The Deposit Business at Large vs. Small Banks*

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Abstract

The deposit business differs at large versus small banks. We provide a parsimonious model and extensive empirical evidence supporting the idea that much of the variation in deposit-pricing behavior between large and small banks reflects differences in preferences and technologies. Large banks offer superior liquidity services but lower deposit rates, and locate where customers value their services. In addition to receiving a lower level of deposit rates on average, customers of large banks also exhibit lower rate elasticities. As a result, despite the fact that the locations of large-bank branches have demographics typically associated with greater financial sophistication, large-bank customers earn *lower* average deposit rates. Our explanation for deposit pricing behavior challenges the idea that deposit pricing is mainly driven by pricing power derived from the large observed degree of concentration in the banking industry.

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1 Introduction

The business of creating and maintaining a deposit franchise is different for large vs. small banks. We document contrasting location, technology, and pricing decisions for large vs. small banks, and show how banks' different deposit-business models arise naturally from variation in the preferences of depositors across deposit markets. Our study builds on the classic idea in industrial organization that product-market competition is heavily influenced by product differentiation and customer preferences. For deposits, we find that such differentiation depends largely on bank size.

We document that, compared with small banks, large banks tend to offer lower, and uniform, deposit rates across their branches. They also cover different geographies, locating their branches in areas with high population density, high incomes, high house prices, and younger populations. Because higher-income, younger, and more-urban consumers tend to display higher financial sophistication (e.g., Campbell, 2006), we argue that large-bank depositors are unlikely to be making more mistakes than their small-bank counterparts in choosing their deposit product. In addition, small banks that operate in markets with a high market share of large bank deposits offer *lower* rates than other small banks, suggesting that local consumer preferences play a pivotal role in shaping deposit-market competition.

We present a simple model of the deposit business at large and small banks.[1] Consistent with our own empirical findings and with a long literature on uniform rate setting in banking, we assume that large banks set uniform rates.[2] Banks decide whether to provide superior liquidity services at a fixed cost, while strategically deciding which markets to enter.[3] The scalability of this technology makes operating across multiple markets profitable but introduces a trade-off: because banks are required to set uniform rates across all markets, they cannot tailor interest rates to maximize profits locally in each market. The free-entry conditions in our simple model establish the type and quantity of banks entering each market. In equilibrium, two bank types emerge: large banks, which enter multiple markets, pay the required fixed cost, and provide superior liquidity services; and small banks, which do not pay the required fixed cost and enter only a single market.[4] Because of uniform pricing, large

[1]For quantitative industry equilibrium models of banking, see the important contributions of Corbae and D'Erasmo (2021, 2013); Wang, Whited, Wu, and Xiao (2022); Bianchi and Bigio (2022).

[2]See, for example, Calem and Nakamura (1998); Radecki (1998, 2000); Biehl (2002); Heitfield (1999); Heitfield and Prager (2004); Park (2009); Park and Pennacchi (2009); Begenau and Stafford (2023); Yankov (2024); Granja and Paixão (2024).

[3]These liquidity services include larger branch and ATM networks, customized online banking, or a broad array of financial services.

[4]This is consistent with the findings of Haendler (2023) regarding small banks' sluggish adoption of mobile-banking services and with those of Koont (2023) and Sarkisyan (2024) on bank-balance-sheet growth from recent improvements in liquidity services.

banks maximize profits by locating in areas with customers that display similar demand curves.

The fundamental difference in preferences across geographies and demographies served by large vs. small bank depositors is a central contribution of our study. We estimate deposit elasticities for each bank in each market, and show that large-bank customers exhibit lower rate elasticities and that depositors' rate-elasticities decline with income. We extend the methodology of Egan, Hortaçsu, and Matvos (2017); Xiao (2020); and Wang et al. (2022) to structurally estimate banks' rate elasticities, focusing on bank size and heterogeneity in depositors' price sensitivities and willingness to pay for superior liquidity services. All banks choose deposit spreads based on local market preferences, and we allow depositors' value of liquidity services to depend on income. Assuming households choose from available local-market banks, we estimate the deposit-demand system at the bank-market level. After estimating the model's demand parameters, we calculate each bank's rate elasticity in each local market. We find that large banks are more likely to be located in markets with less-elastic customers. This supports the results in Egan et al. (2017), who focus specifically on large banks and report low average deposit-rate elasticities.

