Geographical Diversification In Banking: A Structural Evaluation *

JUAN M. MORELLI
Federal Reserve Board

MATÍAS MORETTI
University of Rochester

VENKY VENKATESWARAN
NYU Stern, NBER

March 20, 2025

Abstract. We study the effects of diversification and competition in US deposit markets, using a rich yet tractable spatial model of banking in which deposit rates are driven lower by markups and risk premia (compensation for undiversified idiosyncratic risk in deposit demand). When calibrated using micro data on deposits and rates, the model points to significant risk premia in deposit rates, especially in the smallest/poorest counties. Geographical expansion and consolidation in the banking industry in recent decades has lowered risk premia and only modestly changed markups, with depositors in the small counties benefiting the most. The model also predicts significant gains to depositors from further consolidation – even in the form of large local banks acquiring smaller ones. Such consolidation is also likely to *increase* local lending, especially in areas where small banks have sizeable market shares.

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

JEL Codes: D43, E44, G21.

* Morelli (juan.m.morellileizagoyen@frb.gov): Federal Reserve Board. Moretti (mmorett2@ur.rochester.edu): University of Rochester. Venkateswaran (vvenkate@gmail.com): NYU Stern. Special thanks to Yufeng Wu for an excellent discussion. We would also like to thank Dean Corbae, Pablo D'Erasmo, Joao Granja, Nicholas Trachter, Kyle Herkenhoff, Ezra Oberfield, V.V.Chari, participants at 2023 AEA Meeting, 2023 SED, 2023 EEA-ESEM, 11th Annual CIGS, Boston College, Federal Reserve Board, Richmond Fed, St Louis Fed, Northern Finance Association, RIDGE, SAET, Simon Business School, SITE workshop, University of British Columbia, University of Notre Dame, University of Minnesota, University of Wisconsin, and Wharton School of Business for useful comments and discussions. Disclaimer: The views expressed here are our own and should not be interpreted as reflecting the views of the Board of Governors of the Federal Reserve System or of anyone else associated with the Federal Reserve System.

1. Introduction

The structure of the US banking industry has changed dramatically over the past few decades. Regulatory changes are widely regarded as a key factor behind these trends. The Riegle-Neal Interstate Banking and Branching Efficiency Act (1994), for example, removed many restrictions on branch-network expansion for US banks and allowed bank holding companies to acquire banks in any state. Subsequently, the industry witnessed a wave of geographical expansion and consolidation. Understanding the effects of these changes requires thinking through multiple, intertwined economic mechanisms: from changes in market concentration and competition to reduced idiosyncratic risks through diversification.

In this paper, we use a structural approach to quantify these effects on bank deposit markets. We formulate a general equilibrium model of deposit-taking and lending by heterogeneous banks operating in a large number of oligopolistic markets (US counties in our empirical implementation). They face idiosyncratic risks in the form of county-level shocks to deposit demand. These shocks are imperfectly correlated across locations, so geographical expansion brings diversification benefits.[1] We show how the rich heterogeneity in the model can be disciplined using detailed bank- and county-level data. We then use the calibrated model to recover the effects of risk and markups on deposit spreads and, through that, on aggregate deposit flows and lending.

We begin with some reduced-form evidence as motivation for our analysis. We confirm that, since the 1990s, banks have significantly increased the number of counties in which they operate.[2] On the competition front, we find that national-level market concentration in deposit markets (measured by HHI) has increased since the 1990s, while changes in county-level concentration show a more mixed pattern. These patterns, while suggestive, are hard to interpret without a theoretical framework.

In the model, a representative household values, in addition to a single consumption good, deposit services, modeled as a nested CES aggregate. Deposits at different banks within a county are aggregated into a county-level composite, which is then accumulated to generate the economy-wide bundle. This aggregation is subject to idiosyncratic shocks that shift the

[1] Our model also features idiosyncratic lending return risk, but our analysis suggests that there is little interaction – theoretically (for some specifications) or empirically – with deposit pricing, the key object of interest in this paper.

[2] In Appendix B.1, we show reduced-form evidence that larger banks tend to be less exposed to fluctuations in deposit flows, suggestive of diversification benefits.

household's preferences for deposits in a county. Since an individual bank does not operate in all counties, it is exposed to idiosyncratic risk. This gives rise to a motive for diversification to the extent there is curvature in banks' payoff functions. In our baseline specification, curvature arises from a combination of loan commitments and frictions in the inter-bank market, but we show that the results are quite robust to alternative sources of curvature.

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

The optimal deposit spread (the deposit rate relative to the rate on an asset which does not provide liquidity) is given by a markup times the marginal cost of providing deposit services. In our oligopolistic setting, the markup is a function of the substitution elasticities and appropriately defined market shares. Intuitively, an oligopolist bank internalizes its effect on the county-level deposits. since the elasticity of substitution at the county-level is lower than the one across banks within a county, this raises the optimal markup relative to the monopolistically competitive benchmark. The higher a bank's market share, the stronger is this effect, or equivalently higher is the markup. The two pricing protocols differ in the relevant notion of a market – under uniform pricing, markups are a function of the bank's average market share across all counties, while under local pricing, the markup is market-specific and depends on the bank's share in that county. The marginal cost includes a risk premium component, a novel feature of our framework. The exact form of the risk premium on the pricing protocol: under uniform pricing, there is a single risk premium for the whole bank, a function of the variability

of its total deposit flows, which in turn depends on the covariances of county-level preference shocks. All else equal, the less diversified a bank, the higher this variability and therefore the risk premium. Accordingly, the bank charges a larger spread (or equivalently, offers a less attractive rate to depositors). Diversification reduces this risk premium and, therefore, effective marginal costs and deposit spreads. The local pricing case features a bank- and county-specific risk premium, but the intuition is similar – the more positively a county's deposit demand shock covaries with those of other counties the bank operates in, the higher the risk premium (and therefore, higher the spread) charged by the bank in that county. As with uniform pricing, diversification reduces risk and through that, 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 CDs and money markets (from RateWatch) and bank financial statements. Our calibration strategy has two inter-connected parts. The first part leverages the richness of micro-data to estimate key parameters, such as the within- and across-market elasticities of substitution and the curvature in the banks' payoff function. The second one combines the estimated parameters from the first part with the data to recover preference and cost shifters and through that, idiosyncratic risks.

We use the calibrated model to quantify the effect of risk premia and markups on spreads, both in the cross-section and over time. The results point to a significant risk premium component in deposit spreads. As one would expect, this is most pronounced for smaller banks, which tend to be less diversified and face riskier deposit inflows. For the banks in the smallest decile of size, risk premia increase spreads by a bit over 0.40 log points (or almost 50%). The spreads of the largest banks, on the other hand, contain a much lower compensation for risk, with spreads pushed up by around 0.15 log points. Smaller banks also tend to have somewhat lower average market shares – and therefore, lower markups – than their mid-sized and larger counterparts, although the differences are small.

Across counties, risk premia drive up spreads by about 0.60 log points in the smallest/poorest counties. For the median county, the risk-related increase in spreads is almost 25%. Markups exert the largest effect in smaller/poorer counties, pushing up spreads by up to 0.55 log points. Combined, the risk and markup channels increase spreads by over 1.20 log points for the smallest/poorest counties.

Next, we analyze changes in the effects of risk premia and markups on spreads over the last couple of decades (specifically, between 1993 and 2019). First, we find that the geographical expansion and associated diversification benefits have exerted a significant downward pressure on deposit spreads. These changes are most pronounced for the smallest/poorest counties, where the decrease in marginal costs achieved through lower risk premia imply a reduction of spreads of up to 15%. In the aggregate, the reduction in risk premia lowered the cost of deposit services by about 3.0%. Changes in markups are more modest. Under the uniform pricing assumption, the model shows markups declining by about 5.0% in the smallest counties and remain more or less unchanged in the largest counties.

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

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

We then leverage the tractability of the model to perform various counterfactual experiments. Our first experiment explores the impact of further consolidation in the industry, specifically through the takeover of 'local' banks (defined to mean banks operating in less than two counties) by larger banks (either national, regional or larger local ones). The model predicts that this will lower risk premia. Markups fall modestly under uniform pricing (and rise slightly with local pricing). Interestingly, our results suggest there are significant diversification benefits even when the acquirer is a regional or larger local bank (though the gains are indeed largest with national banks). Once again, smaller counties experience the largest benefits from such restructuring. Our second counterfactual studies the effects of heterogeneous increases in banks' non-interest costs: a rise in the costs faced by local banks shifts market shares towards larger, more diversified banks. This drives county-level risk premia down, partially offsetting the direct effects of the cost increase. The opposite happens when more diversified banks experience cost increases. Finally, we show that increasing spatial inequality (larger counties growing in size

relative to their smaller counterparts) has the effect of reducing spreads in small and medium-sized counties. Intuitively, larger counties are less risky and so, an increase in their relative importance reduces risk premia.

We extend the baseline model in a number of directions, which serve to demonstrate the robustness of our analysis as well as deliver new insights. First, we make the assets side of the banks' balance sheet richer by allowing for multiple assets (including "local" loans, i.e. loans that are linked to the branch network and securities). This leads to an identical expression for optimal deposit spreads, implying that our decomposition results continue to hold in this richer setting. This version also allows us to trace out the effects of consolidation on lending, especially on local loans. For example, we find that a takeover of local banks by larger ones increases local lending. These effects are especially large in areas where smaller banks have large market shares.

Second, we show how additional 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. This version is calibrated to match the aggregate cash-to-deposits ratio as well as its sensitivity to exogenous changes in interest rates. We find that the results about the effects of risk and markups on deposit spreads are very similar, both in the cross-section as well as over time, to baseline findings, albeit with a somewhat larger role for markup variation.

Related literature

This paper contributes to several strands of the literature. First, it is related to the growing body of work that documents and analyzes diversification in the banking sector. Our focus on deposit flow risk is also shared by Aguirregabiria et al. (2016) and Corbae and D'Erasmo (2022), who analyze geographical expansion, taking as given an exogenous deposit process at each location. Our structural approach is complementary to recent empirical work on banks' geographical expansion and diversification of deposit risk (see, for instance, Kundu et al. (2021),

Kundu and Vats (2021), Doerr (2024)).[3] We differ from these papers in our explicit modeling of the market for deposits, while taking location choices as given. This allows us to capture the interplay of risk and diversification with competition and markups.

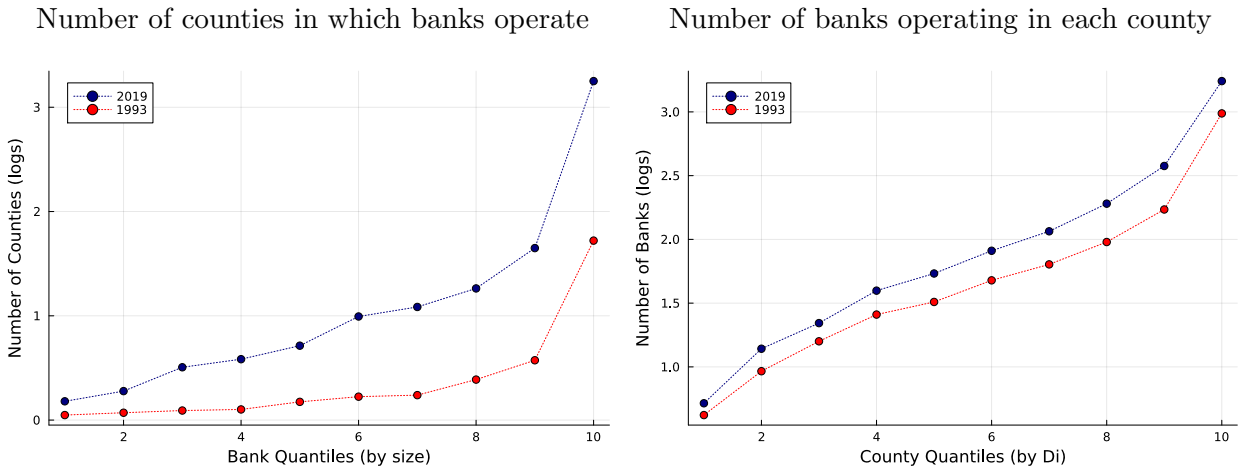
Second, these interactions also distinguish our work from that of Ji et al. (2023) and Oberfield et al. (2024), who endogenize location choice in spatial models of banking without risk. These papers highlight how primitives (e.g., size) of the markets for deposits and loans interact to determine optimal location decisions of banks. For example, Oberfield et al. (2024) show that deregulation induced large US banks to expand into markets that were relatively abundant in deposits relative to lending opportunities. Our analysis, which focuses on how location choices have reshaped funding risks and concentration in deposit markets, complements their substantive findings and helps paint a more complete picture of the effects of geographical expansion. Methodologically, our contribution is a rich yet tractable general equilibrium 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, Redding, and Weinstein (2016), Rossi-Hansberg, Sarte, and Trachter (2020) and Berger, Herkenhoff, and Mongey (2022). We extend and adapt this well-known framework to the banking context, where oligopolist 'firms' compete in multiple markets subject to idiosyncratic risk.

Finally, our paper is related to the literature on banks' market power. Work by Drechsler, Savov, and Schnabl (2017) and Wang, Whited, Wu, and Xiao (2020) analyze how market power affects the transmission of monetary policy through deposit and lending channels. Relatedly, Egan, Hortaçsu, and Matvos (2017) study the implications of banks' oligopolistic competition in markets for uninsured deposits on financial fragility. Analysis has also been done on the implications of bank market power for credit supply and financial stability (Black and Strahan, 2002; Corbae and D'Erasmo, 2021; Carlson et al., 2022; Herkenhoff and Morelli, 2024), and for adverse selection in lending markets (Crawford et al., 2018). We contribute to this literature

[3]Empirical analysis of diversification of other types of idiosyncratic 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). Relatedly, D'Amico and Alekseev (2024) study bank funding and financial integration (measured using regional variation in loan rates) during the era of branching restrictions (their data from 1953-1983).

FIGURE 1. Banks Geographical Expansion



Notes: The left panel shows the the average number of counties in which banks operate (in logs), by bank size. The right panel shows the number of banks operating in each county (in logs), by county size. Both panels show data for 1993 (red) and 2019 (blue).

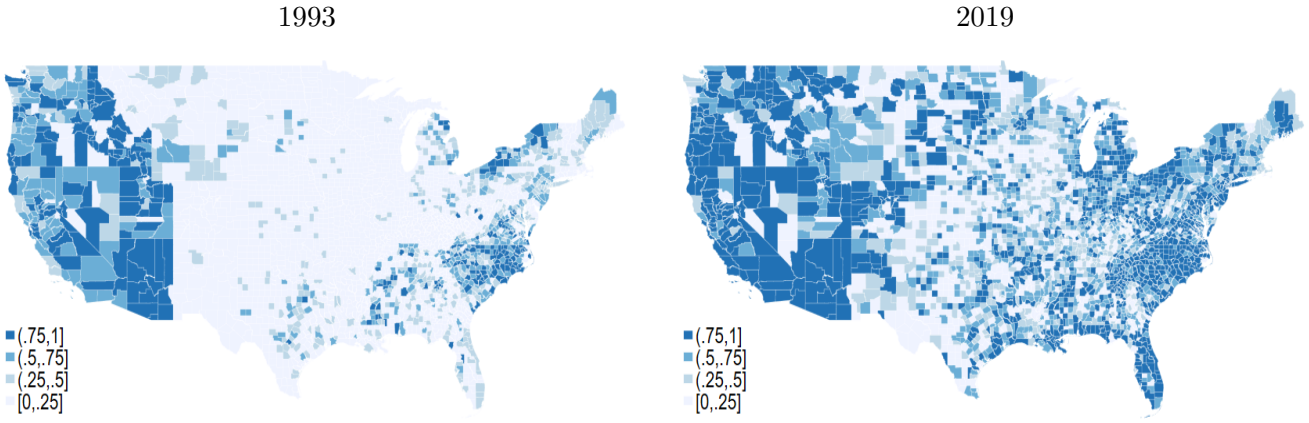
by quantifying the aggregate effects of bank market power on the deposit side, both in the cross-section and the time series.

2. Motivating Facts

We start our empirical analysis by providing evidence on the wave of banks' geographical expansion that occurred since the 1990s. The left panel of Figure 1 depicts the relation between a bank's size (as proxied by deciles on deposits) and the average number of counties in which it operates. The figure provides two main facts. First, larger banks operate in a larger number of counties. Second, banks' geographical expansion has been mainly driven by medium and large banks. By 2019, the largest banks in the sample (deciles 9 and 10) operated in 5 times as many counties as they did before the Riegle-Neal Act. The right panel shows that these changes are not contained to a subset of counties or regions. In fact, we observe a larger number of active banks in both smaller and larger counties.

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

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



Notes: The maps display county-level shares of deposits held by banks that operate in ten or more other counties. The left panel shows the pre-Riegle Neal Act results in 1993, while the right panel shows the results for 2019.

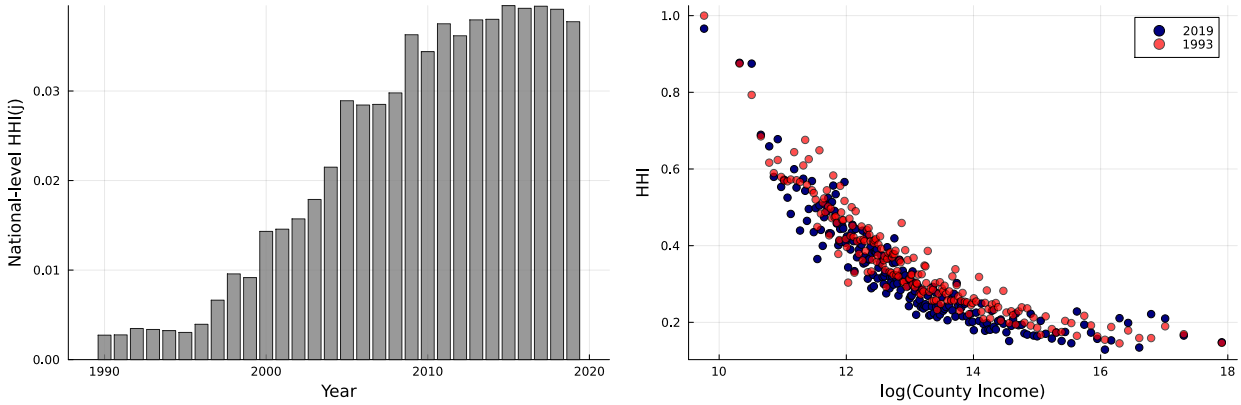
To illustrate the potential gains of diversification simply based on observables, in Appendix B.1 we provide suggestive empirical evidence on the relation between bank-level deposit risk and the number of counties a bank operates at. We construct a panel of bank-level exposures to deposit risks that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

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

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

FIGURE 3. Concentration in Deposit Markets

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



Notes: The left chart shows the national-level Herfindahl in deposit markets. The right panel shows county-level Herfindahl indexes for 1993 (red) and 2019 (blue).

financial sector, since larger banks have a larger leverage and rely less on deposits as a source of funding.

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

3. The Model

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

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

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

3.1. *Households*

The economy has a representative household, which is assumed to be endowed with $\bar{W}$ units of consumption goods. It can invest these funds in three different assets: bank equity (denoted by E), deposits (described in more detail below), or non-deposit funding to banks. In our baseline specification, deposits are the only source of liquidity services. In section 8.1, we extend the model to allow for other assets with liquidity benefits (e.g. cash).

Let D_{ij} denote the household's deposits held with bank j in county i. Deposit services across different banks and markets are aggregated using a nested CES specification – the first level aggregates D_{ij} of different banks in county i to construct a county-level composite D_i. The second level then combines these composites into an economy-wide aggregate D. Formally:

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

The parameter $\theta > 1$ denotes the elasticity of substitution across county-level deposits, while $\eta > 1$ captures the substituability across services provided by banks within a county. We assume $\eta > \theta$, meaning that deposits at different banks within the same county are more substitutable than those across counties.[4] The variable ϕ_i denotes the household's relative preference for deposits in county i. It is meant to capture factors that may affect county-level demand for deposits (including, for instance, income, wealth, or economic conditions). In our empirical strategy, described in Section 4, these preference shifters will be pinned down by the data. Analogously, the term ψ_{ij} captures the relative preference for deposits in bank j within a given county.[5]

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

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

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

given by

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

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

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

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

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

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

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

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

where

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

3.2. *Banks*

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

Banks compete for deposits by setting interest rates on deposits R_{ij}^D. In particular, we assume that banks compete oligopolistically at the county level. That is, when choosing R_{ij}^D, bank j internalizes its effects on R_i^D and D_i, but takes as given the aggregates R^D and D. The bank's overall cost of a unit of deposits from county i is $R_{ij}^D + \kappa_{ij}$, where the parameter κ_{ij} captures non-interest costs. We analyze separately two polar cases for banks' rate setting behavior: in the first, banks set deposit rates at the county level ('local pricing'). The second is a stark form of 'uniform pricing' in which each bank sets a single deposit rate across all the counties. This is equivalent to imposing the restriction $R_{ij}^D = R_j^D \ \forall i \in \mathcal{M}_j$. This second formulation is motivated by an empirical literature documenting that banks often set similar rates across multiple markets (Radecki, 1998; Heitfield and Prager, 2004; Granja and Paixao, 2021; Begenau and Stafford, 2022). Of course, reality lies somewhere in between these two extreme cases. For instance, a bank may set the same rate across all branches of a given state, but different rates across states.[6]

Given our focus on deposit risks, we start with a flexible, general approach to lending and (non-deposit) financing. Let $\Pi_j\left(\{\mathcal{D}_{ij}\}_{i\in\mathcal{M}_j}\right)$ denote the profit from a given vector of deposit, $\{\mathcal{D}_{ij}\}_{i\in\mathcal{M}_j}$, which are a function of banks' deposit rates. The function $\Pi_j(\cdot)$ is to be interpreted as the realized profit from deposits, conditional on optimal choices for lending, securities, and other sources of financing. That is, this general formulation already takes into account returns from banks' loans and other investments (such as securities), as well as all the costs associated with other sources of financing—wholesale funding and interbank borrowing.[7] Specifying the return in this general form allows us to connect to a large literature analyzing, both theoretically and empirically, rich models of lending and wholesale borrowing. Our goal is to derive a general expression for deposit rates—the key object of interest—as a function of $\Pi_j(\cdot)$ and the demand side.

