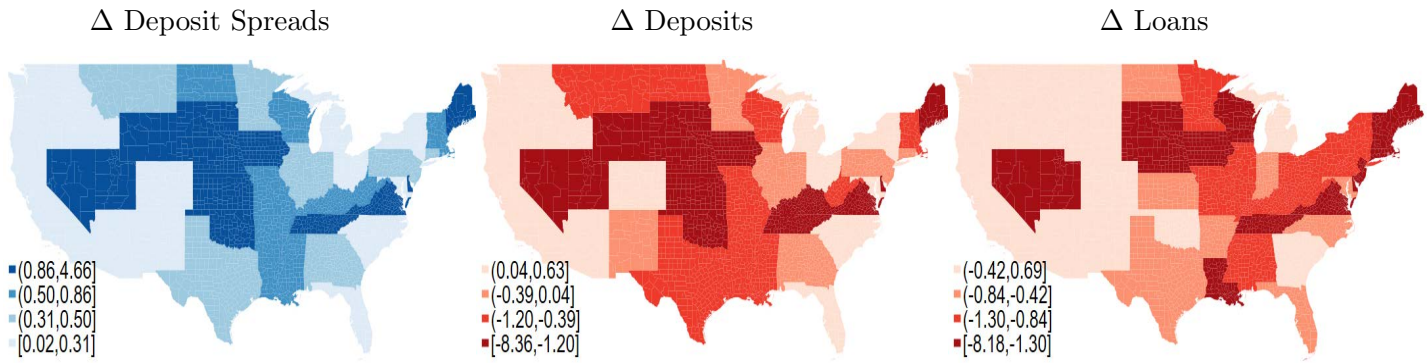
	Δ Deposit Spreads			Risk Premia			Markups		
	Small	Medium	Large	Small	Medium	Large	Small	Medium	Large
A. Higher curvature									
Increase χ_i	3.15	1.12	0.44	3.78	1.34	0.47	-0.00	-0.01	-0.00
B. M&A, acquired banks operate in only 1 county									
Acquirer bank:									
B.1 Top local bank	2.66	0.70	-0.00	-0.80	0.04	0.09	1.18	0.45	0.04
B.2 Top regional bank	-4.98	-2.02	-0.16	-3.93	-0.98	-0.11	0.81	0.48	0.02
B.3 Top national bank	-13.21	-3.95	-0.19	-14.92	-2.45	-0.32	2.03	0.77	0.09
C. M&A, acquired banks operate in at most 2 counties									
Acquirer bank:									
C.1 Top local bank	6.40	2.16	0.08	-1.63	0.39	0.26	3.13	1.23	0.13
C.2 Top regional bank	-5.94	-2.70	-0.06	-8.42	-1.49	0.02	1.96	1.41	0.12
C.3 Top national bank	-26.08	-7.45	-0.65	-37.43	-5.79	-0.74	4.09	2.13	0.29
D. Changes in demographics									
D.1 Increase μ_i	-8.96	-3.10	0.06	-8.79	-2.85	0.01	0.04	0.02	-0.00
D.2 Increase σ_i / μ_i	1.14	0.62	4.80	1.12	0.59	3.83	-0.01	-0.01	0.01

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 $\times 100$.

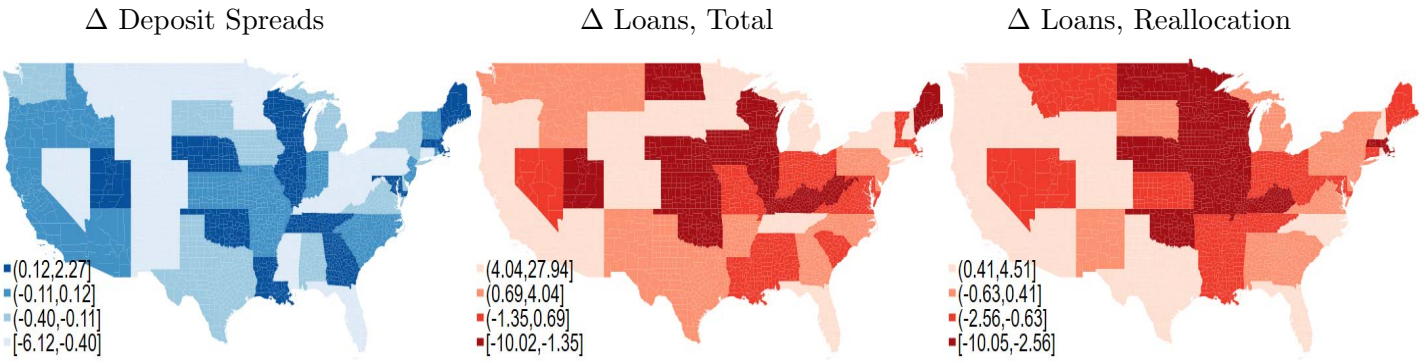
We also examine changes in local lending under local pricing. We begin with the counterfactual scenario in which banks' curvature parameter χ increases (Panel A of Figure D.6). Despite the different pricing protocol, the effects are broadly consistent with those in the main text. Next, we consider the 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.6). The overall patterns closely mirror those observed under uniform pricing.

FIGURE D.6. Changes in Lending and Deposit Spreads under Local Pricing

(A) Higher Bank Curvature



(B) Mergers and Acquisition



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.8 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

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.

currency" (FL153020005), and deposits as "Total time and savings deposits" (FL153030005), both from the "Households and nonprofit organizations" sector.[67] We consider two measures of the monetary policy shock FF_t, both constructed by Jarociński and Karadi (2020).[68] 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:

$$\Delta \ln(R_t - 1) = \beta_0^R + \beta_1^R FF_{t-k} + \boldsymbol{\beta}' \mathbf{X}_t + \epsilon_t^R, \tag{D.4}$$

$$\Delta \ln\left(\frac{M_t}{D_t}\right) = \gamma_0^M + \gamma_1^M \Delta \widehat{\ln(R_t - 1)} + \boldsymbol{\gamma}' \mathbf{X}_t + u_t^M. \tag{D.5}$$

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

[67] 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.

[68] Data source: https://github.com/marekjarocinski/jkshocks_update_fed.

two use the full sample. The point estimates are both economically and statistically significant 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.