Large-bank customers have higher incomes and are likely to be more financially sophisticated, but they both receive lower rates on average and are less rate-sensitive. Large-bank depositors can garner superior liquidity services by keeping a small fraction of wealth in large-bank deposits, while also participating in higher-yield assets with their remaining wealth (see Vissing-Jørgensen, 2002; Smith, Zidar, and Zwick, 2023). Thus, our finding that more financially sophisticated depositors receive lower rates and execute their deposit-withdrawal option "less optimally" is consistent with such depositors having a higher willingness to pay for superior liquidity services. Rural, lower-income, lower house-price, and older customers value the yield generation of small-bank deposits, while their large-bank counterparts place a higher value on deposits' payments and liquidity attributes.

The model offers key insights into the deposit-rate strategies of large and small banks, with a particularly robust prediction: large banks consistently pay lower rates than small banks, because large banks cater to markets with lower rate elasticities and higher preference for liquidity services. Our empirical analysis reveals that the predominant rate elasticity among U.S. depositors is relatively low, with a fat right tail representing more price-sensitive individuals. Because of uniform rates, large banks locate in markets with similar rate elasticities, which are predominantly low in the U.S., and therefore set low rates. In contrast, small banks operate in all markets, which includes the more dispersed higher end of the price-sensitivity distribution. Consequently, across markets, large banks offer lower rates because of the lower average elasticity of the depositors in the markets they serve. Within markets with both large and small banks, small banks pay higher rates than large banks in order to attract depositors without offering superior liquidity services.

Our framework also rationalizes the observation that small banks offer lower deposit rates in markets where large banks have a higher market share than they offer in other markets. This is because, given the empirical distribution of rate elasticities, markets with large banks are markets with predominantly inelastic demand curves. This result would be surprising if small banks that colocate with large banks were induced to compete more vigorously on deposit pricing. However, our finding that colocated small banks offer lower rates is intuitive if, as we argue, underlying customer preferences drive banks' location decisions.[5]

Finally, the model predicts that market-rate elasticities better explain variation in deposit spreads than market-concentration measures such as the Herfindahl-Hirschman index (HHI). Indeed, market concentration can increase either because of higher entry costs or because of higher market-rate elasticity. But higher entry costs result in more market power and lower deposit rates, while a higher rate elasticity results in less market power and higher deposit rates. Thus, the correlation between deposit rates and HHI is ambiguous while that between deposit rates and market-rate elasticity is always positive. We find robust empirical support for these conclusions in the data; our measure of market-rate elasticity explains about 10 times more deposit-rate variation than does HHI.[6,7]

Our contribution is to document and explain the key differences between the deposit businesses of large banks, which have a market share of over 50% of U.S. deposits, and the large number of small banks that have the remaining minority share. Just 14 large banks represent over 50% of deposits.[8] Understanding the deposit business model of these large banks is thus key to understanding deposit pricing on a value-weighted basis. Smaller banks are more numerous, and the small-bank deposit business model is overrepresented in equally-weighted analyses. We provide a unified set of stylized facts, and a model that helps to understand these facts and the prior literature.

[5] Chang, Cheng, and Hong (2023) study small banks only, but also emphasize product differentiation based on heterogeneity in small-business bank services demands.

[6] See the R-squared in Table 2 for HHI and R-squared in Table 7 for the semi-elasticity $\hat{\zeta}$.