Of course, in order to characterize the exact form of $\Pi_j(\cdot)$, we will need to make additional assumptions. There are three key components which influence the $\Pi_j(\cdot)$ function. First, we need to specify banks' lending technology and the assets in which they can invest. Second, in addition to deposits, banks have access to other sources of funding—for instance, wholesale funding H_j and interbank lending B_j—and we need to lay out the structure of these markets.

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

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

Third, implicit in the $\Pi_j(\cdot)$ function are assumptions about the timing of banks' choices. For instance, as we explain next for our baseline specification, we assume that banks choose deposit rates and loans before observing the realized shocks.

We start by presenting the bank's problem of choosing deposit rates for the general function $\Pi_j(\cdot)$. We do this under the local pricing case for brevity. We will come back to the uniform pricing case after imposing additional structure on $\Pi_j(\cdot)$. Under local pricing, bank j sets deposit rates for each market it operates in. Its problem is given by:

$$\max_{\left\{R_{ij}^D\right\}_{i\in\mathcal{M}_j}} \mathbb{E}\left[\Pi_j\left(\left\{\mathcal{D}_{ij}\left(R_{ij}^D\right)\right\}_{\forall i\in\mathcal{M}_j}\right) - \int_0^1 \left(R_{ij}^D + \kappa_{ij}\right)\cdot\mathcal{D}_{ij}\left(R_{ij}^D\right)d\Lambda_j(k)\right], \tag{7}$$

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

Optimality yields the following expression for deposit spreads (see Appendix C.2 for the derivations):

$$R - R_{ij}^D = \frac{\vartheta_{ij}}{\vartheta_{ij}+1}\left[\kappa_{ij} + R - \mathbb{E}\left(\Pi'_{ij}\right) - \frac{\mathbb{C}ov\left(\Pi'_{ij},\mathcal{D}'_{ij}\right)}{\mathbb{E}\left(\mathcal{D}'_{ij}\right)}\right] \tag{8}$$

Equation (8) decomposes spreads into a markup and "marginal cost" component. The markup is given by $\frac{\vartheta_{ij}}{\vartheta_{ij}+1}$, where $\vartheta_{ij} \equiv \left(R - R_{ij}^D\right)\frac{\mathbb{E}\left(\mathcal{D}'_{ij}\right)}{\mathbb{E}\left(\mathcal{D}_{ij}\right)}$ denotes the expected price (i.e., spread) elasticity of deposit demand, and $\mathcal{D}'_{ij} \equiv \frac{\partial\mathcal{D}_{ij}}{\partial\left(R-R_{ij}^D\right)}$ is the slope of deposit demand. The marginal cost component comprises the non-interest costs of raising deposits, κ_{ij}, the gap between R, the return on the illiquid asset, and $\mathbb{E}\left(\Pi'_{ij}\right)$, the expected marginal profit on deposits D_{ij} i.e., $\Pi'_{ij} \equiv \frac{\partial\Pi_j}{\partial\mathcal{D}_{ij}}$. More importantly for our analysis, the marginal cost also depends on how the marginal benefit covaries with the slope of deposit demand. Intuitively, if the benefit of an additional unit of deposits tends to be high when the slope of the demand is also relatively high (in magnitude), that market is a more attractive source of deposit funding since it generates funds precisely when their marginal value is larger. Consequently, the bank finds it optimal to offer a higher deposit rate in that market – or, equivalently, a smaller spread $R - R_{ij}^D$.

Equation (8) does not rely on specific assumptions about demand, lending or borrowing and delivers a general insight – what matters for deposit pricing under uncertainty is the covariance of the slope of deposit demand with marginal benefits. Unfortunately, it cannot be directly taken to the data because the marginal benefit Π'_{ij} is not observable. The additional structure we impose next, will allow us to express Equation (8) in terms of observables, but at the expense of generality.

Baseline Specification

We introduce additional assumption so that we can write Equation (8) in terms of observables. To this end, we start by using the households' CES demand structure to have a closed-form expression for markups:

$$MKP_{ij} \equiv \frac{\eta(1-s_{ij})+\theta s_{ij}}{\eta(1-s_{ij})+\theta s_{ij}-1}, \qquad \text{where} \tag{9}$$

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

denotes the bank's effective share in liquidity-related expenditure in county i. The form of the markup is identical to that of Atkeson and Burstein (2008) and reflects the fact that the effective elasticity of deposit demand is a weighted average of the within-county and across-county elasticity parameters (η and θ, respectively). The weight on θ is the bank's market share s_{ij}. As s_{ij} approaches zero, the elasticity approaches the within-county elasticity parameter η and the optimal markup becomes $\frac{\eta}{\eta-1}$ – the monopolistic competition limit. For $s_{ij} > 0$, the bank internalizes the effects of its own choices on the county-level aggregates which changes the effective demand elasticity. As s_{ij} approaches one, the markup converges to $\frac{\theta}{\theta-1}$. Given the assumption that $\eta > \theta > 1$, this implies that markups are increasing in s_{ij}.

Then, we flesh out additional assumptions necessary for a full characterization of the profit function, $\Pi_j\left(\{\mathcal{D}_{ij}\}_{i\in\mathcal{M}_j}\right)$. First, we assume that banks provide loans L_j in an economy-wide market, regardless of their location choices. Each bank j is endowed with a linear lending technology, with returns $R+z_j$, where z_j denotes an stochastic (bank-specific) loan spread. Under this linear lending technology, the distinction between loans and any other bank asset (such as securities) is irrelevant—we analyze a richer lending model in Section 7. Our interpretation is that each bank has access to a large (potentially economy-wide) market for loans and/or securities.[8] Since z_j may differ across banks, this simple specification still allows for heterogeneity in skill or information acquisition across banks.

Second, banks have three other sources of funding, in addition to deposits. Wholesale funding H_j is available through a competitive economy-wide market. The household's supply for wholesale funding is assumed to be perfectly elastic at R, which fixes the interest rate on H_j at R. Bank j is subject to issuance costs of $\frac{\nu_j}{2}H_j^2$, so the marginal cost for bank j of raising an additional unit of funding from this market is given by $R+\frac{\nu_j}{H_j}$. Bank j is also assumed

[8]Table B.2 in the appendix provides some support for this assumption. It shows that securities, which are traded in large economy-wide markets, constitute a significant proportion of assets for banks of all sizes.

to receive E_j units of equity funding. We treat E_j as exogenous, an innocuous choice, given the absence of financial or agency frictions.[9] Lastly, there is a competitive interbank lending market that opens after all the shocks have been realized. This transaction is subject to costs, given by $\frac{\chi_j}{2}B_j^2$.[10] For simplicity, we will assume that the household also participates in this market with a supply curve that is perfectly elastic at R.[11] This implies that from bank j's perspective, the cost (return) of borrowing (lending) in this market is $R + \frac{\chi_j}{2}B_j$.

Third, we need to explicit the timing of decisions. We assume that banks first choose deposit rates $\{R_{ij}^D\}$ (or equivalently, spreads $\{R - R_{ij}^D\}$), wholesale funding H_j, and loans L_j. Importantly, the county-level deposit demand shifters $\{\phi_i\}$ and the loan returns z_j are unknown at the time banks make these choices (but their joint distribution is known). Then, the shocks are realized, and the household chooses $\{\mathcal{D}_{ij}\}$. Banks cannot adjust their loans once shocks have been realized. Given the realized $\{\phi_i\}$ shocks, the total funds available to bank j from deposits, wholesale funding and equity may differ from its loan commitments L_j. In this case, the bank has to borrow or lend in the interbank market, $B_j = L_j - E_j - H_j - \int_0^1 D_{ij}\mathrm{d}\Lambda_j(i)$.

Given the structure outlined above, we can write the profit function as follows:

$$\Pi_j\left(\{\mathcal{D}_{ij}\}_{i\in\mathcal{M}_j}\right) = (R+z_j)L_j^* - (R+\frac{\nu_j}{2}H_j^*)H_j^* - (R+\frac{\chi_j}{2}B_j)B_j, \tag{10}$$

$$\text{where} \qquad B_j = L_j^* - H_j^* - E_j - \int_0^1 \mathcal{D}_{ij}\mathrm{d}\Lambda_j(i),$$

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

In this baseline specification, it is the combination of loan commitments and costly rebalancing in the interbank market (i.e., a $\chi_j > 0$) that creates curvature in $\Pi_j\left(\{\mathcal{D}_{ij}\}_{i\in\mathcal{M}_j}\right)$, the source of aversion to deposit risk. For a given choice of L_j, H_j, and deposit rates, a larger volatility in the $\{\phi_i\}$ shocks increases the probability that the bank will have to tap interbank market, which is costly. From Equation (10), it is easy to show that:

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

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

[10] Related literature considers convex costs in nondeposit funding as a proxy for market frictions that break with the Modigliani-Miller framework, such as external finance premium, risk from unsecured debt, or agency/information frictions (see, e.g., Bernanke and Gertler (1995), Kashyap and Stein (1995), D'Amico and Alekseev (2024)).

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

Given this structure, we next present and analyze the bank's problem separately under the two pricing assumptions: local pricing and uniform pricing.

Local Pricing

The banks' problem can be expressed as follows:

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

$$\text{s.t. } L_j=\int_0^1\mathcal{D}_{ij}\,d\Lambda_j(i)+H_j+E_j+B_j, \tag{11}$$

Optimal deposit spreads (see Appendix C.3 for the derivation) are given by:

$$R-R_{ij}^D=\frac{\eta(1-s_{ij})+\theta s_{ij}}{\eta(1-s_{ij})+\theta s_{ij}-1}\left[\kappa_{ij}-\mathbb{E}\left(z_j\right)+\chi_j\mathbb{E}\left(\mathcal{D}_j\right)RP_{ij}\right], \tag{12}$$

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

$$RP_{ij}\equiv\int_{k\in\mathcal{M}_j}\omega_{kj}\frac{\rho_{ik}\sigma_i\sigma_k}{\mu_i\mu_k}dk. \tag{13}$$

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

Equation (13) shows how idiosyncratic risk affects marginal costs and through that, deposit spreads. The spread offered by bank j in county i depends on the correlation $\{\rho_{ik}\}$ of that county's deposit shocks with those of the other counties j operates in. The higher this correlation, *ceteris paribus*, the higher is the risk premium and the spread (or equivalently, the lower is the deposit rate R_{ij}^D). Intuitively, it is optimal to charge higher spreads in a county where deposit demand tends to be high when overall deposit demand from the bank's perspective is high. This expression also highlights how geographical expansion affects spreads. To the extent that a bank raises deposits from imperfectly correlated locations ($\rho_{ik}<1$), it has lower risk exposures and therefore, a lower effective marginal cost.

Uniform Pricing

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

set of baseline assumptions, the problem for bank j is as follows:

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

$$\text{s.t. } L_j = \int_0^1 \mathcal{D}_{ij} d\Lambda_j(i) + H_j + E_j + B_j. \tag{14}$$

Equation (15) characterizes the optimal bank deposit spread under uniform pricing (detailed derivations are relegated to Appendix C.3):

$$R - R_j^D = \frac{\eta(1-s_j)+\theta s_j}{\eta(1-s_j)+\theta s_j - 1}\left[\kappa_j - \mathbb{E}\left(z_j\right) + \chi_j \mathbb{E}(\mathcal{D}_j) RP_j\right], \tag{15}$$

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

$$RP_j = \int_{k\in\mathcal{M}_j} \tilde{\omega}_{kj}\left(\int_{i\in\mathcal{M}_j} \omega_{ij}\frac{\rho_{i,k}\sigma_i\sigma_k}{\mu_i\mu_k}di\right)dk, \tag{16}$$

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

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

Equation (15) is similar in structure to (12), which characterized the optimal spread under local pricing. The key difference is that the relevant objects – market shares and risk premia – are now averaged with appropriate weights across all markets in which the bank operates. Under local pricing, markups vary by county and increase with the county-level market share s_{ij}. In contrast, under uniform pricing, markups are determined by a weighted average of market shares in all the markets the bank operates in, s_j. Similarly, the risk premium under uniform pricing depends on the average covariance – or equivalently, on the volatility of the bank's total deposits – while under local pricing, it varies by county and is a function of that county's covariance with others in the bank's portfolio.

4. Mapping the Model to the Data

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

4.1. *Data Sources*

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

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

The second source is Ratewatch. The vendor provides branch-level deposit rates gathered through surveys across different types of deposits, including savings accounts and time deposits. The data are at a weekly frequency and cover the 2011-2019 period. The survey is quite comprehensive, with responding branches covering around 80% of total domestic deposits. Since RateWatch provides rates at the product level, we compute a weighted average deposit rates across deposit products (certificate of deposits and saving accounts) using as weights bank-level balances for each deposit type from Call Reports.[12] Lastly, based on our view of a county as the relevant market, we collapse the RateWatch interest rate data to the year-county-bank level using branch-level deposits as weights.[13]

We use the 5-Year High Quality Market (HQM) Corporate Bond Spot Rate as our measure of the market rate R.[14] We then compute interest rate spreads, $R - R_{ij}^D$ and $R - R_j^D$ as the difference between the market and deposit rates.

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

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

[13]In Appendix D.2, we show that all our results are robust to an alternative definition of a local market to be at the MSA level, instead of at the county level. Also, in Appendix D.3 we show that results are robust to excluding data that could be linked to online banking or banks' central booking practices.

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

TABLE 1. Descriptive Statistics on Deposits and Spreads for 2019

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

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

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

In line with previous studies, we find evidence consistent with uniform pricing by banks. In particular, a bank-year fixed effect accounts for more than 90% of the observed variation in deposit spreads at the bank-county-year level.[15] The residual variation, while small, suggests some degree of local pricing behavior. Later in this section, we will exploit this variation to estimate the within-county demand elasticity, η.

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

4.2. *Calibration*

We describe next our calibration strategy, which proceeds in several steps. While our model is static, we introduce a time subindex, t, to highlight the set of parameters that vary from

[15]Of course, we cannot rule out the possibility that banks engage in local pricing but find it optimal to set very similar rates across the markets in which they operate. To guard against this pattern being driven by banks with few locations, we restrict attention to banks operating in more than 100 counties.

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

Elasticities of Substitution

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

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

where $\text{Wage}^{\text{Tellers}}$ denotes the Metropolitan Statistical Area (MSA) level wages for bank tellers, and $\text{Wage}^{\text{All Ocup}}$ refers to the average wage across all occupations within an MSA.[16] The assumption is that wages constitute a significant portion of the banks' costs of providing deposit services, κ_{ijt}, so these wage changes affect banks' marginal costs and deposit spreads.[17]

Equations (17) and (18) describe our two-stage regression. In the first stage, we regress changes in bank-county level deposit spreads on our Bartik instrument. In the second stage, we regress changes in bank-county level deposits on the instrumented changes in spreads. We include county-bank fixed effects to account for time-invariant characteristics specific to each

[16] We obtain these wages from the Bureau of Labor and Statistics (BLS), where the finest level of disaggregation is at the MSA level.

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

TABLE 2. Estimated Demand Elasticities

Panel A. Estimation of η

$\Delta \ln D_{ijt}$			
	(1)	(2)	(3)
$\widehat{\Delta \ln R_{ijt}}$	-2.03	-2.86	-3.15
	(0.54)	(1.14)	(0.67)
Time FE	Yes	-	-
Bank-county FE	Yes	Yes	Yes
County-time FE	No	Yes	Yes
County Type	All	All	≥ 5 banks
Observations	116,296	115,183	101,871
1st stage F-stat	36.57	13.54	13.54

Panel B. Estimation of θ

$\Delta \ln D_{it}$		
	(1)	(2)
$\widehat{\Delta \ln R_{it}}$	-2.37	-1.75
	(1.04)	(0.68)
Time FE	Yes	Yes
County FE	No	Yes
County Type	All	≥ 5 banks
Observations	17,775	10,208
1st stage F-stat	11.04	30.18

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

bank-county pair, and county-time fixed effects to capture common variation within each county over time. Our coefficient of interest is β^D, which, based on our CES structure, can be directly mapped into the within-county elasticity of substitution (i.e., $\eta = -\beta^D$).

$$\Delta \ln(R - R^D_{ijt}) = \gamma^R_{ij} + \gamma^R_{it} + \beta^R \text{Bartik}^{\text{IV}}_{jt} + \epsilon^R_{ijt}, \tag{17}$$

$$\Delta \ln D_{ijt} = \gamma^D_{ij} + \gamma^D_{it} + \beta^D \widehat{\Delta \ln(R - R^D_{ijt})} + \epsilon^D_{ijt}. \tag{18}$$

The results are shown in Panel (A) of Table 2. Based on our preferred specification in columns (2) and (3) – which includes bank-county and county-time fixed effects – we get a within-county elasticity of substitution close to 3. Column (1) shows the estimated elasticity for a specification without county-time fixed effects. In this case, the point estimate is smaller, which is consistent with the insight in Berger et al. (2022). That is, although the instrument is uncorrelated with bank-specific demand shifters, it still influences equilibrium deposits through its effects on county-level variables.[18] The county-time fixed effect allows us to account for all those interactions and indirect effects, and recover the true structural elasticity η.

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

We follow a similar approach to estimate the cross-county elasticity of substitution, θ. To do this, we aggregate our bank-level Bartik instrument at the county level, weighting by banks' county-level market shares in the base year. More specifically, the instrument is defined as $\text{Bartik}_{it}^{\text{IV}} = \sum_{j \in i} \tilde{s}_{ij0} \text{Bartik}_{jt}^{\text{IV}}$, where $\tilde{s}_{ij0}$ represents county-level market shares in the base year.[19] Changes in $\text{Bartik}_{it}^{\text{IV}}$ affect county-level banks' average marginal costs and thus deposit spreads. The identifying assumption here is that the weighted county-level relative wage changes of bank tellers are orthogonal to the demand-shifter shocks, ϕ_{it}. As before, working with *relative* wage changes mitigates concerns that the instrument could be correlated with deposit demand. We argue that this assumption is reasonable, especially for counties where many large banks operate, as their exposure to local conditions tends to be smaller.

Equations (19) and (20) describe our two-stage regression, analogous to the approach used for estimating η. Under our CES demand system, the coefficient α^D can be directly mapped to the cross-county elasticity of substitution, θ:

$$\Delta \ln(R - R_{it}^D) = \gamma_i^R + \gamma_t^R + \alpha^R \text{Bartik}_{it}^{\text{IV}} + \epsilon_{it}^R, \tag{19}$$

$$\Delta \ln D_{it} = \gamma_i^D + \gamma_t^D + \alpha^D \Delta \widehat{\ln(R - R_{it}^D)} + \epsilon_{it}^D. \tag{20}$$

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

Time-varying Demand Parameters

Given the elasticities η and θ, the optimality conditions of the model can be used to recover the yearly county-level shocks $\{\phi_{it}\}_{\forall\{i,t\}}$ and the relative demand shifters $\{\psi_{ijt}\}_{\forall\{i,j,t\}}$ parameters. Combining the definition for D_i in Equation (1) with bank-county level demand function (3) and the county-level ideal price index (4), we obtain the bank-county level demand shifters:

$$\psi_{ijt} = \frac{\hat{\psi}_{ijt}}{\left(\sum_j \hat{\psi}_{ijt}^{\eta}\right)^{\frac{1}{\eta}}}, \qquad \text{where} \tag{21}$$

$$\hat{\psi}_{ijt} = \left(R - R_{ijt}^D\right) D_{ijt}^{\frac{1}{\eta}} \left(\sum_j \left(R - R_{ijt}^D\right) D_{ijt}^{\frac{1}{\eta}}\right)^{-1}. \tag{22}$$

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

TABLE 3. Moments for time-varying Parameters

Parameter	Description	Mean	Cross Sectional SD	Skewness
ϕ_{it}	County-level demand shocks	0.53	0.85	7.06
ψ_{ijt}	Relative preference for bank j	0.39	0.23	0.39
$k_{ijt} - z_{jt}$ (pp)	Non-interest expenses	0.99	0.45	-8.69
$k_{jt} - z_{jt}$ (pp)	Non-interest expenses (UP)	0.73	0.65	-10.11

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

Equation (21) imposes a normalization (specifically, $\sum_j \psi_{ijt}^{\eta} = 1$).[20] Once we have the $\{\psi_{ijt}\}$, we can use Equations (1), (4), and (9) to directly compute the county-level $\{D_{it}\}_{\forall\{i,t\}}$ and $\left\{R - R_{it}^{D}\right\}_{\forall\{i,t\}}$ as well as the market shares $\{s_{ijt}\}_{\forall\{i,j,t\}}$.

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

$$\phi_{it} = \frac{\hat{\phi}_{it}}{\left(\sum_j \hat{\phi}_{it}^{\theta}\Lambda_i\right)^{\frac{1}{\theta}}}, \qquad \text{where} \tag{23}$$

$$\hat{\phi}_{it} = \left(R - R_{it}^{D}\right) D_{it}^{\frac{1}{\theta}} \left(\sum_i \left(R - R_{it}^{D}\right) D_{it}^{\frac{1}{\theta}}\Lambda_i\right)^{-1}. \tag{24}$$

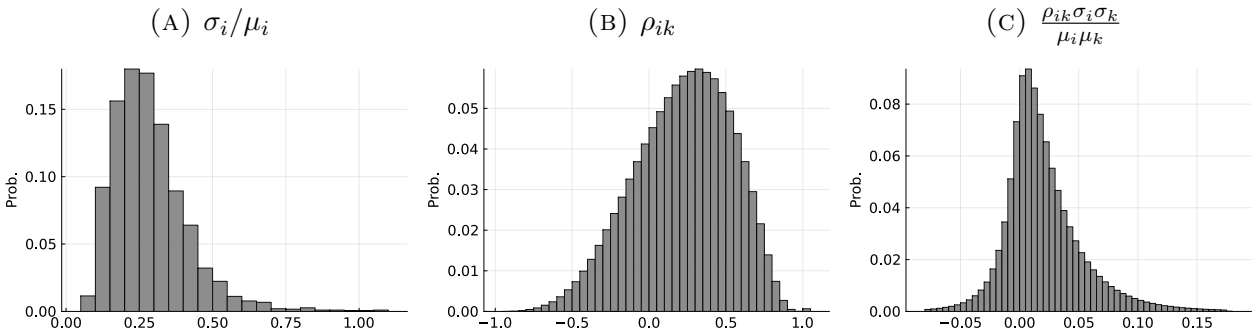
As before, the first expression reflects a normalization ($\sum_i \phi_{it}^{\theta}\Lambda_i = 1$).[21] Table 3 summarizes the moments for $\{\psi_{ijt}\}$ and $\{\phi_{it}\}$.

Given a panel of observed shocks $\{\phi_{it}\}$, we can then directly back out the $\{\rho_{ik}, \sigma_i, \mu_i\}_{\forall\{i,k\}}$ parameters. Figure 4 depicts these moments. Panel (A) shows that the coefficient of variation, σ_i/μ_i, can reach values up to around 75%, indicating a non-trivial amount of risk. In addition, panel (B) shows that the mean of the distribution of the pairwise correlation, ρ_{ik}, is well below one, which suggests a potential role for geographical diversification. Panel (C) shows that the covariance matrix that matter for the risk premia component of optimal spreads in equation (12) is well-dispersed.

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

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

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



Notes: The figure depicts a set of moments for the estimated $\{\phi_i\}$ distribution.

Curvature of the Pricing Equation

The last step of the calibration involves recovering the remaining parameters that characterize marginal costs: $\{\kappa_{ij}, \mathbb{E}z_{jt}\}_{\forall\{i,j,t\}}$ and $\{\chi_j\}_{\forall\{j\}}$. In our formulation, χ_j indexes the degree of frictions in the inter-bank lending market. As we show in Appendix C.8, there are other mechanisms (such as diminishing returns in lending or risk aversion) that also generate a risk premium component. For this reason, we use the model's optimal pricing equation and observed spreads to estimate χ_j. The advantage of this is that we are agnostic about the mechanisms that lead to risk premia and our estimates are robust to alternative micro-foundation of them.

In principle, one could estimate χ_j for each bank separately. However, data limitations force us to impose some structure.[22] In order to make progress, we posit that χ_j is systematically related to bank size. Specifically, for our baseline specification, we assume that χ_j is inversely proportional to bank size (expected total deposits). This assumption reduces the exercise to estimating a single parameter $\chi \equiv \chi_j \mathbb{E}(D_j)$. It also implies that any variation across banks in the effect of risk on spreads comes from the riskiness of their portfolio (more precisely, the RP_{ijt} term) rather than curvature heterogeneity (later in this section, we will show the effect of moving to a more flexible specification). Under this assumption, rearranging the optimal pricing equation (12), and allowing for a time subscript t, we obtain the following regression specification:

$$MC_{ijt} = \kappa_{ijt} - \mathbb{E}z_{jt} + \chi RP_{ijt}, \tag{25}$$

[22] Although we have more than 16,000 banks in our dataset, we only have 9 years of data from RateWatch. Moreover, many of the banks are active for only part of the sample period. This limits our ability to estimate χ_j for each bank.

where $MC_{ijt} \equiv \frac{R-R^D_{ijt}}{MKP_{ijt}}$. It is clear that one cannot directly estimate χ by OLS, since the risk premium term may be correlated with the cost shifters. In order to identify χ, one would need to isolate the variation in RP_{ijt} that is orthogonal to changes in κ_{ijt}. To this end, we exploit variation in RP_{ijt} that is only driven by changes in the demand shifters ψ_{ijt}. These changes affect the county-level demand for bank j and through that influences the county-level weights ω_{ij} that are used to construct the risk premium measure, as shown in Equation (13). Our identifying assumption is that changes in ψ_{ijt} are orthogonal to fluctuations in the operating costs κ_{ijt}.

Equations (26) and (27) describe our two-stage regression for the local pricing case.

$$\Delta RP_{ijt} = \kappa^{RP}_{ij} + \kappa^{RP}_{it} + \kappa^{RP}_{jt} + \zeta^{RP} \Delta \log \psi_{ijt} + \epsilon^{RP}_{ijt}, \tag{26}$$

$$\Delta \ln MC_{ijt} = \kappa^{MC}_{ij} + \kappa^{MC}_{it} + \kappa^{MC}_{jt} + \zeta^{MC} \widehat{\Delta RP_{ijt}} + \epsilon^{MC}_{ijt}. \tag{27}$$

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

Equations (26)-(27) are derived from our local-pricing framework. A potential concern is that they focus on a narrow source of variation – within bank-county pairs – which may be limited when banks engage in uniform pricing. To address this concern, we run a similar specification at the bank level under uniform pricing. We first aggregate our bank-county level demand shifter to a bank level instrument, by weighting changes in ψ_{ijt} with the relative size of that county. Specifically, the first-stage instrument is given by: $\overline{\psi}_{jt} = \sum_{i \in \mathcal{M}_j} \omega_{ij0}\, \psi^{\eta}_{ijt} \mathbb{E}\left(D_{it}\right)$, where ω_{ij0} denotes bank j's relative exposure to county i in the base year. Using this instrument, our 2SLS regression follows from:[23]

$$\Delta RP_{jt} = \kappa^{RP}_{j} + \kappa^{RP}_{j}\, t + \kappa^{RP}_{t} + \zeta^{RP} \Delta \log \overline{\psi}_{jt} + \epsilon^{RP}_{jt}, \tag{28}$$

$$\Delta \ln MC_{jt} = \kappa^{MC}_{j} + \kappa^{MC}_{t} + \zeta^{MC} \widehat{\Delta RP_{jt}} + \epsilon^{MC}_{jt}. \tag{29}$$

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

TABLE 4. Estimated Curvature, χ

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

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

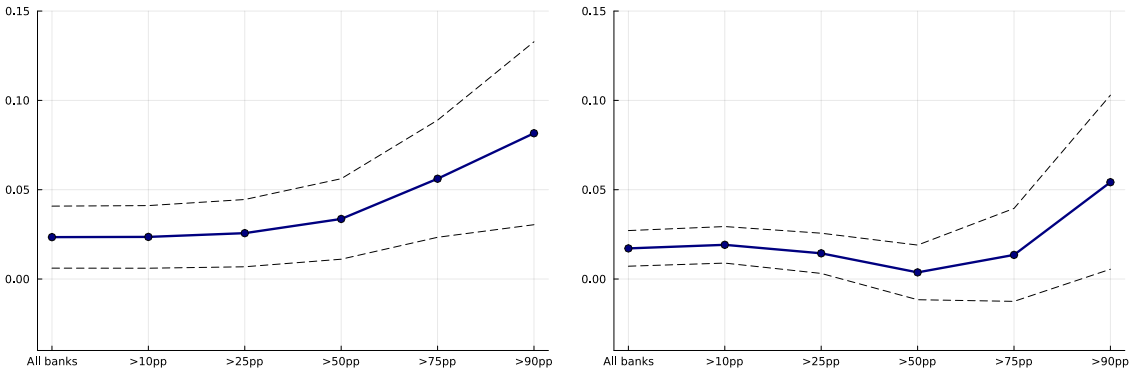
Table 4 presents the estimates for ζ^{MC} (or equivalently, χ). The point estimates are consistent across both the local price and uniform price specifications. Based on these results, we set $\chi = 0.03$ for our model calibration.

So far, we have maintained the assumption of a tight inverse relationship between χ_j and bank size $\mathbb{E}(D_j)$. We now explore the effect of allowing a more flexible relationship between bank size and χ. In Figure 5, we sort banks into bins based on their total deposits and estimate χ separately for each group. The figure reveals a clear pattern: curvature is estimated to rise with bank size, i.e. larger banks penalize risk more heavily compared to smaller banks. We view these results as suggesting that the estimates in Table 4 are a lower bound for the overall effect of risk premia on spreads, especially for the largest banks.

To conclude, given a value for χ, we use Equation (25) to back out the exogenous component of marginal costs, namely $\{\kappa_{ijt} - \mathbb{E}z_{jt}\}_{\forall\{i,j,t\}}$. Table 3 shows summary statistics.

FIGURE 5. Estimated χ, by Bank Group

(A) Local Pricing (B) Uniform Pricing



Notes: The figure displays the estimates for χ by bank group. Banks are sorted into bins based on their total loans. For instance, the "> 10pp" bin includes banks with total loans greater than the 10th percentile. In the local-pricing specification, standard errors are clustered at the county-year level. Dashed lines show 90% confidence intervals.

5. Effects of Risk Premia and Markups

We use our calibrated model to quantify the effects of markups and risk premia on deposit spreads.[24] To this end and for the uniform-pricing case, we use a first-order approximation of Equation (15) around some value for marginal cost $MC^{\star}$:

$$\ln\left(R - R_{jt}^{D}\right) \approx \ln MKP_{jt} + \frac{\chi}{MC^{*}} RP_{jt} + \frac{1}{MC^{*}}\left(\kappa_{jt} - \mathbb{E}z_{jt} + \chi\right) + \left(\ln MC^{*} - 1\right) \tag{30}$$

where $\ln MKP_{jt}$ and $\frac{\chi}{MC^{*}} RP_{jt}$ captures the markup and risk premium component of deposit spreads, respectively. We use an analogous decomposition for the local-pricing case, based on Equation (12).

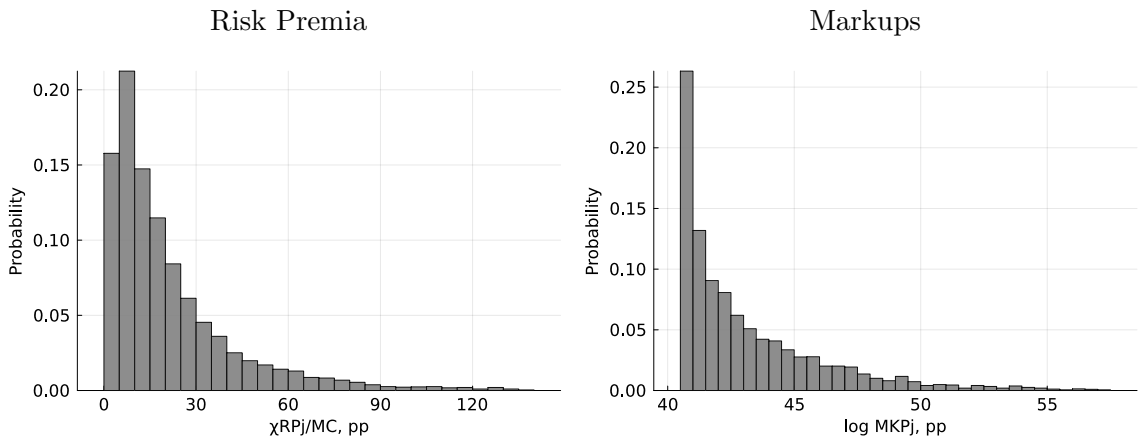
5.1. *Cross-sectional Patterns*

We start by analyzing current cross-sectional patterns in the effects of markups and risk premia on spreads for 2019, the last year in our sample. Figure 6 shows the distributions of $\frac{\chi}{MC^{*}} RP_{jt}$ and $\ln MKP_{jt}$, i.e. the contributions of risk (left panels) and markups (right panels) to (log) spreads (in percentage points). The top panel depicts the bank-level distribution for

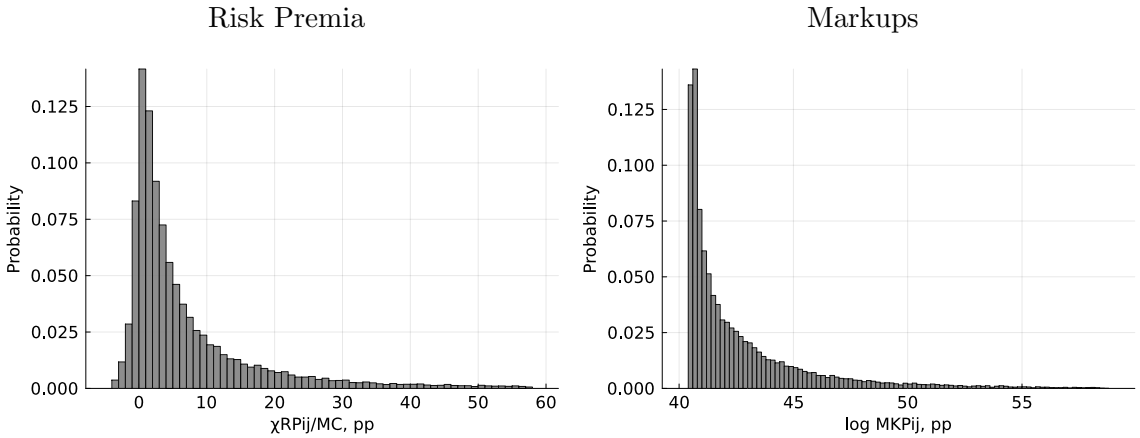
[24] All the results in this section are based on our interpretation of a county as defining the boundaries of the local market. In Appendix D.2, we also show that our results are robust to alternative definitions of local markets. In particular, we show that all of our results hold if we define a local market as an MSA instead.

FIGURE 6. Effect on (log) Spreads

(A) Uniform Pricing (bank level)



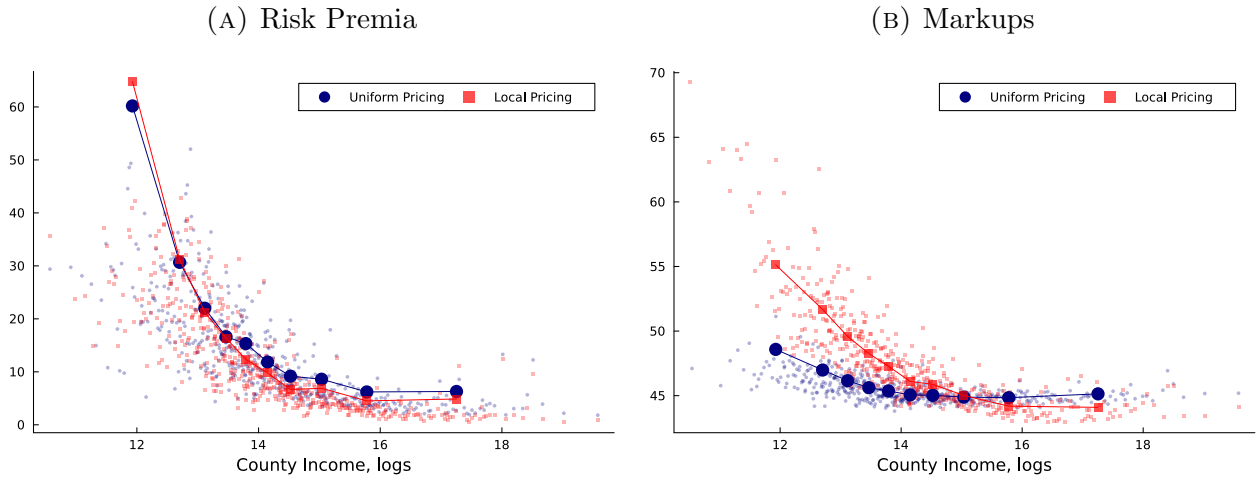
(B) Local Pricing (bank-county level)



Notes: The figure presents histograms for the components of deposit spreads: markups and risk premia, based on the decomposition in Equation (30). The top panel illustrates the results under the uniform-pricing scenario, while the bottom panel displays the outcomes for the local-pricing case.

the uniform pricing case while the bottom panel shows the bank-county level case under local pricing (rates are from RateWatch). Both display considerable heterogeneity, whether across banks or bank-county pairs. For the median bank, the risk premium accounts for about 25% of its marginal costs and markups more than 40%. At the ij-level, the effects of risk premia are relatively smaller, on average accounts for less than 10% of a bank's marginal costs. This is because banks with low risk premia are typically large banks that operate in many locations and, thus, they shift the bank-county risk distribution to the left. Still, the ij-level distribution exhibits a long right tail, which indicates that risk can account for a sizable share of banks' marginal costs.

FIGURE 7. Effects on (log) Spreads, by County



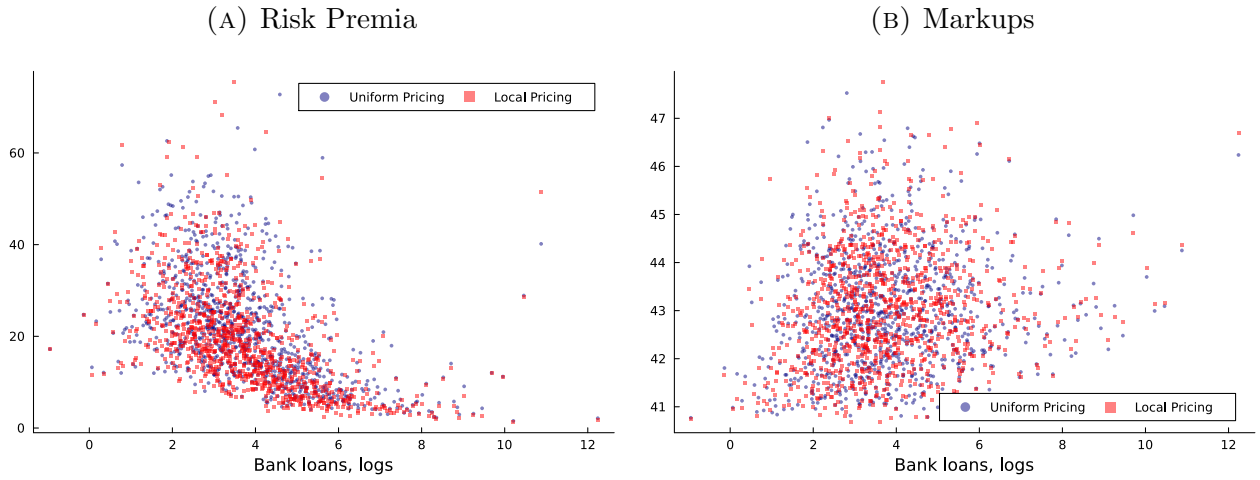
Notes: The figure displays markups and risk premia components of deposits spreads, by county income, based on the decomposition in Equation (30). Blue dots show the results under uniform pricing, while red squares depict the local-pricing case. The larger (darker) dots and squares depict the average risk premium and markup for each decile of the income distribution.

Next, we explore how the effects of risk premia and markups covary with county and bank characteristics. The effects of risk premia and markups on county-level spreads are obtained by a weighted average of their effects on spreads offered by banks in that county, using the model-consistent market share s_{ij} as weights. For example, under uniform pricing, the contribution of risk to county-level spreads is $\sum_{j\in\mathcal{J}_i} s_{ijt} \frac{\chi}{MC_i^*} RP_{jt}$ and that of markups is $\sum_{j\in\mathcal{J}_i} s_{ijt} \ln MKP_{jt}$, respectively, where $\mathcal{J}_i$ denotes the set of banks that operate in county i.[25] The definitions are analogous for the local-pricing case.

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 show the local-pricing case. Larger dots represent the 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 0.60 log points. Panel (B) depicts the effects of markups, which are also declining 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 1.20 log points in smallest/poorest counties.

[25]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 8. Effects on (log) Spreads, by Bank



Notes: The figure displays markups and risk premia components of deposits spreads, by bank size (total assets), based on Equation (30). Blue dots show the results under uniform pricing, while red squares depict the local-pricing case. The larger (darker) dots and squares depict the average risk premium or markup for each decile of the distribution.

We now turn to bank-level patterns. Under uniform pricing, we can directly use the decomposition in Equation (30), since it is at the bank-level. For the local-pricing case, we first aggregate the bank-county level variables using banks' deposit shares, i.e. $\sum_{i\in\mathcal{M}_j}\omega^D_{ijt}\frac{\chi RP_{ijt}}{MC^*_{jt}}$ and $\sum_{i\in\mathcal{M}_j}\omega^D_{ijt}\ln MKP_{ijt}$ respectively, and then apply the decomposition in Equation (30).[26]

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 premia is small (close to zero for the top national banks). Panel (B) shows the pattern for markups. Larger banks tend to have, on average, a higher market share and thus larger markups, though the differences are quite small.

5.2. *Changes Across Time*

Next, we use the model to decompose changes in banks' deposit spreads across time. Our goal is to quantify the effects of the observed changes in banks' geographical allocation on county-level markups, marginal costs, and risk premia. To this end, we compute changes in these objects between 1993, the pre-Riegle-Neal Act period ($t = 0$), and 2019 ($t = 1$). For brevity,

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

we only show results under uniform pricing. In Appendix D.1, we show that the patterns are quite similar under the local pricing assumption as well.[27]

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

$$\Delta \ln(R - R_{it}^D) \approx \Delta \sum_{j \in \mathcal{J}_{it}} s_{ijt} \ln MKP_{jt} + \frac{\chi}{MC_i^*} \Delta \sum_{j \in \mathcal{J}_{it}} s_{ijt} RP_{jt} + \frac{1}{MC_i^*} \Delta \sum_{j \in \mathcal{J}_{it}} s_{ijt} (\kappa_{jt} - \mathbb{E} z_{jt}), \quad (31)$$

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 $\frac{\chi}{MC_i^*} \Delta \sum_{j \in \mathcal{J}_{it}} s_{ijt} RP_{jt}$, capture county-level changes in deposits spreads driven by changes in markups and risk premia, respectively.[28]

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 they imply a reduction of deposit spreads of over 15%. For larger counties, on the other hand, the effects on risk premia on marginal costs are smaller since the banks that operate in these counties were already well-diversified in the 1990s. Perhaps surprisingly, we find that markups actually *decreased* for smaller counties and implied a 5% reduction (on average) in deposit spreads.