[7] While our finding on the relevance of HHI may seem surprising in light of the use of HHI to explain deposit pricing behavior in recent work by Drechsler, Savov, and Schnabl (2017), and older contributions including Berger and Hannan (1989); Hannan and Berger (1991), Hannan (1991, 1997), Neumark and Sharpe (1992), Rhoades (1992), and Sharpe (1997), we show in Appendix C that the relation between HHI and the sensitivity of deposit rates to the Federal Funds rate is driven by small banks. This is consistent with the literature from the 1980s and 1990s, which questioned the role of local market concentration as banks grew in size, as documented in Bassett and Brady (2002) (see, for example Berger, Kashyap, and Scalise, 1995; Demyanyk, Ostergaard, and Sørensen, 2007). Note that Drechsler et al. (2017) also discusses competition along non-rate dimensions, which would include the superior liquidity services that we emphasize, and our results strongly support their findings on deposit stickiness.

[8] See also Corbae and D'Erasmo (2020).

Prior research documents a number of other differences between large and small banks. Bassett and Brady (2002) find that large and small banks have quite different liabilities, with small banks' liabilities composed mainly of FDIC-insured retail deposits, while larger banks have larger quantities of uninsured deposits. Park and Pennacchi (2009), supported empirically by Berger, Miller, Petersen, Rajan, and Stein (2005); Cole, Goldberg, and White (2004); Haynes, Ou, and Berney (1999), note that larger banks face lower funding costs than smaller banks due to their access to wholesale financing, and that the greater organizational complexity of large banks may mean that they face higher costs of servicing small businesses and consumers, and may be more likely to rely on simple decision rules regarding lending and pricing that are based only on "hard" information. In a comparison of the capital structure of traditional banks and shadow banks, Jiang, Matvos, Piskorski, and Seru (2024a) show that bank leverage is insensitive to bank size and that uninsured deposits increase with bank size.[9] Our complementary focus is on the different business models for deposits at large vs. small banks.

Our emphasis on the bank size distribution is also shared by the earlier literature starting with Mester (1987), who noted that allowing bank branching would change competition by allowing banks to interact at multiple locations. Oberfield, Rossi-Hansberg, Trachter, and Wenning (2024) study the spatial expansion of banks after deregulation in the 1980s and 1990s.[10] Calem and Nakamura (1998) showed theoretically that branching might lead to uniform pricing and a long literature emerged verifying this effect for large banks, while showing that small banks priced to local markets (see, for example, Radecki, 1998, 2000; Biehl, 2002; Heitfield, 1999; Heitfield and Prager, 2004; Park and Pennacchi, 2009).

Understanding the deposit business at large and small banks is crucial for understanding bank valuations and for measuring financial stability. The franchise values of deposit businesses has been documented as a key driver of bank value, and hence bank solvency, in the cross section and time series. Minton, Stulz, and Taboada (2019) show that large banks do not appear to be valued more highly than small banks, and that the size of banks' deposits relative to total liabilities is positively correlated with bank value.[11] Egan, Lewellen, and Sunderam (2022) show that deposit productivity is more important than loan productivity for understanding the cross section of bank values. Atkeson, d'Avernas, Eisfeldt, and Weill (2018) develop a calibrated Gordon-growth model (Gordon and Shapiro, 1956) framework

[9] See also Buchak, Matvos, Piskorski, and Seru (2024), which shows that bank lending is not constrained by balance sheet size due to bank access to securitization markets.

[10] See also recent work by Corbae and D'Erasmo (2013), who develop a large-scale quantitative DSGE model that embeds Stackelberg-game imperfect competition between small and large banks.

[11] See also Calomiris and Nissim (2014) for a related empirical study of bank valuation ratios, and Bolton, Li, Wang, and Yang (2024) for a dynamic q-theoretic model of banking and the value of the deposit franchise.

which quantifies the impact of post-Great-Financial-Crisis changes in the value of the deposit franchise on the financial soundness of the banking sector. Ma and Scheinkman (2021) show that the leverage of banks is supported by their going-concern value, which includes the deposit-franchise value. It is important to note that despite the importance of deposit franchises for bank values, and despite the higher spreads that large banks have and the lower rate elasticities of their customers, large banks exhibit *lower* valuation ratios (Minton et al., 2019; Atkeson et al., 2018). This fact cuts against explanations of large banks' pricing behavior that rely on high profitability.