Figure 10 shows a map of the US with a decomposition of changes in spreads. The largest risk-related reductions were observed in Wyoming, South Dakota, West Virginia, Oklahoma, and Nebraska (Panel A). For larger/richer regions (for instance, California or the North East region), reductions in risk premia were modest (in part because those regions were served by diversified banks even before the Riegle-Neal Act). As for markups – shown in Panel (B) – we find much smaller changes with mild increases in the North East region (particularly, in Connecticut, New York, and New Jersey) and in Nevada. Markups declined in a large number of counties, particularly in the Midwest and South regions.

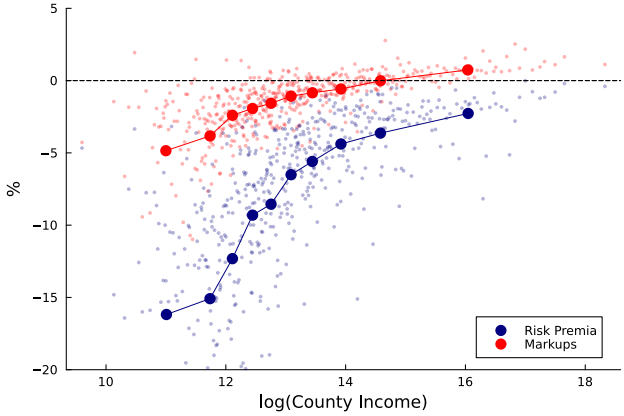
We can further decompose the changes in risk premia into variation in the extent of geographical diversification and other movements in the riskiness of a bank's deposit flows (for instance, the composition of its deposits could have shifted towards less volatile counties). To disentangle these forces,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

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

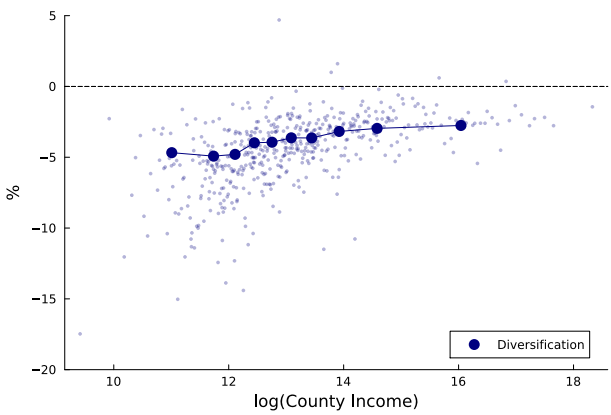
[28] Whenever we compare changes across time, we approximate marginal costs around the time-0 county average, i.e $MC_i^* = \sum_{j \in \mathcal{J}_{i0}} s_{ij0} MC_{j0}$.

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

(A) Markups and Risk Premia



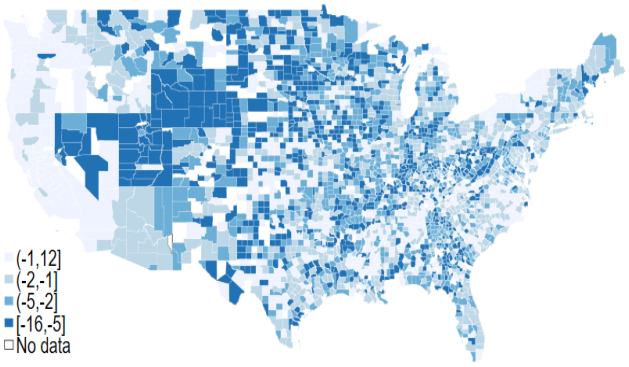
(B) Diversification



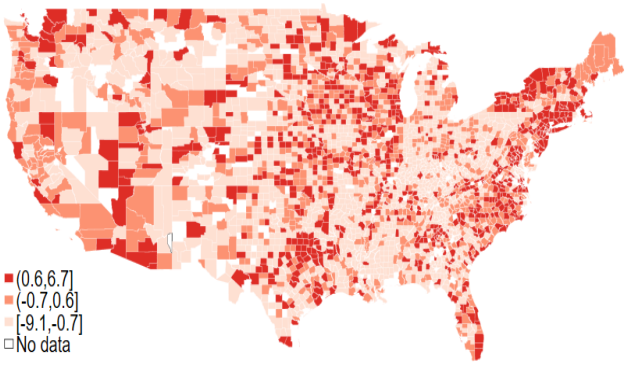
Notes: Following the decomposition in Equation (31), Panel (A) shows changes in markups and risk premia components of deposits spreads between 1993 and 2019, by deciles of county income for the uniform-pricing case. Blue dots show the model-implied changes in risk premia, while red dots indicate changes in markups. Panel (B) further decomposes the changes in risk premia into contributions from "diversification gains", following Equation (32).

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

(A) Risk premia



(B) Markups



Notes: Based on the decomposition in Equation (31), the maps display county-level changes in the markups and risk premia components of deposits spreads between 1993 and 2019, under the uniform-pricing case. Darker blue shades represent a larger drop in deposit spreads driven by reductions in risk premia, while darker red shades represent a larger increase in spreads driven by higher markups.

we define:

$$Diver_{jt} \equiv RP_{jt} - RP_{jt}\mid_{\rho=1} = RP_{jt} - \int_{k\in\mathcal{M}_{jt}} \tilde{\omega}_{kjt} \left(\int_{i\in\mathcal{M}_j} \omega_{ijt} \frac{\sigma_i \sigma_k}{\mu_i \mu_k} di \right) dk, \tag{32}$$

where $RP_{jt}\mid_{\rho=1}$ is the (bank-level) risk premium under the assumption that all counties are perfectly correlated (but the other moments and weights remain the same). We then use Equation (31) to aggregate this measure to the county level using the bank market shares s_{ijt} as weights, so the effect of changes in diversification on (log) spreads in county i is given by $\frac{\chi}{MC_i^*}\Delta\sum_{\mathcal{J}_{it}} s_{ijt}Diver_{jt}$. Overall, we find that changes in diversification accounts for almost half of the drop in risk premia in smaller counties —as shown in Panel (B) of Figure 9. As for larger counties, we find that most of the reduction in risk premia can be attributed to diversification.

We explore the role of the extensive margin in the observed time variation in risk premium. We do this by allocating county-level changes across surviving incumbents, entrants, and exiting banks. We define a survivor as a bank that operated in county i in both periods (1993 and 2019). On the other hand, an entrant (exiting) bank is one that only operated in county i during 2019 (1993). Let $\{\hat{J}_i\}$ be the set of survivors, $\{\tilde{J}_{i0}\}$ the set of exiters, and $\{\tilde{J}_{i1}\}$ the set of entrants. For each period $t\in\{0,1\}$, let $M_{it}\equiv\sum_{j\in\tilde{J}_{it}} s_{ijt}$ denote the combined market share of banks in county i that operate only in period t.

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

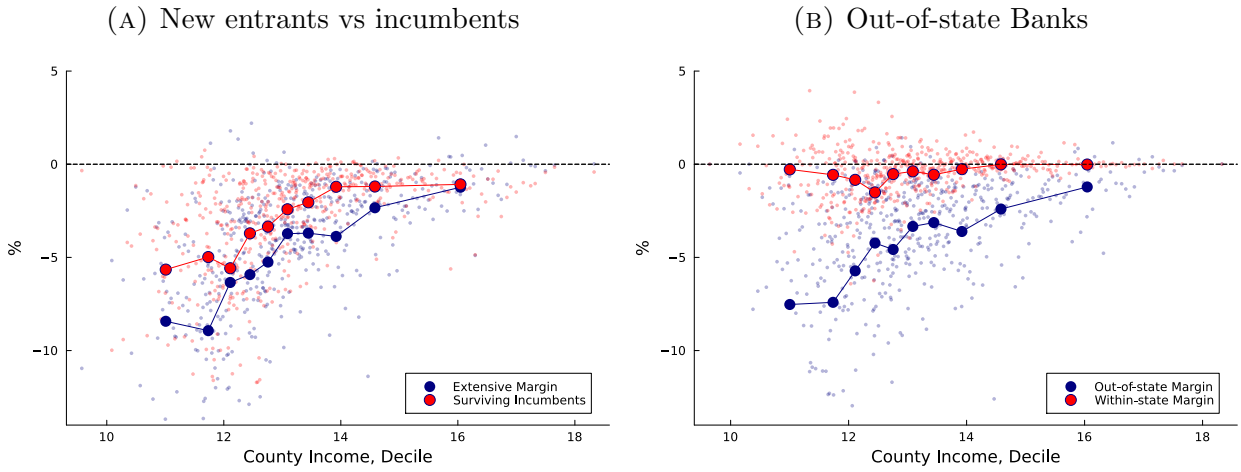
$$\Delta\sum_{j\in\mathcal{J}_{it}} s_{ijt}RP_{jt} = \underbrace{M_{i1}\Big(\sum_{j\in\{\tilde{J}_{i1}\}}\frac{s_{ij1}}{M_{i1}}RP_{j1}-\sum_{j\in\{\hat{J}_i\}}\frac{s_{ij1}}{1-M_{i1}}RP_{j1}\Big)}_{\text{Entrants vs. Survivors}} + \underbrace{M_{i0}\Big(\sum_{j\in\{\hat{J}_i\}}\frac{s_{ij0}}{1-M_{i0}}RP_{j0}-\sum_{j\in\{\tilde{J}_{i0}\}}\frac{s_{ij0}}{M_{i0}}RP_{j0}\Big)}_{\text{Survivors vs. Exiters}}$$
$$+\underbrace{\sum_{j\in\{\hat{J}_i\}}\Big(\frac{s_{ij1}}{1-M_{i1}}RP_{j1}-\frac{s_{ij0}}{1-M_{i0}}RP_{j0}\Big)}_{\text{Within Survivors}}. \tag{33}$$

The first term on the right-hand side captures changes in county-level risk driven by new entrants. It compares the average risk of banks that entered county i in period $t=1$ relative to that of the average survivor.[29] We multiply this difference by the market share of entrants, M_{i1} to arrive at a measure of their contribution to changes in the county-level risk premium. The second term repeats this procedure, but for exiters relative to survivors. We define the sum of these two terms as the "extensive margin". The last term on the right-hand side captures changes in risk across surviving incumbents.

Given the previous decomposition for RP_{jt}, we can then use Equation (31) 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. The decline in risk premia came mostly through changes in the extensive margin, particularly for smaller counties. We further decompose the extensive margin into within-state and out-of-state entrants and exiters. An

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

FIGURE 11. Extensive Margin



Notes: Following the decomposition in Equation (33), Panel (A) shows changes in risk premia driven changes in the extensive margin (entrant and exiter banks) and by surviving incumbents. Panel (B) further decompose the extensive margin and shows the role of out-of-state entrants and exiters.

out-of-state entrant is a bank that only operated in county i during 2019 (but not in 1993) and in 1993 was not even operating in the state to which county i belongs to.[30] We find that more than half of the extensive-margin change can be attributed to out-of-state entrants and exiters (Panel B).

Aggregate Changes

Following a similar decomposition of changes to the one in Equation (31), by aggregating across counties, we can decompose aggregate changes in deposit spreads as follows:

$$\Delta \ln(R - R_t^D) \approx \Delta \int_i s_{it} \left\{ \sum_{j \in \mathcal{J}_{it}} s_{ijt} \ln MKP_{jt} \mathrm{d}i + \frac{\chi}{MC_i^*} \sum_{j \in \mathcal{J}_{it}} s_{ijt} RP_{jt} + \frac{1}{MC_i^*} \sum_{j \in \mathcal{J}_{it}} s_{ijt} \left(\kappa_{jt} - \mathbb{E} z_{jt}\right) \right\} \mathrm{d}i \,, \tag{34}$$

where s_{it} denote the county-level market shares. The previous decomposition captures not only county-level variation in markups and risk premia but also shifts in the composition of counties. For instance, these terms may reflect a drop in risk premia driven by the relative growth of counties that already exhibited low risk premia in the pre-period. To isolate those

[30] 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 to. See Appendix C.4 for further details on this decomposition.

TABLE 5. Changes Across Time: The Role of Diversification and Markups

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

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

(B) Share of total change in spreads

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

Notes: Panel (A) decomposes changes in log aggregate spreads, $\ln(R - R^D)$, between 1993 and 2019 into a change in markups and risk premia, using Equation (34). The 'fixed s_i shares' row shows the case in which we keep the count-level shares fixed to their 1993 values. The 'Diver' column shows the change in risk premium driven by our measure of diversification. The last three rows show the results by groups of counties, based on their total income in 1993. Small (large) counties are the bottom (top) 10th percentile. Medium counties are those between the 45- and 55- percentiles. Panel (B) expresses the values in Panel (A) as a share of the total change in spreads. Since deposit spreads have decreased between 1993 and 2019, a positive (negative) value means that the particular channel led to a reduction (increase) in spread.

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. Panel (A) shows the contribution of each channel to changes in the national deposit spread (log points) as well as for three broad county groups (small, medium, and large). Panel (B) depicts these contributions as shares of total change in spreads.

We find that changes in the industrial structure between 1993 and 2019 induced a modest decrease in the aggregate deposit spread. Changes in risk premium push spreads down by a little less than 3 log points (in pp) while markup changes contributed to around 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 —as shown in Figure 9. For smaller, however, the net effect of banks' geographical changes accounts for a sizable share of spreads. For the "small counties" and "medium counties" groups, we find that changes in risk premia and markups account for more than half of the observed decrease in deposits 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 calibrated model to conduct counterfactual exercises to analyze the effects of various changes in the economic environment – from the structure of the banking industry to demographics – on markups, risk premia, and spreads. We use the year 2019 as the benchmark and focus on the uniform pricing case. We begin by specifying functional forms for preferences. We assume a quasi-linear structure $U(C, D) = C + \xi \log D$. Optimality implies the following relationship between the aggregate deposit composite and spreads: $R - R^D = \frac{U_D}{U_C} = \xi D^{-1}$. Then, we plug in values for $R - R^D$ and D for 2019 into the aforementioned equation to obtain a value for ξ. Appendix C.5 describes our solution algorithm.

Our first counterfactual quantifies the effects of further consolidation in the banking industry. Specifically, we analyze a type of M&A activity that has been widely prevalent over the last couple of decades: the acquisition of relatively *undiversified* banks by larger ones. We consider two sets of targets (i.e., banks that are acquired). First, we look at banks operating in only one county. Second, we examine banks operating in at most two counties.[31] As for acquirers, we consider separately 3 cases: the top (i.e., largest) *local* bank operating in the same county,

[31] We also impose mild restrictions on banks' assets to avoid acquisitions of large (potentially online) banks. Specifically, we exclude banks with assets above the 95th national percentile.

the largest *regional* operating in the same state, or the largest *national* bank. A *local* bank is one that operates in 10 or fewer counties; a *regional* bank operates in more than 10 but fewer than 100 locations; a *national* bank operates in 100 or more locations. With these definitions, we get 4,803 local banks, 274 regional banks, and 20 national banks.

Following a merger, the acquiring bank is assumed to absorb the county-level demand of the acquired (local) banks. Formally, the new demand shifter for acquirer bank j in county i is given by $\psi^{\eta}_{ijt} + \sum_a \psi^{\eta}_{iat}$, where ψ_{iat} denotes the demand shifter of the acquired banks.[32] We also assume that after the takeover, the merged entity inherits the non-interest costs k_j of the acquirer.

Table 6 presents the change in county-level deposit spreads for small, medium, and large counties (based on their total income) when absorbed banks are those operating in only one county. Panel (A) shows the results for the case in which the absorbed banks are those operating in only one county. We find that spreads generally rise as a result of the M&As. This is because larger banks generally have higher non-interest costs (k_j) compared to the target banks. Changes are larger for small counties, where *undiversified* banks have non-trivial market shares. The increase however is significantly mitigated by a reduction in risk premia, particularly when the acquirer is either a regional or national bank. Lastly, we find that markups decline slightly, despite the smaller number of banks and higher county-level concentration. This is because of uniform pricing, where markups depend on the bank's average (not county-specific) market share.[33]

Panel (B) presents results for the M&A scenario where absorbed banks operate in at most two counties. The results are qualitatively similar to those in panel (A), but the changes in spreads and risk premia are roughly twice as large. Two main factors explain this increase. First, including banks operating in up to two counties increases the total size of absorbed banks, which amplifies the effects discussed in panel (A). Second, and more importantly, banks operating in at most two counties remain geographically undiversified, so substantial diversification gains still occur when these local banks are acquired by regional or national banks.

In Table 7, we present additional counterfactual exercises. Panel (A) analyzes changes in non-interest costs, k_j. Specifically, we separately consider a 1 percentage point increase in k_j for local, regional, and national banks. Unsurprisingly, deposit spreads rise due to higher

[32]Consistent with out baseline normalization, we re-normalize the $\{\psi_{ijt}\}$ so that $\sum_j \psi^{\eta}_{ijt} = 1$.

[33]Appendix Table D.1 shows that markups do increase slightly under local pricing, but this increase is smaller than the risk reduction.

TABLE 6. Counterfactuals: Mergers and Acquisitions

	Δ Deposit Spreads			Risk Premia			Markups		
	Small	Medium	Large	Small	Medium	Large	Small	Medium	Large
A. Acquired bank: 1-location bank									
Acquirer bank:									
A.1 Top local bank	3.77	1.03	-0.82	-0.85	0.52	-0.11	0.74	0.41	-0.01
A.2 Top regional bank	4.28	0.56	-0.75	-11.55	-1.32	-0.34	-1.43	-0.00	-0.00
A.3 Top national bank	6.84	2.50	-0.22	-11.92	-1.34	-0.41	-1.04	0.23	0.05
B. Acquired bank: 2-location bank									
Acquirer bank:									
B.1 Top local bank	7.07	2.64	-0.98	-3.82	1.02	0.11	2.11	0.96	0.10
B.2 Top regional bank	9.36	1.17	-0.85	-26.64	-3.38	-0.42	-2.53	-0.02	0.09
B.3 Top national bank	15.49	5.24	0.19	-27.59	-3.68	-0.56	-1.85	0.36	0.17

Notes: Table shows log changes in deposit spreads, risk premia, and markups (under uniform pricing) relative to the baseline results for 2019. The columns show average changes for 3 groups of counties —small, medium, large (based on total income). In Panel A, banks that operate in 1 county are acquired by the largest local bank (A.1), the largest regional bank (A.2), or the largest national bank (A.3)—see main text for definitions of local, regional, and national banks. In Panel B, banks that operate in at most 2 counties are acquired.

marginal costs. More interestingly, the effect on risk premia can either amplify or dampen the impact of higher k_j, depending on which banks face the increase. When local banks experience higher costs, small counties see a substantial reduction in risk premia as market shares shift toward more diversified regional and national banks. In contrast, when costs increase for larger banks, risk premia rise, amplifying the initial shock.

Changes in market shares also drive the results shown in Panel (B) of Table 7, which examines how shifts in households' relative preferences across bank types affect deposit spreads and risk premia. Specifically, we reduce the relative demand shifter (ψ_{ij}) for each type of bank separately.[34] When households' preferences shift away from local banks, regional and national banks gain market share, resulting in lower risk premia, especially in small and medium-sized counties.

Panel (C) examines the impact of changes in the spatial distribution of economic activity. In row C.1, we consider a scenario in which the largest deposit markets become relatively larger. Specifically, we increase market size (μ_i) by 10% for all large counties, while keeping total deposits fixed by proportionally reducing μ_i for all other counties.[35] This exercise provides a

[34]In all cases, we re-normalize ψ_{ij} so that $\sum_j \psi_{ijt}^{\eta} = 1$.

[35]We also hold constant the ratio $\frac{\rho_{ik}\sigma_i\sigma_k}{\mu_i\mu_k}$ to avoid mechanically affecting risk premia.

TABLE 7. 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	56.86	25.90	7.53	-22.89	-5.46	-0.83	0.09	0.04	0.52
A.2 Regional banks	15.46	18.09	11.17	2.88	1.34	-0.17	0.62	0.52	0.91
A.3 National banks	7.43	14.22	34.56	4.26	3.44	1.80	0.17	0.40	-0.63
B. Decrease in ψ_{ij}									
B.1 Local banks	1.78	3.06	1.83	-4.17	-4.10	-0.76	0.80	0.28	0.63
B.2 Regional banks	2.45	2.43	3.66	4.80	3.00	0.16	0.99	0.99	1.39
B.3 National banks	0.17	0.34	-3.12	0.80	3.50	3.64	0.24	0.63	-0.57
C. Demographics									
C.1 Increase μ_i	-9.26	-4.32	-0.05	-7.43	-2.89	0.04	0.00	-0.19	-0.06
C.2 Increase σ_i / μ_i	1.94	2.43	5.86	1.88	2.38	4.76	0.03	0.06	0.13

Notes: Table shows log changes in deposit spreads, risk premia, and markups (under uniform pricing) relative to the baseline results for 2019. The columns show average changes for 3 groups of counties —small, medium, large (based on total income). In Panel A, we increase the cost parameters, separately for local, regional, or national banks. In Panel B, the bank-county demand shifter ψ_{ij} term is varied for each type of bank. In Panel C.1, we increase μ_i for large counties (those above the 90th percentile in terms of total income) and decrease μ_i for all the other counties such that $\sum_i \mathbb{E}(D_i)$ remains the same. In Panel C.2, we double volatility for the large counties.

simple way to capture a continued increase in spatial inequality, consistent with trends observed in recent decades (e.g., Gaubert et al. (2021)). Results show a modest decline in spreads, primarily because larger counties typically exhibit lower risk premia (as documented in Section 5). Thus, increasing their relative importance effectively reduces overall bank risk, with the strongest impact observed in small and medium-sized counties. The final counterfactual, shown in row C.2, doubles the volatility of deposit demand in large counties. As expected, this leads to higher risk premia and spreads within the large county group. More interestingly, we find that roughly half of this increase is passed through to small and medium-sized counties. This significant pass-through occurs because large banks typically operate across both large and smaller locations.

7. Local Lending

So far, we have assumed that banks' lending opportunities are not directly related to the locations of their branches. In particular, we assumed a linear return technology, which made the distinction between different types of assets (loans, securities, etc.) irrelevant.

In this section, we relax this assumption by modifying our baseline model in two ways. First, we allow for two types of assets: local loans L_j and securities S_j. The former can only be extended in states where the bank has branches, i.e., $L_j = \int_{\mathcal{M}_j} L_{ij} di$, and is meant to capture forms of lending that require a physical presence, e.g., loans to small businesses. Second, we introduce curvature in the return functions for both types of assets, aimed at capturing diminishing marginal returns. Despite these changes, the optimal pricing equation remains identical to the baseline version. Here, we present the key equations, leaving derivation details to Appendix C.6.

We start by deriving bank j's gross interest income as a function of total assets $A_j = L_j + S_j$. The revenue function $Rev(A_j)$ is given by the following maximization problem:

$$Rev\left(A_j\right) \equiv \max_{\{L_{ij}\}_{\forall i \in \mathcal{M}_j}, S_j} \int_{\mathcal{M}_j} \left(R + z_j - \frac{1}{2}\alpha_i \alpha_j L_{ij}\right) L_{ij} di + \left(R + z_j - \frac{1}{2}\beta_j S_j\right) S_j, \tag{35}$$

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

The optimal choices of loans and securities is given by

$$L_{ij} = \frac{L_j}{\varrho_j \alpha_i} \qquad \text{where} \qquad \varrho_j \equiv \int_{i \in M_j} \frac{1}{\alpha_i} di, \tag{36}$$

$$L_j = \ell_j A_j \qquad \text{where} \qquad \ell_j \equiv \frac{\varrho_j \beta_j}{\varrho_j \beta_j + \alpha_j}, \tag{37}$$

$$S_j = \left(1 - \ell_j\right) A_j. \tag{38}$$

Substituting in the objective (35), we get:

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

Given this revenue function, optimal deposit spreads are given by:

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

with s_j and k_j being defined as in Section 3. Note that this is very similar to the one of our baseline model.[36] The only change is the $\vartheta_j A_j$ term, which reflects the effect of curvature in asset returns. This implies that the decompositions of deposit spreads in the preceding sections go through unchanged.

More interestingly, perhaps, this version allows us to shed new light on changes in local lending. To this end, the key objects are the bank-level loan ratios $\{\ell_j\}_{\forall j}$ and the parameters

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

$\{\alpha_i\}_{\forall i}$, which govern the county-level curvature in lending. We can easily recover $\{\ell_j\}_{\forall j}$ using observed ratios of loans to assets. As for the α_i parameters, we estimate them using county-level data on small business loan originations. Specifically, we solve for the vector of $\{\alpha_i\}$ that minimizes the distance between the model-implied $\{L_i/L\}$ and its observed counterpart in the data. This step is not trivial, as a change in a particular α_i affects all banks operating in that county. To reduce the dimensionality of the problem, we perform this estimation at the state level—see Appendix C.6 for additional details.

Using this framework, we consider the same counterfactual experiment as in Section 6, where local banks (defined as those operating in only one county) are acquired, and analyze its implications for local lending. Table 8 shows the results under the uniform pricing case.[37] The table depicts changes in state-level loans, $\{L_{ij}\}$. States are split into terciles based on the share of their total deposits held by banks that only operate in that state. The table reports the average for each tercile, under 3 assumptions about the acquirer bank. In the first row, the acquirer is a large local bank, whereas in the next two rows, the local bank is taken over by the largest regional and national bank respectively.

The first set of columns show the overall change in local lending: for states in the top tercile, loans rise by 2-6% when the acquirer bank is a large local or regional bank (effects are much larger when a national bank is the acquirer). The second and third set of columns (labeled the 'IO Channel' and the 'Risk Premia Channel') provide some intuition about the source of these lending gains. The IO Channel captures the change coming from the re-allocation of assets across banks: more precisely, it is the change in local lending if the assets of the acquired bank were simply re-assigned to the acquirer.

The Risk Premia Channel highlights the role of deposit risk. Specifically, we re-calculate the change in local lending under the assumption that risk premiums remains the same after the acquisition, i.e. the acquirer bank (sub-optimally) continues to charge the same risk premium as the acquired bank. Since the acquired bank typically charged higher risk premia, this amounts to reducing the deposit market share of the acquirer bank: in some cases, this effect is sufficiently powerful as to reduce local lending. For example, when the acquirer is a large local bank, holding the risk premium fixed would have resulted in a 3% average decline in local lending for states in the top tercile.

[37] See Appendix D.4 for results under local pricing.

TABLE 8. M&A Counterfactual: Effects on Lending

	Total Change			IO Channel			Risk Premia Channel		
	Low	Medium	High	Low	Medium	High	Low	Medium	High
Acquirer bank:									
1 Top local bank	4.16	5.38	5.82	-0.04	-0.14	-0.39	1.01	0.22	-3.15
2 Top regional bank	4.98	4.03	2.24	0.27	-0.82	-2.29	1.16	0.87	-0.65
3 Top national bank	1.35	17.72	38.64	1.23	-0.97	-2.43	2.29	3.17	4.71

Notes: The table shows model-implied changes in lending due to the assumed mergers and acquisitions. Total change column shows the overall change in lending. The IO Channel shows the changes directly attributable to shift in banks' loans after the M&A, keeping all other variables fixed. The Risk Premia Channel shows the change in lending explained by changes in deposit risk premia. States are split into terciles based on their share of local deposits—defined as deposits held by banks that operate in just one state. In each row, we replace local banks—those that operate in just one location— with the largest local, regional, or national bank. In all cases, we exclude from the M&A's those acquired local banks whose total assets are larger than the 95th percentile—as these may be online banks or banks with central booking practices.

8. Extensions and Robustness

8.1. *Other Assets with Liquidity*

In our baseline model, only deposits provided liquidity. In this subsection, we show how our model can be extended to allow for multiple assets with liquidity benefits. We modify the preferences of the representative household to: $u(C, X) = C - \xi \log(X)$, where X denotes a liquidity composite, defined by the following aggregator:

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

with X_i being a county-level composite of liquidity services from a portfolio of assets

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

The parameter ε is the elasticity of substitution between liquidity services offered by different assets while the $\{\zeta_l\}$ are share parameters. Note that the $\{\phi_i\}$ shocks affect the county-level preferences for all liquidity services, not just deposits.

Appendix C.7 contains detailed derivations for an arbitrary set of assets. Here, we focus on the case with just 1 additional asset: cash, an asset that pays a gross return of 1 and has a share parameter ζ. The household's cash holdings in county i are denoted M_i. Then, the

county-level demand functions for cash, deposits and liquidity services are given, respectively, by

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

where the ideal spread indices are defined as:

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

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

Notice that the demand function facing an individual bank in a given county is still given by equation (3). Combining (3) with (43), we get

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

When setting spreads, banks internalize their effect on not just 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. This implies that the elasticity of demand faced by bank j in market i becomes:

$$\begin{aligned}\frac{d\ln D_{ij}}{d\ln\left(R - R_{ij}^D\right)} = &-\eta\left[1 - \frac{d\ln\left(R - R_i^D\right)}{d\ln\left(R - R_{ij}^D\right)}\right] - \varepsilon\left[\frac{d\ln\left(R - R_i^D\right)}{d\ln\left(R - R_{ij}^D\right)} - \frac{d\ln\left(R - R_i^X\right)}{d\ln\left(R - R_{ij}^D\right)}\right] \\ &- \theta\left[\frac{d\ln\left(R - R_i^X\right)}{d\ln\left(R - R_{ij}^D\right)}\right]. \end{aligned} \quad (47)$$

Thus, the demand elasticity is a weighted average of the three structural elasticity parameters: η, ε and θ. We can rewrite equation (47) more succinctly as

$$\frac{d\ln D_{ij}}{d\ln\left(R - R_{ij}^D\right)} = -\left[(1 - s_{ij})\eta + s_{ij}\widehat{\theta}_i\right], \quad (48)$$

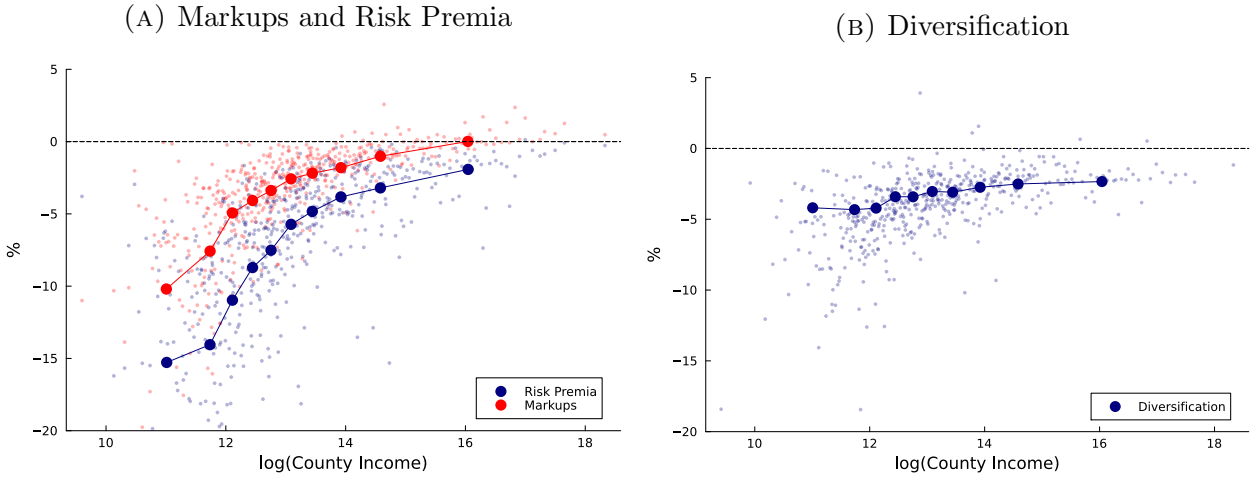
with

$$\widehat{\theta}_i = \theta(1 - s_i^M) + s_i^M \varepsilon \, , \quad (49)$$

where $s_i^M \equiv 1 - \frac{R-R_i^D}{R-R_i^X}\frac{D_i}{X_i}$ is the market share of cash.[38] Relative to the baseline model, markups can vary (both in the cross-section and over time) due to variation in s_i^M.

[38]Note that this version nests our baseline model when $s_i^M = 0$.

FIGURE 12. Changes in (log) Spreads, 1993-2019, by County



Notes: Following the decomposition in Equation (31), Panel (A) shows changes in markups and risk premia components of deposits spreads between 1993 and 2019 for the model with cash extension, by deciles of county income for the uniform-pricing case. Blue dots show the model-implied changes in risk premia, while red dots indicate changes in markups. Panel (B) further decomposes the changes in risk premia into contributions from "diversification gains", following Equation (32).

Quantitative Analysis. We calibrate ε by targeting the elasticity of the aggregate cash-to-deposit ratio to R. We measure this elasticity in the data by using monetary policy shocks as an instrument for exogenous variation in R and estimating the elasticity of cash-to-deposits.[39] Note that this is a reduced-form elasticity, which differs from the structural parameter ε because an change in R will induces an equilibrium response in deposit spreads. This procedure leads to an estimate for ε of 1.24. [40] In turn, the share parameter ζ is assumed to be time-varying and set to match the level of aggregate cash-to-deposit ratio.

Panel (A) of Figure 12 shows the changes in risk premium and markups between 1993 and 2019.[41] The estimated changes in risk premia are very similar in magnitude to the baseline's (see Figure 9), while the fall in markups is more pronounced. This occurs because the share of cash, $\{s_i^M\}$, falls over time, from an average of 39% in 1993 to 15% in 2019. From (49), this increases $\hat{\theta}_i$ (since $\varepsilon < \theta$), pushing markups down.

[39] See Appendix D.5 for details on data and regressions.

[40] Note that $\varepsilon < \theta$, implying that cash is less substitutable than deposits with banks outside the market.

[41] While not shown, results for the effects of risk premium on deposit spreads in the cross-section are quantitatively similar to panel (A) of Figure 7. The effect of markups also show the same patterns as in the baseline, albeit with somewhat larger magnitudes.

Panel (B) shows the decomposition of the changes in risk premia into contributions from diversification gains. The results are quantitatively similar to the baseline model, with diversification gains explaining a larger share of the reduction in risk premia for smaller counties. In summary, the introduction of cash leads to very similar picture about how risk and marker power have changed over time.

8.2. *Lending: Alternative Timing and Curvature*

In our baseline specification, the risk premium in deposit spreads term emerges in the pricing of deposits due to a combination of loan commitments and costly re-balancing in the interbank market. We consider next a modified version where banks can adjust their loan commitments after shocks have been realized, but are subject to curvature in lending returns. In Appendix C.8 we consider a similar timing assumption, but with a linear lending technology. In that case, we introduce curvature on banks' problem by assuming that banks dislike variability in deposits either or are subject to regulatory constraints that penalize deposit variance. Importantly, we show next that the equations characterizing optimal deposit spreads in these alternative specifications, are analogous to those of our baseline model.

As in the baseline, banks raise funds from the household in the form of equity, wholesale funding and deposits. These markets operate exactly as in baseline. But, there are no *ex-ante* loan commitments, instead banks lend out the total funds available to them *ex-post* (i.e. after deposit shocks are realized).[42] Crucially, the lending technology is subject to diminishing returns, so that the rate of return on loans is $R + z_j - \frac{\chi_j}{2} L_j$, where $\chi_j > 0$ indexes the degree of diminishing returns.

The timing of events is as follows. First, banks choose deposit rates R_{ij}^D and wholesale funding H_j. Second, all shocks are realized, and households choose $\{\mathcal{D}_{ij}\}$. Third, loans are made and repaid. Thus, the quantity of loans, L_j, is stochastic and depends on the realized $\{\phi_i\}$ shocks.

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

$$\Pi_j(\{D_{ij}\}) = \left(R + z_j - \frac{\chi_j}{2} L_j\right) L_j - (R + \frac{\nu_j}{2} H_j^*) H_j^* \qquad \text{where} \tag{50}$$

$$L_j = E_j + H_j^* + \sum_i D_{ij}, \tag{51}$$

[42] For simplicity, we abstract from ex-post interbank borrowing and lending. Adding it leads to a more complicated expression for curvature – which now reflects the curvature parameters in both markets – but does not materially alter our conclusions.

and thus its derivative is given by $\Pi'_{ij} \equiv \frac{d\Pi_j}{dD_{ij}} = R + z_j - \chi_j L_j$. Based on the previous expressions, and for the local-pricing case, one can show that the optimal deposit spreads are given by (see Appendix C.8 for derivations):

$$R - R^D_{ij} = \frac{\eta\left(1 - s_{ij}\right) + \theta s_{ij}}{\eta\left(1 - s_{ij}\right) + \theta s_{ij} - 1}\left[k_{ij} - \mathbb{E}\left(z_j\right) + \chi_j \mathbb{E}\left(L_j\right)\left(1 + \widetilde{RP_{ij}}\right) - \frac{\mathbb{C}ov\left(z_j, \phi^\theta_i\right)}{\mu_i}\right], \quad (52)$$

where $\widetilde{RP_{ij}}$ is given by:

$$\widetilde{RP_{ij}} \equiv \omega^D_j \int_{k \in \mathcal{M}_j} \omega_{kj} \frac{\rho_{ik}\sigma_i\sigma_k}{\mu_i\mu_k} dk,$$

where $\omega^D_j \equiv \frac{\int_{k\in\mathcal{M}_j} \mathbb{E}\left(D_{kj}\right)\mathrm{d}_k}{\mathbb{E}(L_j)}$ denotes the share of bank j's total loans that are expected to come from deposits. Note that $\widetilde{RP_{ij}}$ is simply the risk premium in the baseline version scaled by the deposits share ω^D_j.

Equation (52) is analogous to our baseline pricing equations, with two main differences. First, there is an extra term that penalizes bank size, arising directly from the assumption of diminishing returns to lending. Second, and more importantly, there is an additional term that accounts for the covariance between lending returns and shocks to the deposit demand. If $\mathbb{C}ov\left(z_j, \phi^\theta_i\right) > 0$, i.e. deposit flows in county i are positively associated with high returns, the bank optimally charges a lower deposit spread in that county.

To assess the quantitative importance of this covariance term for our results, we proxy z_j with bank-level average returns on loans using Call Report data and directly calculate $\frac{\mathbb{C}ov\left(z_j,\phi^\theta_i\right)}{\mu_i}$. Our estimates show that it is quite small, with a median value of -1.21×10^{-5} (the 5th and 95th percentiles are -1.68×10^{-3} and 1.13×10^{-3} respectively). In other words, the data suggest that accounting for the relation between lending returns and deposit demand shocks does not materially alter our estimates of risk premia in deposit spreads. This also means that the spread decompositions under this variation are almost identical to those of our baseline model.[43]

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

$$R - R^D_j = \frac{\eta\left(1 - s_j\right) + \theta s_j}{\eta\left(1 - s_j\right) + \theta s_j - 1}\left[\kappa_j - \mathbb{E}\left(z_j\right) + \chi_j \mathbb{E}\left(L_j\right)\left(1 + \widetilde{RP_j}\right) - \int_0^1 \tilde{\omega}_{kj} \frac{\mathbb{C}ov\left(z_j, \phi^\theta_k\right)}{\mu_k} \mathrm{d}\Lambda_j\left(k\right)\right], \quad (53)$$

[43] The size penalty does not alter our results because, in our estimation of χ_j, we impose $\chi = \chi_j \mathbb{E}\left(L_j\right)$. A small difference does arise relative to our baseline model through the presence of ω^D_j term, which captures the share of deposits relative to total loans.

where the bank-level risk premium is defined as

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

To conclude, we extend this setup to allow for local lending, where each bank chooses loans across each location in which it operates. Unlike in our baseline local-lending model, we further allow the heterogeneity for the bank-location-specific loan spread, z_{kj}. For a given amount of loans, L_j, the bank problem is to choose $\{L_{kj}\}_{\forall k\in\mathcal{M}_j}$ to maximize:

$$Rev_j\left(L_j\right) = \max_{\{L_{kj}\}_{\forall k\in\mathcal{M}_j}} \int_{k\in\mathcal{M}_j} \left(R + z_{kj} - \frac{\chi_j}{2} L_{kj}\right) L_{kj} \mathrm{d}k, \tag{54}$$

$$\text{where} \qquad L_j = \int_{k\in\mathcal{M}_j} L_{kj} \mathrm{d}k \tag{55}$$

as the maximized revenue for bank j from extending a total of L_j loans across its locations.[44] The optimal allocation of loans is given by $L_{kj}^{\star}\left(L_j\right) = \frac{1}{\chi_j}\left(z_{kj} - \bar{z}_j\right) + \frac{L_j}{\int_{k\in\mathcal{M}_j} dk}$, where $\bar{z_j} \equiv \frac{\int_{k\in\mathcal{M}_j} z_{kj} d_k}{\int_{k\in\mathcal{M}_j} dk}$ is the average loan return for bank j across its locations. The maximized objective thus becomes $Rev_j(L_j) = \left(R + \bar{z}_j - \frac{\widetilde{\chi_j}}{2} L_j\right) L_j$, where $\widetilde{\chi_j} \equiv \frac{\chi_j}{\int_{k\in\mathcal{M}_j} \mathrm{d}k}$.

Substituting into the definition of the general deposit return function $\Pi(\cdot)$, we obtain

$$\Pi_j(\{D_{ij}\}) = \left(R + \bar{z}_j - \frac{\widetilde{\chi_j}}{2} L_j\right) L_j - (R + \frac{\nu_j}{2} H_j^*) H_j^* \tag{56}$$

$$\text{where} \qquad L_j = E_j + H_j^* + \int_{i\in\mathcal{M}_j} D_{ij} di \tag{57}$$

Note that this return function takes the same form as Equation (50) above, which implies that the equations characterizing the pricing of deposits spreads remains the same.

9. Conclusion

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

The calibrated model shows that both risk premia and markups are significant contributors to the spread between deposit rates and benchmark 'illiquid' rates. Their role is particularly

[44] Note that this assumes there are no frictions in the internal markets for funds within banks.

significant in smaller, poorer counties. Our results also suggest that the changes in the structure of the banking industry over the past few decades have resulted in meaningful reductions in risk premia in these counties.

References

Aguirregabiria, V., R. Clark, and H. Wang (2016): "Diversification of geographic risk in retail bank networks: evidence from bank expansion after the Riegle-Neal Act," *RAND Journal of Economics*, 47.

Amel, D. F., A. B. Kennickell, and K. B. Moore (2008): "Banking Market Definition: Evidence from the Survey of Consumer Finances," *FEDS. Washington: Board of Governors of the Federal Reserve System*.

Anenberg, E., A. C. Chang, S. Grundl, K. B. Moore, , and R. Windle (2018): "The Branch Puzzle: Why Are there Still Bank Branches?" *FEDS Notes. Washington: Board of Governors of the Federal Reserve System*.