Our deposit-rate-setting framework contributes to understanding recent bank failures and to discussions regarding bank-interest-rate risks.[12] Small banks may be more vulnerable in a tightening environment because their customers are more sensitive to deposit-rate changes, and because they need to incur higher funding costs by offering higher rates to retain deposits.[13] This is despite the fact that, on average, small banks have a lower fraction of uninsured deposits.[14] Consequently, small-bank deposit franchises may have weaker hedging benefits (Drechsler et al., 2021) and a shorter duration. However, it is important to note that the canonical study of the effect of uninsured deposit share on deposit-rate elasticities, Egan et al. (2017), finds strong effects from measures of bank solvency within the set of larger banks. Our contribution emphasizes that banks do not compete solely on rates and that large and small banks operate different deposit business models. We offer a framework that highlights the differences in these business models and structurally links them to the banks' pricing behavior, location choices, and customer rate elasticities.

The remainder of this paper is organized as follows: Section 2 details the data. Section 3 provides comprehensive evidence describing banks' deposit-rate-setting behavior and investigates the different rate-setting behavior of large vs. small banks. Section 4 presents empirical evidence on the different market selections of large and small banks. Section 5 presents and analyzes our model. Section 6 presents estimates of rate elasticities, and Section 7 concludes.

[12]See Jiang, Matvos, Piskorski, and Seru (2024b); Haddad, Hartman-Glaser, and Muir (2023); Chang et al. (2023); Drechsler, Savov, Schnabl, and Wang (2024); Benmelech, Yang, and Zator (2024) for studies of the 2023 bank failures. Jermann and Xiang (2023) develops a dynamic model of banking in which depositors optimally withdraw conditional on bank leverage and default risk. Fleckenstein and Longstaff (2024) studies whether maturity-transformation risk is priced into the term structure of CD rates. Drechsler, Savov, and Schnabl (2021) is the classic study of the effect of the deposit franchise on bank interest rate exposures. Begenau, Piazzesi, and Schneider (2015) study bank-interest-rate exposures, but focus on the asset side of banks' balance sheet.

[13]Chang et al. (2023) shows that smaller banks with more uninsured deposits had greater profitability and market valuations prior to the bank failures in the spring of 2023.

[14]Among others, see Jiang et al. (2024b), which includes recent data.

2 Data

We define large banks as the fourteen depositories that were identified as large, complex bank-holding companies subject to the Supervisory Capital Assessment Program (SCAP) of 2009 with year-end 2008 assets exceeding $100 billion.[15] These fourteen banks also participated in the 2011 Comprehensive Capital Analysis and Review (CCAR) for complex bank-holding companies, and accounted for 29% of all U.S. deposits in 2000 and 54.7% in 2019.[16] The fourteen banks are all designated as either Systemically Important Financial Institutions (SIFIs) or U.S.-domiciled Global Systemically Important Financial Institutions (G-SIBs).[17] We designate all branches that are acquired by these institutions over our analysis period of 2001 to 2020 as 'large-bank branches' post-acquisition. In the spirit of the definition for large banks, our analysis defines a bank at the bank holding company level, combining banks owned by the same bank holding company into a single entity. In Appendix B, we replicate our structural analysis with the top 1% of large bank holding companies by deposits.[18]

Our empirical analyses rely on three major datasets for information on bank-deposit product types and the rates that banks pay customers for those deposits. First, we investigate branch-level deposit rates using the RateWatch data from S&P Global. The RateWatch data has the advantage of accounting for nearly 100,000 banks from 2001 to 2020, RateWatch includes extensive branch-level geographic coverage of the U.S., and they are easily merged to both the FDIC Summary of Deposit data and the FDIC Consolidated Report of Condition and Income (Call Report) data. The RateWatch data are collected weekly at the branch-level for precisely defined deposit products and include the advertised deposit rates for these products.[19] We focus on the four deposit products with the greatest coverage in RateWatch,

[15]See https://www.federalreserve.gov/newsevents/pressreleases/files/bcreg20090424a1.pdf. A similar definition for large banks is used in Berndt, Duffie, and Zhu (2024).