Atkeson, A. and A. Burstein (2008): "Pricing-to-Market, Trade Costs, and International Relative Prices," *American Economic Review*, 98, 1998–2031.

Baele, L., O. De Jonghe, and R. Vander Vennet (2007): "Does the stock market value bank diversification?" *Journal of Banking & Finance*, 31, 1999–2023.

Begenau, J. and E. Stafford (2022): "Uniform Rate Setting and the Deposit Channel," *SSRN*.

Berger, D., K. Herkenhoff, and S. Mongey (2022): "Labor Market Power," *American Economic Review*, 112, 1147–93.

Bernanke, B. S. and M. Gertler (1995): "Inside the Black Box: The Credit Channel of Monetary Policy Transmission," *Journal of Economic Perspectives*, 9, 27–48.

Black, S. E. and P. E. Strahan (2002): "Entrepreneurship and Bank Credit Availability," *Journal of Finance*, 57, 2807–2833.

Carlson, M., S. Correia, and S. Luck (2022): "The Effects of Banking Competition on Growth and Financial Stability: Evidence from the National Banking Era," *Journal of Political Economy*, 130, 462–520.

Cetorelli, N. and L. S. Goldberg (2012): "Banking Globalization and Monetary Transmission," *Journal of Finance*, 67.

Chu, Y., S. Deng, and C. Xia (2019): "Bank Geographic Diversification and Systemic Risk," *The Review of Financial Studies*, 33, 4811–4838.

Corbae, D. and P. D'Erasmo (2021): "Capital Buffers in a Quantitative Model of Banking Industry Dynamics," *Econometrica*.

——— (2022): "Banking Industry Dynamics Across Time and Space," *Working Paper*.

Correa, R. and L. S. Goldberg (2020): "Bank Complexity, Governance, and Risk," Working Paper 27547, National Bureau of Economic Research.

Crawford, G. S., N. Pavanini, and F. Schivardi (2018): "Asymmetric Information and Imperfect Competition in Lending Markets," *American Economic Review*, 108, 1659–1701.

D'Amico, L. and M. Alekseev (2024): "Capital Market Integration and Growth Across the United States," *Working Paper*.

Doerr, S. (2024): "Bank Geographic Diversification and Funding Stability," *BIS Working Papers No 1221*.

Doerr, S. and P. Schaz (2021): "Geographic Diversification and Bank Lending During Crises," *Journal of Financial Economics*, 140, 768–788.

Drechsler, I., A. Savov, and P. Schnabl (2017): "The Deposits Channel of Monetary Policy*," *The Quarterly Journal of Economics*, 132, 1819–1876.

Egan, M., A. Hortaçsu, and G. Matvos (2017): "Deposit Competition and Financial Fragility: Evidence from the US Banking Sector," *American Economic Review*, 107.

Ergungor, O. E. (2010): "Bank Branch Presence and Access to Credit in Low- to Moderate-Income Neighborhoods," *Journal of Money, Credit and Banking*, 42, 1321–1349.

Gaubert, C., P. Kline, D. Vergara, and D. Yagan (2021): "Trends in US Spatial Inequality: Concentrating Affluence and a Democratization of Poverty," *AEA Papers and Proceedings*, 111, 520–25.

Gilje, E. P., E. Loutskina, and P. E. Strahan (2016): "Exporting Liquidity: Branch Banking and Financial Integration," *The Journal of Finance*, 71, 1159–1183.

Goetz, M. R. and J. C. Gozzi (2022): "Financial integration and the co-movement of economic activity: Evidence from U.S. states," *Journal of International Economics*, 135, 103561.

Goetz, M. R., L. Laeven, and R. Levine (2016): "Does the geographic expansion of banks reduce risk?" *Journal of Financial Economics*, 120, 346–362.

Granja, J., C. Leuz, and R. Rajan (2022): "Going the Extra Mile: Distant Lending and Credit Cycles," *Journal of Finance*.

Granja, J. and N. Paixao (2021): "Market Concentration and Uniform Pricing: Evidence from Bank Mergers," Staff Working Papers 21-9, Bank of Canada.

Heitfield, E. and R. A. Prager (2004): "The Geographic Scope of Retail Deposit Markets," *Journal of Financial Services Research*, 25, 37—55.

Herkenhoff, K. and J. M. Morelli (2024): "Local and National Market Power in the Credit Card Industry," *Working Paper*.

Hottman, C. J., S. J. Redding, and D. E. Weinstein (2016): "Quantifying the Sources of Firm Heterogeneity," *The Quarterly Journal of Economics*, 131, 1291–1364.

Jarociński, M. and P. Karadi (2020): "Deconstructing Monetary Policy Surprises—The Role of Information Shocks," *American Economic Journal: Macroeconomics*, 12, 1–43.

Ji, Y., S. Teng, and R. M. Townsend (2023): "Dynamic Bank Expansion: Spatial Growth, Financial Access, and Inequality," *Journal of Political Economy*, 131, 2209–2275.

Kashyap, A. K. and J. C. Stein (1995): "The impact of monetary policy on bank balance sheets," *Carnegie-Rochester Conference Series on Public Policy*, 42, 151–195.

Kleibergen, F. and R. Paap (2006): "Generalized reduced rank tests using the singular value decomposition," *Journal of Econometrics*, 133, 97–126.

Kundu, S., S. Park, and N. Vats (2021): "The Geography of Bank Deposits and the Origins of Aggregate Fluctuations," *SSRN Working Paper*.

Kundu, S. and N. Vats (2021): "Banking Networks and Economic Growth: From Idiosyncratic Shocks to Aggregate Fluctuations," *SSRN Working Paper*.

Laeven, L. and R. Levine (2007): "Is there a diversification discount in financial conglomerates?" *Journal of Financial Economics*, 85, 331–367.

Oberfield, E., E. Rossi-Hansberg, N. Trachter, and D. Wenning (2024): "Banks in Space," *Working Paper*.

Radecki, L. J. (1998): "The expanding geographic reach of retail banking markets," *Economic Policy Review*, 4, 15–34.

Rossi-Hansberg, E., P.-D. Sarte, and N. Trachter (2020): "Diverging Trends in National and Local Concentration," in *NBER Macroeconomics Annual 2020, volume 35*, National Bureau of Economic Research, Inc, NBER Chapters, 115–150.

Sakong, J. and A. Zentefis (2023): "Bank Branch Access: Evidence from Geolocation Data," *Working Paper*.

Stiroh, K. (2006): "A Portfolio View of Banking with Interest and Noninterest Activities," *Journal of Money, Credit and Banking*, 38, 1351–1361.

Verboven, F. (1996): "The nested logit model and representative consumer theory," *Economics Letters*, 50, 57–63.

Wang, Y., T. Whited, Y. Wu, and K. Xiao (2020): "Bank Market Power and Monetary Policy Transmission: Evidence from a Structural Estimation," NBER Working Papers 27258,

National Bureau of Economic Research, Inc.

Appendix A. Data

A.1. *Data Sources*

County-level economic activity, urbanization, and risk-free rate. County-level economic activity data at yearly frequency since 1969 can be obtained from the BEA.[45] Classification of degree of urbanization for counties was obtained from the CDC, with counties being identified by FIPS codes.[46] The categories in this dataset, in decreasing order of urbanization, are large central metro, large fringe metro, medium metro, small metro, micropolitan counties, and non-core counties. Both large central and fringe metro counties are those in MSAs that have at least 1 million population but differ in density. Counties in medium metro areas are those in MSAs with population between 250,000 and 999,999, while small metro counties are those in MSAs with population less than 250,000. Micropolitan counties are those in micropolitan statistical areas. Non-core counties are non-metropolitan counties that are not in a micropolitan statistical area. Data for households' rate of return, R, is obtained from FRED: 5-Year High Quality Market (HQM) Corporate Bond Spot Rate (HQMCB5YR).[47] Data is at monthly frequency and we compute yearly averages.

Summary of Deposits (SOD). Historical data is publicly available at the FDIC website but we pull the data from a nonconfidential internal dataset from the Board of Governors.[48] The dataset is at yearly frequency with banks reporting at June each year. Some of the fields in the dataset are unique identifiers for a branch (UNINUMBR) and a bank (IDRSSD), location variables (zip code, city, county, state, etc), and volume of deposits (in thousands of USD).

Call Report Data. Bank-level balance-sheet and income statement data is reported to the FFIEC through forms 031, 041, and 051. [49] Most data is at quarterly frequency and contains a unique bank identifier (IDRSSD) that allows to merge it with the SOD data. While raw Call Reports data is publicly available, we use a dataset that is internally available at the Board of Governors that adjusts for mergers and acquisitions. Data is available from 1985:Q1 until the present. Among various fields, the dataset contains information on deposit types and its

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

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

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

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

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

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

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

A.2. *Construction of Interim Datasets*

Our analysis is done at the bank-county level, merging several datasets, so some data processing is needed prior to the analysis. SOD data is filtered to only include US states (i.e., exclude territories). We also adjust a few county names to make them consistent with names and FIPS codes in BEA's county-level economic activity dataset.[50] We then aggregate deposits data to the year-bank-county level, keeping track of the number of branches in the triplet.

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

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

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

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

cleaned from promo rates. Since data is at the product-branch-year level, we collapse it to the product-bank-county-year level by using a branch's deposits as weights.[51]

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

Since RateWatch has comprehensive data starting only on 2011, we construct an alternative database of average deposit rates based on Call Reports data starting on 1990. To this end, we pull data on volumes and interest expenses on time deposits (small and large) and savings accounts (including MMDAs), add time and savings values within expenses and volumes, and compute the ratio of interest expenses to volumes.[52] Since interest expenses are flows, we accumulate to the fourth quarter of each year before computing the ratio. In a few cases, we do not have information on time and savings deposits separately, so we use the average deposit rate in overall domestic deposits instead. We then merge this data with the risk-free rate (HQMCB5YR), compute spreads, and *winsorize* spreads at the lower and upper 1 percent.

We also use Call Reports data to compute bank-level ratios of equity, wholesale funding, and deposits to total assets. For comparison, we also compute ratios of deposits to total assets using SOD data, collapsed to the bank-level. In very few cases, the ratio based on Call Reports differs from the one based on SOD by more than 10% in absolute value, so we drop them.[53] We also drop outliers of deposits to assets ratios that are on the top 0.5 percent of the distribution, or ratios that are lower than 10 percent. We then calculate bank equity as total assets minus total liabilities, and compute its ratio to total assets. We also drop the low/top 0.1 percent of the distribution, which renders equity values that are always positive and ratios far away

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

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

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

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

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

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

We then use the risk-free rate variable (HQMCB5YR) to compute deposit spreads. We then exclude counties that, despite the imputation procedure, do not have deposit rate data on all years. These are very few, and represent less than 0.1% of deposits in total. Finally, de-trend deposits based on the growth rate of aggregate loans.[54]

A.4. *Historical Data on Deposits*

In addition to 1990-2019 yearly data on average deposit rates based on Call Reports, we obtain historical data on bank-county deposits from SOD. We merge SOD and Call Report datasets for 1990-2010 using IDRRSD bank identifier and, as before, compute ratios of equity, wholesale funding, and deposits to total assets. We also follow the same steps as before to process the data: (1) apply the share of savings and time deposits (over total deposits) from Call Reports; (2) drop bank-county pairs with deposit volume less than 1 million USD; (3) drop counties that are not present for the entire period 1990-2009 (very small in magnitude, both in raw count and share of deposits); (4) de-trend deposits based on growth rate of total loans.[55]

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

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

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

Appendix B. Motivation: Additional Evidence

B.1. *Banks' Exposure to Risk*

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

Given the wave of geographical expansion of US banks, we perform a variance decomposition exercise where we decompose bank-level deposits between number of branches (extensive margin) and deposits per branch (intensive margin). Each bank has total deposits equal to $N_{jt} \times D_{jt}/N_{jt}$. Taking logs, we can perform the following variance decomposition over the period 1995-2019:

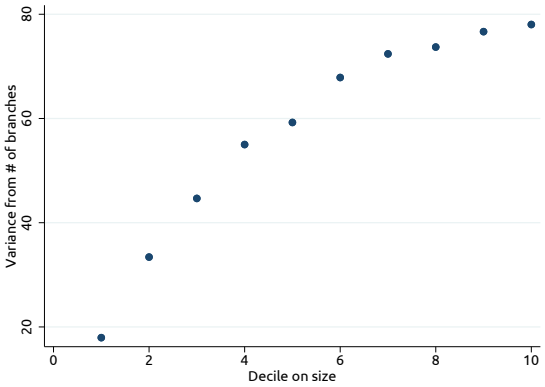
$$Var\left(\ln D_{jt}\right) = Var\left(\ln N_{jt}\right) + Var\left(\ln\left(D_{jt}/N_{jt}\right)\right) + 2Cov\left(N_{jt}, \ln\left(D_{jt}/N_{jt}\right)\right). \tag{B.1}$$

Table B.1 shows that both sources of growth are relevant, with the variation in the number of branches and in deposits per branch explaining on average, 48% and 66% of a bank's total deposit variance, respectively. Figure B.1 shows that the relative importance of each component varies with bank size. In particular, the fraction of deposit variance explained by the extensive margin is increasing in bank size, while the opposite happens with the intensive margin.[56] Overall, these results suggest that county-level shocks to deposits are relatively more relevant for smaller banks.

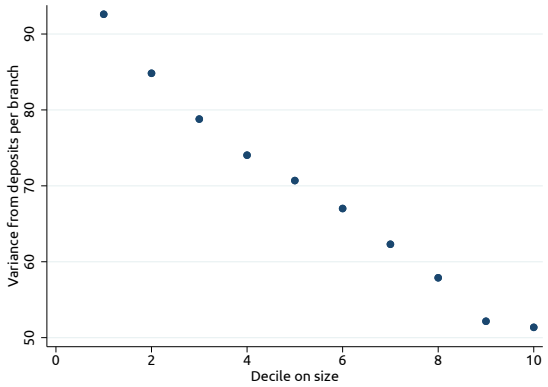
[56]Although not shown, the covariance between the extensive and intensive margins is negative. It is around -10% for small banks and -30% for large banks.

FIGURE B.1. Deposits variance decomposition by bank size

(A) Number of branches



(B) Deposits per branch



Notes: This figure shows a variance decomposition of log deposits, based on equation (B.1), by bank size. Panel (A) shows the share of the variance explained by the number of branches, and panel (B) by the deposits per branch. The sample period is 1995-2019.

TABLE B.1. Variance decomposition on deposit growth

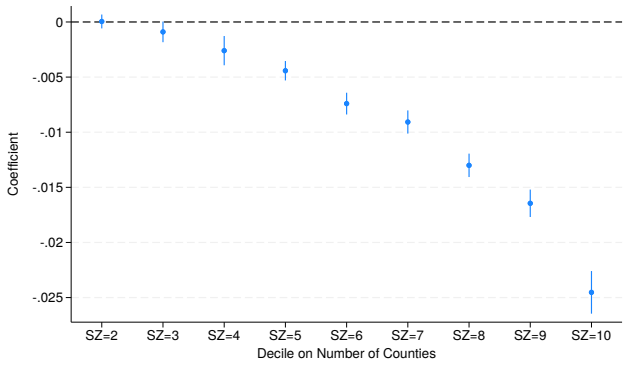
	Mean	Median
Number of branches	48%	31%
Deposits per branch	66%	55%

Notes: This table shows the mean and median values across banks of a variance decomposition of log deposits based on equation (B.1). The sample period is 1995-2019.

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

We now analyze how this county-level heterogeneity affects bank-level risk. Let ω_{ij}^{τ} be a bank j's relative weight on county i at time τ, defined as $\omega_{ij}^{\tau} = \frac{D_{ij}^{\tau}}{\sum_i D_{ij}^{\tau}}$, where D_{ij}^{τ} is the total stock of deposits that bank j has on county i at time τ. For a given weight ω_{ij}^{τ}, we can then use

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



Notes: This figure shows results from the regression equation (B.3) for data on deposits over the period 1995-2019.

$\Delta \ln D_{it}$ to construct bank j's weighted deposit change at time t as $\Delta \ln D^{\tau}_{jt} = \sum_i \omega^{\tau}_{ij}(\Delta \ln D_{it})$. We then compute the time-series standard deviation as

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

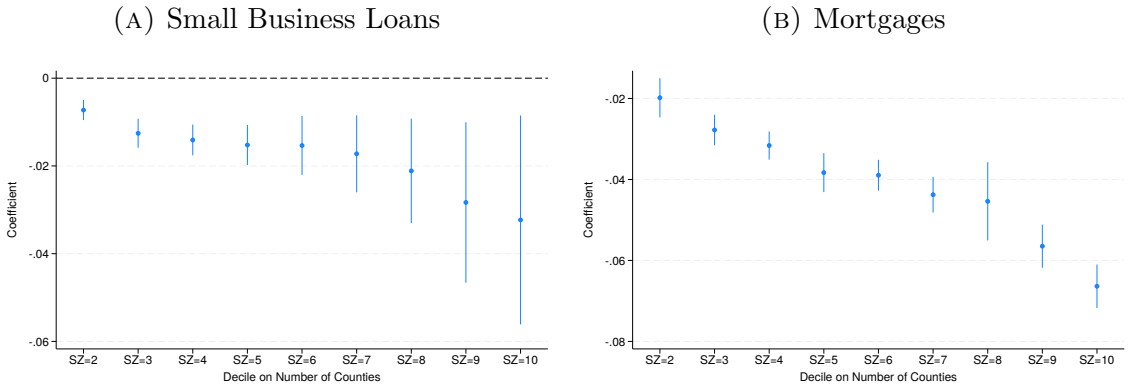
We make use of the panel of exposures $\{\sigma^{\tau}_{j}\}$ to study how deposit risk relates to different banks' characteristics. To this end, we regress σ^{τ}_{j} onto decile dummies on the number of counties the bank operates ($\{\mathbf{1}_{k,\tau}\}_{k=2}^{10}$), bank fixed effects ($\alpha_j$),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

$$\sigma^{\tau}_{j} = \beta_1 + \sum_{k=2}^{10}\beta_k \times \mathbf{1}_{k,\tau} + \alpha_j + \alpha_\tau + \epsilon_{j,\tau}. \tag{B.3}$$

Figure B.2 presents the estimates for the β_k parameters. The figure shows that exposure to deposit fluctuation risk falls monotonically with the number of counties a bank operates at.[57] Although not shown, similar results hold when considering deciles on bank size (as proxied by deposits).

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

FIGURE B.3. Banks' Exposure to Loan Originations, by Size



Notes: This figure shows results from the regression equation (B.3) for data on loan originations over the period 2005-2019. Panel (A) shows results for data on small business loans originations from the Community Reinvestment Act. Panel (B) shows results for data on mortgage originations from the Home Mortgage Disclosure Act. Source: Federal Reserve Board.

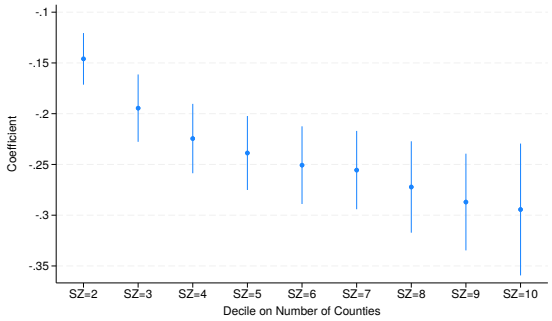
Figure B.3 shows a similar analysis but based on originations of small business loans (panel (A)) and morgages (panel (B)) over the period 2005-2019.[58] Data for small business loans is from the Community Reinvestment Act (CRA), while data for mortgage originations is from the Home Mortgage Disclosure Act (HMDA), both obtained from the Federal Reserve Board.[59] In both cases, we observe that banks operating in more counties are less exposed to risk on loan originations. We can observe a similar pattern whenm studying exposures to loan delinquencies, as shown in Figure B.4. Panel (A) shows results when computing delinquencies from the Consumer Financial Protection Bureau (CFPB) during 2008-2017. Panel (B), in turn, uses fluctuations in county-level nonfarm personal income for the period 1995-2019 as a proxy for delinquency rates as an attempt to capture a broader set of loans than just consumers'.

[58]Data limitations on loan originations and delinquencies preclude analysis since the 1990s.

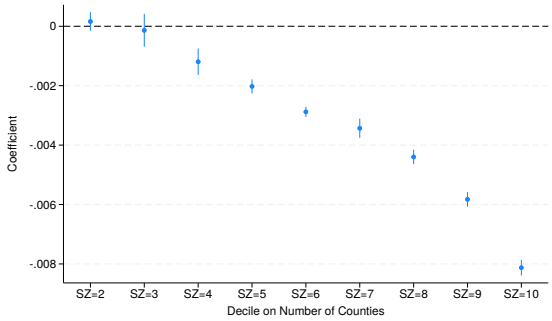
[59]See: https://www.federalreserve.gov/consumerscommunities/data_tables.htm

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

(A) Delinquency Rates



(B) Personal Income (Nonfarm)



Notes: This figure shows results from the regression equation (B.3) for data on loan delinquency rates. Panel (A) shows results for data on delinquency rates on consumer loans obtained from the Consumer Financial Protection Bureau for the period 2008-2017. Panel (B) shows results for data on nonfarm personal income (serving as a proxy for delinquency or default) obtained from the Bureau of Economic Analysis for the period 1995-2019.

B.2. *Composition of Banks' Financial Assets*

For our main analysis, we have assumed that banks lend at the national level. To motivate our assumption, Table B.2 shows the composition of financial assets of U.S. commercial banks, sorted by bank size, for 1995 and 2019.[60] It differentiates bank assets between loans to households (including mortgage-backed securities, MBS), commercial loans, cash and non-MBS securities, and other types of financial assets. The table shows that both large and small banks hold significant amounts of securities, which are traded in nation-wide markets. This provides some support for our assumption that the asset side is not linked to physical presence.

[60]We present results as of 1995 instead of 1993 due to limited data availability for mortgage-backed securities.

TABLE B.2. Financial Assets by Bank Size

	Bank size					
	Lowest 1%		Percentiles 90-99		Top 1%	
	1995	2019	1995	2019	1995	2019
Household						
Non-residential	9%	4%	15%	5%	19%	13%
Residential*	17%	18%	28%	26%	24%	29%
Commercial†	17%	24%	28%	49%	26%	30%
Cash & (non-MBS) securities	43%	44%	26%	16%	19%	17%
Other	14%	11%	3%	5%	12%	11%
Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
*MBS	4%	4%	9%	10%	9%	15%
†Small business	-	6%	-	9%	-	3%

Notes: This table presents the financial assets of U.S. commercial banks, sorted by bank size, for 1995 and 2019. Source: Call Reports.

APPENDIX C. THE MODEL: DERIVATIONS AND ADDITIONAL MATERIAL

C.1. *Microfoundation for CES Demand System*

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

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

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

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

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

The depositor's optimization yields

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

so that we can compute D_{ij} as

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

We can define the indexes

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

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

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

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

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

We provide the derivation for optimal deposits spreads under our most general specification —Equation (8) in the main text. Let $\Pi_j\left(\{D_{ij}\}_{i\in\mathcal{M}_j}\right) \equiv \widehat{\Pi}_j\left(\{D_{ij}\}_{i\in\mathcal{M}_j}, \left\{L_{ij}^*\right\}_{i\in\mathcal{N}_j}, F_j^*\right)$ denote bank's realized profits net of all financing costs, except those related to deposits, from receiving a vector of deposit inflows $\{D_{ij}\}_{i\in\mathcal{M}_j}$ across the $\mathcal{M}_j$ set of markets in which it operates. The $\left\{L_{ij}^*\right\}_{i\in\mathcal{N}_j}$ denotes the optimal loans made by bank j in location k across the set $\mathcal{N}_j$ of locations —which does not need to be equal to the $\mathcal{M}_j$ set. The return on these loans may be stochastic and heterogeneous across locations or banks. At this point, we do not need to make any assumptions on them. Lastly, the F_j^* captures bank j's all other sources of funding, which include wholesale funding, inter-bank loans, equity, and others.

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

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

Given these definitions, the bank problem can thus be written as in Equation (7) in the main text, which we rewrite below for convenience:

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

where $\Lambda_j(\cdot)$ denotes the measure indexing counties in which bank j operates and $\mathcal{D}_{ij}(\cdot)$ captures the demand for deposits faced by bank j in county i.

Using the envelope theorem, the first-order condition with respect to $R_i^D j$ is as follows:

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

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

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

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

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

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

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

Combining the last two equations, we get Equation (8) in the main text.

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

C.3.1. *Local-Pricing Case*

We provide additional derivations for optimal deposit spreads under local pricing. As described in the main text, the bank chooses $R-R_{ij}^{D}$, together with wholesale funding H_j, and inter-bank loans B_j to solve the problem in Equation (11). In this analysis, we also allow the bank to choose its equity E_j. For simplicity, we assume that equity issuance costs are given by $\left(R+\frac{\tau_j}{2}E_j\right)E_j$, where τ_j can be viewed as a capturing frictions in the equity market. After

replacing B_j using the bank's balance sheet equation, the problem can be written as follows:

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Replacing this in Equation (C.6) and after some algebra we get our baseline pricing equation under local pricing:

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

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

C.3.2. *Uniform-Pricing Case*

For the uniform-pricing case, we assume that bank j sets a single deposit rate R_j^D across all the markets in which it operates. That is, $R_{ij}^D = R_j^D \;\forall i$. Following the derivation in the previous subsection, the problem of bank j can be written as follows:

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

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

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

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

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

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

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

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

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

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

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

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

In the main text, we decomposed county-level changes in risk premia to analyze the role of entrants and exiters. In particular, Equation (33), which we rewrite below, shows that county-level changes in risk can be written as follows:

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

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 as the sum of the first two terms on the right-hand side of the previous expression as the "extensive margin".

In this appendix, we further decompose the extensive marging 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 definition, after some algebra, one can show that:

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

The sum of the first two terms on the right-hand-side of Equation (C.10) capture the "out-of-state extensive margin". That is, changes in risk premia driven by banks entering or exiting the state in which county i is located. The sum of the third and fourth terms capture the "within-state extensive margin", which is driven by banks that enter or exit county i but were already operating in the state in which i is located. In Figure 11 in the main text, we show that more than half of the extensive-margin is explained by out-of-state entrants and exiters.

C.5. *Solution Algorithm*

Below, we outline the algorithm developed to solve the model and conduct counterfactual analysis. The algorithm is iterative, designed to determine the equilibrium prices and allocations given the model parameters. Although we describe the algorithm specifically for the local-pricing case, 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 $R - R_t^D$ (for a given value of ϕ_{it}).

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

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

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

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

and

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

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

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

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

(7) Based on the estimated parameters for the volatility and correlations of county-level shocks, compute the model-implied measure of risk premia

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

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

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

(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.

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 in which they have branches, $L_j = \int_{\mathcal{M}_j} L_{kj} dk$, 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. In what follows, 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 only show results for the uniform pricing case, but derivations for local pricing are very similar to those in Appendix C.3.1..

Let the revenue function of a banks j be given by:

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

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

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

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

Combining these two expressions, and assuming $z_j^L = z_j^S = z_j$, we get:

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

Summing across all locations,

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

Replacing equation (C.13) back in equation (C.12), we get L_{ij} as a function of L_j:

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

Then, using $L_j + S_j = A_j$ and equation (C.13), we get L_j and S_j as functions of A_j:

$$L_j = \ell_j A_j, \tag{C.15}$$

$$S_j = (1 - \ell_j) A_j, \tag{C.16}$$

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 some terms, we obtain:

$$\begin{aligned} Rev\left(A_j\right) =& \mathbb{E}\left\{\left(R + z_j\right)\left(\int_0^1 \frac{1}{\alpha_i \varrho_j} \frac{\varrho_j \beta_j}{\varrho_j \beta_j + \alpha_j} \mathrm{d}\Lambda_j(i) + \frac{\alpha_j}{\varrho_j \beta_j + \alpha_j}\right) A_j\right\} \\ & - \mathbb{E}\left\{\int_0^1 \frac{1}{2} \frac{\alpha_j}{\varrho_j} \frac{\varrho_j \beta_j}{\varrho_j \beta_j + \alpha_j} A_j \frac{1}{\alpha_i \varrho_j} \frac{\varrho_j \beta_j}{\varrho_j \beta_j + \alpha_j} A_j \mathrm{d}\Lambda_j(i) + \frac{1}{2} \beta_j \frac{\alpha_j}{\varrho_j \beta_j + \alpha_j} A_j \frac{\alpha_j}{\varrho_j \beta_j + \alpha_j} A_j\right\} \\ =& \mathbb{E}\left[\left(R + z_j\right) A_j - \frac{1}{2} \frac{\alpha_j}{\varrho_j} l_j A_j^2\right] \\ =& \mathbb{E}\left[\left(R + z_j\right) A_j - \frac{1}{2} \vartheta_j A_j^2\right], \end{aligned} \tag{C.17}$$

where we defined $\vartheta_j \equiv \frac{\alpha_j}{\varrho_j} l_j$ to simplify notation.

Based on the revenue function defined by equation (C.17), we can define the problem of bank j:

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

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

Notice that the objective function is very similar to the baseline in problem (14), the difference being that instead of having the revenues term $(R + z_j)L_j$ we now have $\left(R + z_j - \frac{1}{2}\vartheta_j A_j\right) A_j$.

Following steps similar to the ones shown in Appendix C.3.2, but taking E_j as exogenous, we get that optimal spreads are given by

$$R - R_{ij}^D = \frac{\eta\left(1 - s_j\right) + \theta s_j}{\eta\left(1 - s_j\right) + \theta s_j - 1}\left[\kappa_j - \mathbb{E}\tilde{z}_j + \chi_j \mathbb{E}\left(D_j\right) \int_0^1 \omega_{kj} \frac{\rho_{ik} \sigma_i \sigma_k}{\mu_i \mu_k} d\Lambda_j(k)\right], \tag{C.18}$$

where $\mathbb{E}\tilde{z}_j \equiv \mathbb{E}z_j - \vartheta_j A_j$. Specification (C.18) for optimal spreads under local lending is identical to our baseline solution for spreads under uniform pricing shown in equation (15).

Next, we briefly explain how to compute the vector $\{\alpha_i\}$ in the data. The starting point is having a measure of location-level relative stocks of loans. To this purpose, we use data on

small business loans from the CRA.[61] Since a location-level loan is givne by $L_i = \sum_{j \in i} L_{ij}$, using equation (C.14) we get

$$\frac{L_i}{L} = \frac{1}{\alpha_i} \sum_{j \in i} \frac{1}{\varrho_j} \frac{L_j}{L}, \tag{C.19}$$

where we divided both sides by total loans L. Given data for $\{(L_i/L)\}_{\forall i}$ and $\{(L_j/L)\}_{\forall j}$, our objective is to recover the vector $\{\alpha_i\}$ gets closest to satisfying equation (C.19). To do so, we setup the following distance minimization problem:

$$\min_{\{\alpha_i\}} \sqrt{\sum_{\forall k} Loss_k(\{\alpha_i\})^2}, \tag{C.20}$$

$$\text{where } Loss_k = (L_k/L) - \frac{1}{\alpha_k} \sum_{j \in k} \left(\frac{1}{\sum_{i \in \mathcal{M}_j} \frac{1}{\alpha_i}} \frac{L_j}{L} \right).$$

Since the minimization problem (C.20) recovers $\{\alpha_i\}$ up to a normalization constant, we can express the α_i's in (C.20) relative to the α_i of the largest location, $\frac{\alpha_i}{\alpha_{LG}}$, and set $\alpha_{LG} = 1$. Lastly, since it is close to computationally unfeasible to identify α_i at the county-level, for the quantitative analysis of Section 7 we collapse the data to the state-level and solve for $\{\alpha_i\}$ at the state-level.

C.7. *Model Extensions: Multiple Assets*

While Section 8.1 focuses on an extension with cash, our model can be generalized to allow for other assets which provide liquidity services. Consider the same composite goods X and X_i as defined in equations (41) and (42), respectively. In what follows, we present demand functions under this general case, with a straightforward application to the cash-only extension.

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:

$$\frac{R - R_{li}}{R - R_i^X} = \zeta_l \left(\frac{X_{li}}{X_i} \right)^{-\frac{1}{\epsilon}}, \tag{C.21}$$

$$\frac{R - R_i^D}{R - R_i^X} = \left(\frac{D_i}{X_i} \right)^{-\frac{1}{\varepsilon}}, \tag{C.22}$$

[61] Data on small business loans from the CRA are flows, so we are implcitly assuming that relative flows are proportional to relative stocks.

as well as the county-wide inverse demand function for liquidity services,

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

From (C.21) and (C.22), we get that the ratio of county-level deposits D_i over an asset X_{li} is given by

$$\frac{D_i}{X_{li}} = \zeta_l^{-\epsilon} \left(\frac{R - R_i^D}{R - R_{li}} \right)^{-\epsilon}. \tag{C.24}$$

In turn, the county-level ideal price index for liquidity services can be obtained by substituting equation (C.21) and (C.22) into the definition of X_i (equation (42), replicated below for convinience):

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

$$R - R_i^X = \left(\sum_l \zeta_l^{\varepsilon} \left(R - R_{li} \right)^{1-\varepsilon} + \left(R - R_i^D \right)^{1-\epsilon} \right)^{\frac{1}{1-\epsilon}}. \tag{C.25}$$

Similarly, substituting (C.23) into the definition for X in equation (41), we obtain the ideal price index for liquidity services at the national-level,

$$R - R^X = \left(\int \phi_i^{\theta} \left(R - R_i^X \right)^{1-\theta} di \right)^{\frac{1}{1-\theta}}. \tag{C.26}$$

Notice that the demand for deposit D_{ij} can still be specified as in equation (46), so the deposit demand elasticity can still be expressed as in equation (47) where, from equation (C.25), we get that

$$\begin{aligned} \frac{d \ln \left(R - R_i^X \right)}{d \ln \left(R - R_{ij}^D \right)} =& \frac{d \ln \left(R - R_i^D \right)}{d \ln \left(R - R_{ij}^D \right)} \left[\frac{\left(R - R_i^D \right)^{1-\varepsilon}}{\sum_l \zeta_l^{\varepsilon} \left(R - R_{li} \right)^{1-\varepsilon} + \left(R - R_i^D \right)^{1-\epsilon}} \right] \\ =& \frac{d \ln \left(R - R_i^D \right)}{d \ln \left(R - R_{ij}^D \right)} \left(\frac{R - R_i^D}{R - R_i^X} \right)^{1-\varepsilon} \end{aligned} \tag{C.27}$$

Substituting (C.27) onto the elasticity of demand for deposits (47), after some simple algebraic manipulation we get

$$\frac{d\ln D_{ij}}{d\ln\left(R-R_{ij}^{D}\right)}=-\left[\left(1-s_{ij}\right)\eta+s_{ij}\hat{\theta}_{i}\right], \tag{C.28}$$

where we used $s_{ij}=\frac{d\ln\left(R-R_{i}^{D}\right)}{d\ln\left(R-R_{ij}^{D}\right)}$ and defined $\hat{\theta}_{i}\equiv\varepsilon+\left(\theta-\varepsilon\right)s_{i}^{D}$, with $s_{i}^{D}=\left(\frac{R-R_{i}^{D}}{R-R_{i}^{X}}\right)^{1-\varepsilon}$.

C.8. *Alternative Model Specifications*

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

For the local-pricing case, each bank j solves the problem in Equation (50). After replacing with the banks' balance sheet and simplifying terms, we can rewrite the problem as follows:

$$\max_{\left\{R_{ij}^{D}\right\}_{\forall i\in\mathcal{M}_{j}},H_{j}}\mathbb{E}\Bigg\{\int_{0}^{1}\left(R-R_{ij}^{D}+z_{j}-\kappa_{ij}\right)\mathcal{D}_{ij}\mathrm{d}\Lambda_{j}(i)-\frac{\chi_{j}}{2}\left(\int_{0}^{1}\mathcal{D}_{ij}d\Lambda_{j}(i)+H_{j}+E_{j}\right)^{2}+$$
$$+\left(R+z_{j}\right)E_{j}-\left(\frac{\nu_{j}}{2}H_{j}\right)H_{j}\Bigg\}. \tag{C.29}$$

After some algebra, we can express the first-order condition with respect to deposit spreads as:

$$R-R_{ij}^{D}+\frac{\mathbb{E}\left(\mathcal{D}_{ij}\right)}{\mathbb{E}\left(\mathcal{D}_{ij}'\right)}=k_{ij}-\mathbb{E}\left(z_{j}\right)-\frac{\mathbb{C}ov\left(z_{j},\mathcal{D}_{ij}'\right)}{\mathbb{E}\left(\mathcal{D}_{ij}'\right)}+\chi_{j}\frac{\mathbb{E}\left[\left(\int_{0}^{1}\mathcal{D}_{kj}\mathrm{d}\Lambda_{j}\left(k\right)+H_{j}+E_{j}\right)\mathcal{D}_{ij}'\right]}{\mathbb{E}\left(\mathcal{D}_{ij}'\right)}.$$

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

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

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

$$\begin{aligned}\chi_j \frac{\mathbb{E}\left[\left(\int_0^1 \mathcal{D}_{kj}\mathrm{d}\Lambda_j(k) + H_j + E_j\right)\mathcal{D}'_{ij}\right]}{\mathbb{E}\left(\mathcal{D}'_{ij}\right)} =& \chi_j\left(H_j + E_j\right) + \chi_j \frac{\mathbb{E}\left[\left(\int_0^1 \mathcal{D}_{kj}\mathrm{d}\Lambda_j(k)\right)\mathcal{D}'_{ij}\right]}{\mathbb{E}\left(\mathcal{D}'_{ij}\right)} \\ =& \chi_j\mathbb{E}\left(L_j\right) + \chi_j \frac{\mathbb{C}ov\left[\int_0^1 \mathcal{D}_{kj}\mathrm{d}\Lambda_j(k), \mathcal{D}'_{ij}\right]}{\mathbb{E}\left(\mathcal{D}'_{ij}\right)} \\ =& \chi_j\mathbb{E}\left(L_j\right) + \chi_j \int_0^1 \mathbb{E}\left(D_{kj}\right)\frac{\rho_{ik}\sigma_i\sigma_k}{\mu_i\mu_k}\mathrm{d}\Lambda_j(k) \\ =& \chi_j\mathbb{E}\left(L_j\right)\left(1 + \omega_j^D \int_0^1 \omega_{kj}\frac{\rho_{ik}\sigma_i\sigma_k}{\mu_i\mu_k}\mathrm{d}\Lambda_j(k)\right) \\ \equiv& \chi_j\mathbb{E}\left(L_j\right)\left(1 + \widetilde{RP_{ij}}\right).\end{aligned}$$

Lastly, we use the fact that $D_{ij} = \psi_{ij}^{\eta}\left(\frac{R-R_i^D}{R-R_{ij}^D}\right)^{\eta} D_i$ and $D_i = \phi_i^{\theta} \times \left(\frac{R-R^D}{R-R_i^D}\right)^{\theta} \times D$ to rewrite the $\frac{\mathbb{C}ov\left(z_j, \mathcal{D}'_{ij}\right)}{\mathbb{E}\left(\mathcal{D}'_{ij}\right)}$ as follows:

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

Combining all these expressions, the first-order condition is then:

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

which is Equation (52) in the main text.

Under uniform pricing, the bank's problem is analogous to that in Equation (C.29), with the additional condition that $R_{ij}^D = R_j^D$, for every location $i \in \mathcal{M}_j$. After some algebra, one can show that the first-order condition with respect to deposit spreads is:

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

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

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

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

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

where

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

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

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

where $\tilde{\omega_{ij}} \equiv \frac{[(\eta-\theta)s_{ij}-\eta]\mathbb{E}(\mathcal{D}_{ij}\Lambda_j(i))}{\int_0^1 [(\eta-\theta)s_{kj}-\eta]\mathbb{E}\left(\mathcal{D}_{kj}\Lambda_j(k)\right)}$.

Combining all these results, the pricing equation under uniform pricing is then:

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

which is Equation (53) in the main text.

Risk Aversion or Regulatory Constraints. Given the timing assumption of this extension, one can obtain similar pricing equations without the need to assume diminishing marginal returns on lending. For instance, another mechanism that gives rise to risk premia is a case in which banks penalize the variance of deposits, due to their own preferences or some regulatory constraint. For easiness of exposure, we assume bank j simply dislikes variability in deposits.

Moreover, 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:

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

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

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

which analogous to Equation (12) of our baseline model.

Local-lending Alternative. In the main text, we consider a local-lending extension under the assumption that loans are chosen ex post (i.e., after shocks are realized). In this section, we explore a variant of local lending under our baseline setup, in which lending is chosen ex ante. In particular, we consider a case in which a bank's loan returns in county i, z_{ij}, are affected by its deposits in that county, $\mathcal{D}_{ij}$. This reduced-form specification is a more general case than the local-lending extension of the main text. It allows us to capture different mechanisms that may link a bank's geographical presence with its returns.

We assume that loan returns for bank j in location i are given by

$$z_{ij}=z_i\,e^{(\gamma_i\mathcal{D}_{ij}-\beta_i L_{ij})}, \tag{C.30}$$

where z_i is a stochastic county-level shock, and $\gamma_i>0$ and $\beta_i>0$ capture the sensitivity of loan returns with respect to bank j's deposits and loans in county i. We view β_i as capturing decreasing marginal returns in local-level lending. The γ_i parameter, on the other hand, captures any channel through which a higher deposit base in county i may affect bank j's loan returns in that location, such as information frictions (e.g., see Ergungor (2010) and Granja et al. (2022)).

Under this setup, our baseline bank problem —Equation (11)— can be re-written as follows:

$$\max_{\substack{\{R_{ij}^D\}_{\forall i\in\mathcal{M}_j}\\ \{L_{kj}\}_{\forall k\in\mathcal{N}_j}\\ H_j}} \mathbb{E}\Big\{\int_{k\in\mathcal{N}_j}\left(R+z_{kj}\right)L_{kj}\mathrm{d}k-\left(R+\frac{\nu_j}{2}H_j\right)H_j-\left(R+\frac{\chi_j}{2}B_j\right)B_j-\int_{i\in\mathcal{M}_j}\left(R_{ij}^D+\kappa_{ij}\right)\mathcal{D}_{ij}\mathrm{d}i\Big\},$$

with $L_j=\int_0^1\mathcal{D}_{ij}\mathrm{d}\Lambda_j(i)+H_j+B_j+E_j$ and $L_j=\int_{k\in\mathcal{N}_j}L_{kj}\mathrm{d}k$. We allow for $\mathcal{N}_j\neq\mathcal{M}_j$, so that banks may lend even in counties in which they do not operate (for which $z_{ij}=z_i e^{-\beta_i L_{ij}}$). In

this setup, the optimal deposit spread is given by:[62]

$$R-R_{ij}^{D}=\frac{\eta\left(1-s_{ij}\right)+\theta s_{ij}}{\eta\left(1-s_{ij}\right)+\theta s_{ij}-1}\left[\kappa_{ij}-\mathbb{E}\left(z_{j}\right)-\gamma_{i}L_{ij}\mathbb{E}\left(z_{ij}\right)+\chi_{j}\mathbb{E}\left(\mathcal{D}_{j}\right)RP_{ij}-\gamma_{i}L_{ij}\frac{\mathbb{C}ov\left(z_{i},\phi_{i}^{\theta}\right)}{\mu_{i}}\right], \tag{C.31}$$

where $\mathbb{E}\left(z_{j}\right)\equiv\mathbb{E}\left(z_{ij}\right)\left(1-\beta_{i}L_{ij}\right)$. This expression is similar to our baseline —Equation (12), with two main differences. First, banks charge lower deposit spreads in locations in which the effect of an additional unit of local deposit on loan return is higher. Second, banks charge lower deposit spreads in locations for which $\mathbb{C}ov\left(z_{i},\phi_{i}^{\theta}\right)>0$. For those location, the deposit demand shocks are such that the bank can capture more financing in times when lending returns are high.