[16]The fourteen banks are Bank Of America Corporation, BB&T Corporation, Capital One Financial Corporation, Citigroup Inc., Fifth Third Bancorp, Goldman Sachs Group, Inc., The JP Morgan Chase & Co., Keycorp, Morgan Stanley, PNC Financial Services Group, Inc., The Regions Financial Corporation, Suntrust Banks, Inc., U.S. Bancorp, and Wells Fargo & Company. The SCAP and CCAR reviews also included three other non-depositories (Ally Financial, American Express Company, Metlife Inc.) and two processing banks (State Street Corporation and Bank of New York Mellon Corporation) (see https://www.federalreserve.gov/newsevents/pressreleases/files/bcreg20110318a1.pdf).

[17]Under Section 117 of the Dodd-Frank Act, the SIFI designation applies to any bank holding company with total consolidated assets of at least $50 billion (https://home.treasury.gov/policy-issues/financial-markets-financial-institutions-and-fiscal-service/fsoc/designations). The G-SIB designation is determined by the Financial Stability Board (FSB) in consultation with the Basel Committee on Banking Supervision (BCBS) and national authorities of the Group of Twenty (see https://www.bis.org/bcbs/publ/d445.pdf).

[18]In 2000, the top 1% of banks consisted of 89 banks which accounted for 57% of total U.S. deposits. In 2019 the top 1% of banks consisted of 53 banks accounting for 72% of deposits.

[19]Although the RateWatch data includes a flag for a subset of branches that are labelled "rate setter" branches, RateWatch advised us that the designation was an in-house data-storage identification number

namely interest checking account with a balance of $2,500 (CHECK $2.5K), savings account with a balance of $2,500 (SAV $2.5K), 12-month certificate of deposit with a balance of $10,000 (12M CD $10K), and money-market account with a balance of $25,000 (MM $25K). RateWatch's SAV $2.5K accounts are very similar to checking accounts, except for limitations on the number of withdrawals. A limitation of the data is that about 32% of small banks' branches are not tracked by RateWatch.

Our second two major data sets are the Bank Regulatory data, including Consolidated Report of Condition and Income (Bank Call Reports) and Consolidated Financial Statements for Holding Companies (FR-Y9C), and the Summary of Deposits, both from the Federal Deposit Insurance Corporation. The Call Report data include bank-level asset and liability structure, the income statement, and supporting schedules for all of the FDIC regulated banks in the U.S. A key variable for our analysis is the annual bank-level deposit rate which we compute using the Call Report data by dividing the reported end-of-year bank deposit interest expenses by the reported end-of-year bank deposit balance for each year 2001 through 2020. FR-Y9C data has a similar structure to the Call Report data, except that it is reported at the bank-holding-company (BHC) level.

The Bank Regulatory data also reports aggregates of deposit products such savings deposits and time deposits, in contrast to the more narrowly defined specific deposit product types that are reported in RateWatch.[20] The savings deposits data include interest bearing bank accounts with transfers and withdrawal restrictions. These accounts include passbook savings accounts, statement savings accounts, and money market deposit accounts. Time deposits data include all interest-bearing bank accounts that have a required preset date of maturity to earn the stated rate of interest. Certificate of deposits (CD) are the dominant form of time deposit accounts. Transaction deposits include interest bearing bank accounts that allow the depositor to make transfers from the account without regard to the number of transfers made. Interest checking accounts are the common type of transaction deposits. We combine the Call Report data and FR-Y9C data, as detailed in Appendix D. For simplicity, we will refer to the combined Bank Regulatory data as Call Report data throughout the rest of the paper.