Appendix D. Additional Results

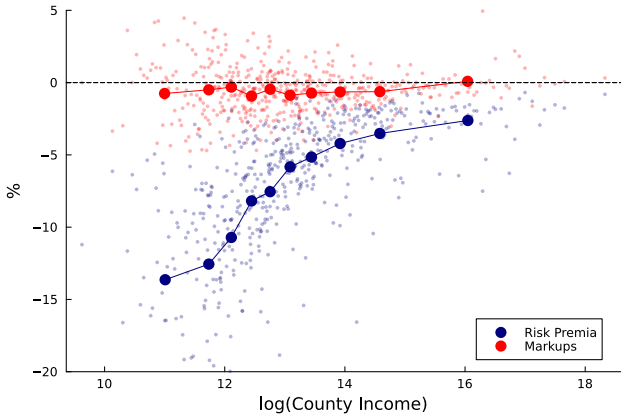
D.1. *Changes Across Time under Local Pricing*

In this section, we provide analyze changes in deposit spreads under local pricing, and the role of markups and risk premia. Overall, the results are relatively similar to the uniform pricing case: smaller counties exhibit larger decrease in risk premia, which is mostly driven by banks' larger diversification. The reduction in risk is also mostly explained by changes in the extensive margin (entrants and exiters). As for markups, we also find mild changes across the entire county distribution.

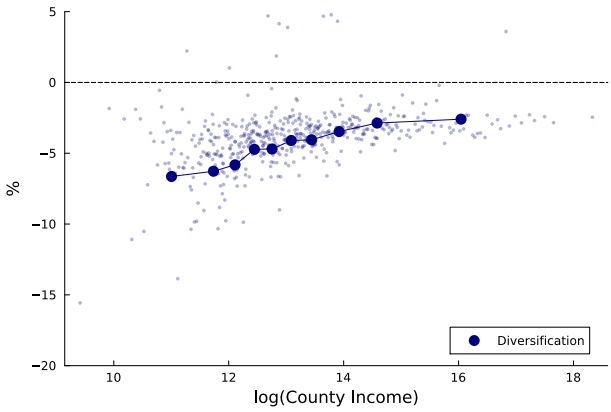
[62] This expression is based on a first-order approximation around around $\mathbb{E}\left(\mathcal{D}_{ij}\right)$ and $L_{ij}^{\star}$ such that $e^{\gamma_{i}\mathbb{E}\mathcal{D}_{ij}-\beta_{i}L_{ij}^{\star}}=1$.

FIGURE D.1. Changes in (log) Spreads, 1993-2019, by County

(A) Markups and Risk Premia



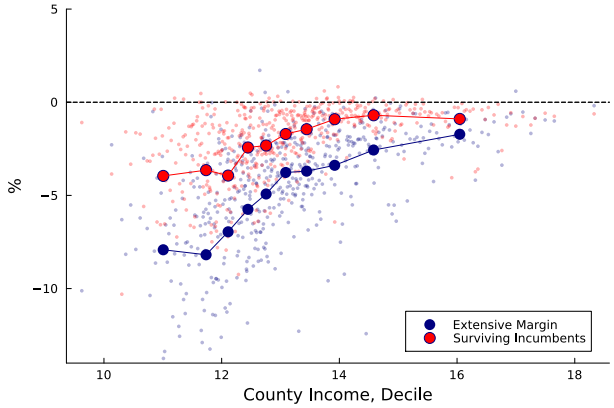
(B) Diversification



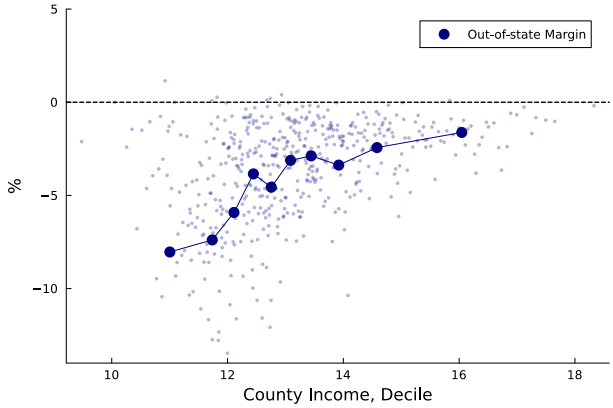
Notes: Following the decomposition in Equation (31), Panel (A) presents changes in markups and risk premia components of deposits spreads between 1993 and 2019, by deciles of county income for the uniform-pricing case. Blue dots show the model-implied changes in risk premia, while red dots indicate changes in markups. Panel (B) further decomposes the changes in risk premia into contributions from "diversification gains", following Equation (32).

FIGURE D.2. Extensive Margin

(A) New entrants vs incumbents



(B) Out-of-state Banks



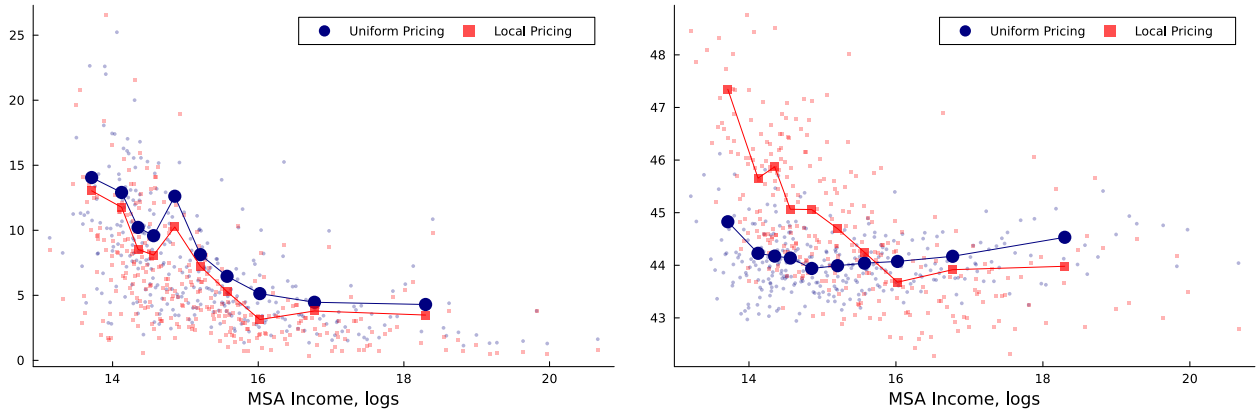
Notes: Following the decomposition in Equation (33), Panel (A) shows changes in risk premia driven changes in the extensive margin (entrant and exiter banks) and by surviving incumbents. Panel (B) further decompose the extensive margin and shows the role of out-of-state entrants and exiters.

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

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

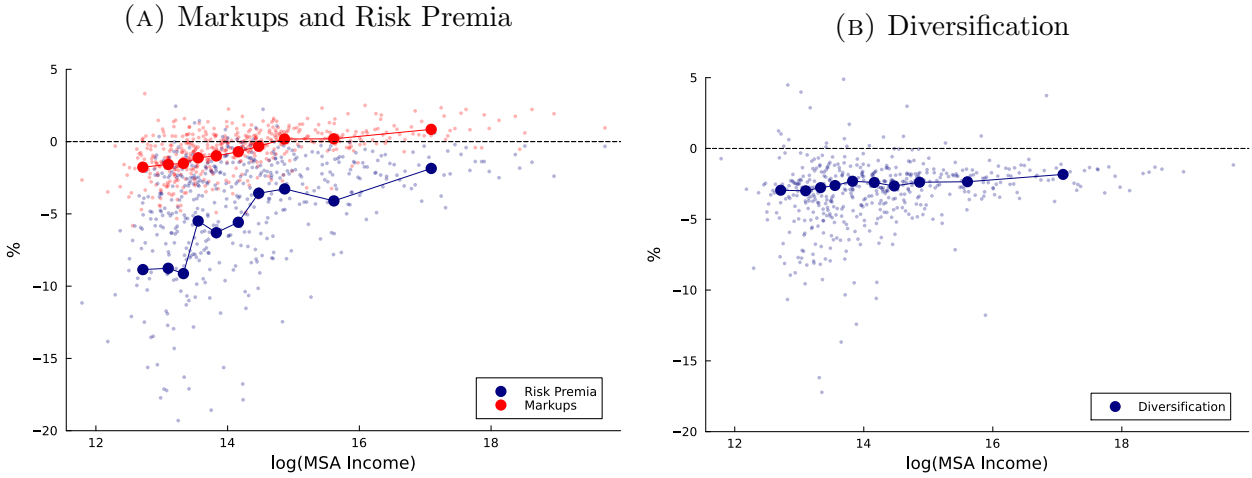
FIGURE D.3. Effects on (log) Spreads, by MSA

(A) Risk Premia (B) Markups, logs



Notes: Based on the decomposition in Equation (30), the figure displays markups and risk premia components of deposits spreads, by MSA income. Blue dots show the results under uniform pricing, while red squares depict the local-pricing case. The larger (darker) dots and squares depict the average risk premium and markup for each decile of the income distribution.

FIGURE D.4. Changes in (log) Spreads, 1993-2019, by MSA



Notes: Following the decomposition in Equation (31), Panel (A) shows changes in markups and risk premia components of deposits spreads between 1993 and 2019, by deciles of MSA income for the uniform-pricing case. Blue dots show the model-implied changes in risk premia, while red dots indicate changes in markups. Panel (B) further decomposes the changes in risk premia into contributions from "diversification gains", following Equation (32).

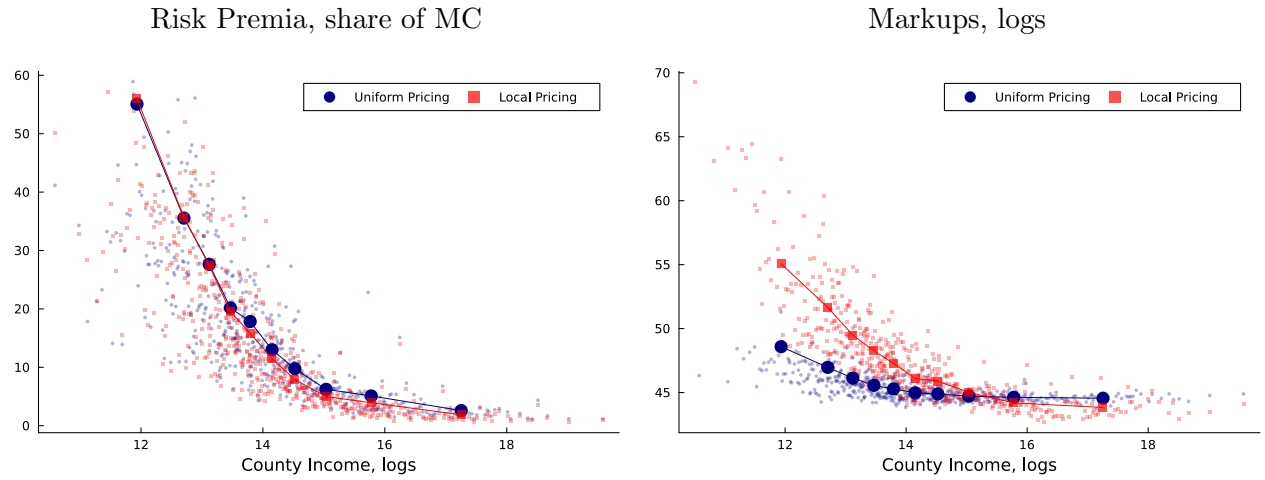
D.3. *On the Role of Online Banking and Central Booking*

In our baseline analysis, we have included all banks reporting deposit holdings in the SOD dataset. However, it's important to note that some of these banks may operate primarily online, rendering the geographical location of their branches irrelevant for assessing their regional risk and market concentration. For example, banks like Ally Bank serve customers nationwide despite having limited physical branches. However, research covering our period of analysis has shown that households still extensively used physical bank branches for banking services, despite the increased relevance of online banking, with the number of branches decreasing only slightly between 2013-2017 (see, for example, Amel et al. (2008); Anenberg et al. (2018); Sakong and Zentefis (2023)). Furthermore, a 2019 FDIC survey found that around 83 percent of banked households visited a bank branch in the past 12 months, and that local banking (ie, tellers or ATMs) were the main access point during 2015-2019.[63]

A second aspect to consider is that some banks may not consistently report deposit holdings across branches, opting instead to aggregate all deposits under one branch——a practice known

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

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



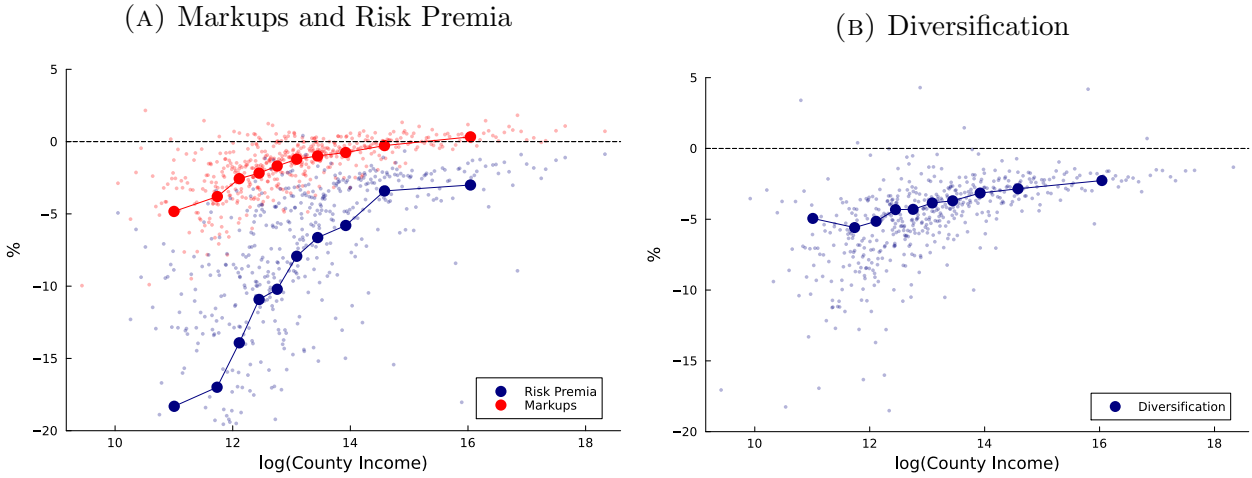
Notes: Based on the decomposition in Equation (30), the figure displays markups and risk premia components of deposits spreads, by county income. Blue dots show the results under uniform pricing, while red squares depict the local-pricing case. The larger (darker) dots and squares depict the average risk premium and markup for each decile of the income distribution. Data is adjusted to exclude online banks and banks employing central booking practices.

as central booking. This can distort assessments of deposit concentration and geographical risk for individual branches.

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

Figures D.5 and D.6 present the results after removing online banks and banks employing central booking practices from the analysis. Our baseline results are robust to these filters.

FIGURE D.6. Changes in (log) Spreads, 1993-2019, by County



Notes: Following the decomposition in Equation (31), Panel (A) shows changes in markups and risk premia components of deposits spreads between 1993 and 2019, by county income for the uniform-pricing case. Blue dots show the model-implied changes in risk premia, while red dots indicate changes in markups. Panel (B) further decomposes the changes in risk premia into contributions from "diversification gains", following Equation (32). Data is adjusted to exclude online banks and banks employing central booking practices.

D.4. *Counterfactuals under Local Pricing*

TABLE D.1. Counterfactuals under Local Pricing

	Δ Deposit Spreads			Risk Premia			Markups		
	Small	Medium	Large	Small	Medium	Large	Small	Medium	Large
A. M&A									
A.1 Top local bank	4.07	1.35	0.11	-0.76	0.49	0.25	1.19	0.45	0.04
A.2 Top regional bank	-6.55	-1.67	-0.21	-6.39	-0.59	0.09	1.07	0.49	0.02
A.3 Top national bank	-10.75	-2.36	0.34	-13.78	-1.37	0.31	1.57	0.53	0.06
B. Increase in k_{ij}									
B.1 Local banks	53.11	23.77	6.70	-21.46	-4.28	-0.77	0.86	0.72	0.31
B.2 Regional banks	14.30	15.94	9.45	1.96	0.68	-0.09	0.20	0.20	0.45
B.3 National banks	7.14	12.69	29.38	4.37	2.62	1.19	0.07	0.48	-0.35
C. Decrease in ψ_{ij}									
C.1 Local banks	2.58	6.21	2.25	-3.60	-3.04	-0.72	1.48	1.71	0.50
C.2 Regional banks	2.01	2.48	2.34	3.95	2.34	0.06	0.64	0.85	0.81
C.3 National banks	-0.08	-0.44	-3.09	0.81	2.73	2.74	0.27	1.43	-0.02
D. Demographics									
D.1 Increase μ_i	-9.88	-3.75	-0.01	-8.86	-3.10	-0.04	0.04	0.03	-0.00
D.2 Increase σ_i / μ_i	0.89	0.52	3.62	0.82	0.48	2.83	-0.00	-0.00	0.02

Notes: Table shows percentage changes in deposit spreads, risk premia, and markups across different counterfactuals. Results are shown for 3 groups of counties —small, medium, large—, based on their total income, and correspond to the local-pricing case. See the note in Table D.1 for additional details.

TABLE D.2. M&A Counterfactual: Effects on Lending — Local Pricing

	Total Change			IO Channel			Risk Premia Channel		
	Low	Medium	High	Low	Medium	High	Low	Medium	High
Acquirer bank:									
1 Top local bank	1.01	2.06	4.38	-0.04	-0.14	-0.39	-0.27	-1.23	-3.00
2 Top regional bank	8.06	5.53	5.03	0.27	-0.82	-2.29	5.46	4.14	3.21
3 Top national bank	14.42	38.29	82.16	1.23	-0.97	-2.43	15.25	22.62	42.07

Notes: The table shows model-implied changes in lending due to the assumed mergers and acquisitions. Total change column shows the overall change in lending. The IO Channel shows the changes directly attributable to shift in banks' loans after the M&A, keeping all other variables fixed. The Risk Premia Channel shows the change in lending explained by changes in deposit risk premia. States are split into terciles based on their share of local deposits—defined as deposits held by banks that operate in just one state. In each row, we replace local banks—those that operate in just one location— with the largest local, regional, or national bank. In all cases, we exclude from the M&A's those acquired local banks whose total assets are larger than the 95th percentile—as these may be online banks or banks with central booking practices.

D.5. *Estimating Elasticity of Substitution with Cash*

This section provides details on the procedure to estimate the reduced-form elasticity of the cash-to-deposits ratio M_t/D_t to the net rate of return $R_t - 1$. This is used in Section 8.1 as a target to set a value for 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 MP shocks as an instrument for the latter.

Data on households' holdings of cash and deposits is obtained from Board of Governors' Financial Accounts of the United States (Z.1). We define cash as "Checkable deposits and currency" (FL153020005), and deposits as "total time and savings deposits" (FL153030005), both from "households and nonprofit organizations."[64] We consider two measures for the monetary policy shock FF_t, both constructed by Jarociński and Karadi (2020).[65] The first one ("PC1") is the first principal component of the surprises in interest rate derivatives with maturities from 1 month to 1 year (MP1, FF4, ED2, ED3, ED4). The second measure ("JK") is the shock adjusted to exclude any *news* component present during an FOMC announcement. The 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 the household's preference for cash relative to deposits (i.e. to the share parameter ζ). The two-stage IV regression is:

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

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

where FF_{t-k} is the monetary policy shock and X_t is a vector of controls (namely, the lagged values of both the dependent variables). The coefficient of interest is γ_1^M, which estimates how the instrumented variation in $\ln(R_t - 1)$ translates into changes in $\ln\left(\frac{M_{t-1}}{D_{t-1}}\right)$.

Table D.3 presents the estimates for γ_1^M for the various specifications for the period 1990-2019. The first two columns show results when excluding the Great Financial Crisis period 2008-2013 while the last two columns use the full sample. The point estimates are economically and statistically significant across all specifications, with values ranging from -1.1 to -1.6. Standard errors are robust to heteroskedasticity, and the F-statistic suggest that the instruments chosen are relevant. While not shown, the first-stage estimates for β_1^R are also positive and

[64] Note that this aggregate is not the same as the model-consistent aggregate D_t. Accordingly, for the purposes of this calibration, we construct the same object in the model by summing up deposits.

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

statistically significant. We adopt a target reduced-form elasticity of -1.3, roughly in the middle of the range of estimates in the table.

TABLE D.3. Elasticity of Cash-to-deposits to R_t

	(1)	(2)	(3)	(4)
$\Delta \widehat{\ln(R_t - 1)}$	-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: This table displays estimates for the cash-to-deposits ratio to R_t. The full sample is 1990-2019, at yearly frequency. "PC1" is the first principal component of the surprises in interest rate derivatives with maturities from 1 month to 1 year (MP1, FF4, ED2, ED3, ED4). "JK" is an adjustment to exclude any news component present during an FOMC announcement; see Jarociński and Karadi (2020). The first two columns exclude 2008-2013. Standard errors are robust to heteroskedasticity and F-statistic follows Kleibergen and Paap (2006).