We also supplement the Bank Regulatory data with the FDIC's Summary of Deposits, which reports branch-level total deposit balances and branch locations. This additional data source allows us to explore banks' branch-site choices and to obtain local market shares for

and did not indicate that a flagged branch actually set rates for other branches. Thus, they recommended that we ignore this flag.

[20] Definitions for time deposits, savings deposits, and transaction deposits are reported in Part 204 of the Reserve Requirements of the Depository Institutions (see https://www.ecfr.gov/current/title-12/chapter-II/subchapter-A/part-204).

our rate-elasticity analysis. Additionally, we used the Summary of Deposits data to compute the Herfindahl-Hirschman Indices (HHI) for market shares at the county level.

We utilize both RateWatch and Bank Regulatory data where feasible. The advantage of RateWatch is that it contains granular product-level data at the branch level, while Bank Regulatory deposit rate data are at the bank/BHC level. Thus, RateWatch data are required for any analysis of local product-market pricing. However, wherever possible, we replicate our analyses using Bank Regulatory data in Appendix A, and show that all overlapping analyses are consistent between the two data sources.

To explore the demographics of customers and their potential impact on deposit rates, we rely on Data Axle's U.S. Consumer database, formerly known as Infogroup. This dataset provides annual information on household income for about 67 million U.S. households from 2006 to 2020 and is available at the household level using latitudinal and longitudinal geo-identifiers.[21] The county-level population and income data is from U.S. Bureau of Economic Analysis. Further details on the data construction process are provided in Appendix D.

3 Rate-setting behavior of large and small banks

In this section we document three facts regarding the rate-setting behavior of large vs. small banks. First, rate setting is uniform across branches within banks, as already documented by a long literature.[22] Second, large banks pay lower average deposit rates than small banks. Finally, small banks located in areas with a higher market share of large banks set lower deposit rates than those in areas where large banks have a lower market share.

3.1 Uniform pricing

To establish that large banks offer uniform deposit rates across large geographical areas, we first regress weekly product-type deposit rates on fixed effects using the RateWatch data between 2001 and 2020:

$$\text{Rate}_{b,t} = \text{FE} + \epsilon_{b,t}, \tag{1}$$

where $\text{Rate}_{b,t}$ is the weekly product-type deposit rate at the branch b and the fixed effects, FE, are measured as either Time or Bank×Time.

[21] Data Axle models the annual income of the household heads using the MRI/Simmons annual Survey of the American Consumer. The estimated income model is updated based on changes in Census Bureau data, changes from the latest MRI survey, actual changes in the surveyed household income, and changes in the Data Axle consumer data. The data used in the Data Axle income model include about 35 individual, household, and consumer lifestyle characteristics and about 26 geoprocessed Census data fields.

[22] See, for example, Radecki (2000); Biehl (2002); Heitfield (1999); Heitfield and Prager (2004); Park and Pennacchi (2009); Begenau and Stafford (2023); Yankov (2024); Granja and Paixão (2024).

FE	(1) Time	(2) Bank×Time
MM $25K		
Observations	51,792,987	50,355,985
R-squared	0.583	0.947
SAV $2.5K		
Observation	54,507,772	52,982,180
R-squared	0.474	0.942
12M CD $10K		
Observations	55,144,063	53,612,603
R-squared	0.866	0.988
CHECK $2.5K		
Observations	52,600,971	51,108,483
R-Squared	0.351	0.915

Table 1: **Rate variation within banks.** The data consist of weekly deposit rates from RateWatch, covering the period from 2001 to 2020 at the branch level. The selected deposit products include money market accounts with a balance of $25,000, savings accounts with a balance $2,500, 12-month CDs with a balance of $10,000, and interest checking accounts with a balance $2,500. Column (1) incorporates week fixed effects, while column (2) includes bank-week fixed effects.

Table 1 reports the regression results. The first panel concentrates on the MM $25K rates. The R-squared values indicate that 58.3% and 94.7% of rate variation can be explained by time fixed effects and bank-time fixed effects, respectively, confirming quite minimal rate variation within banks. The remaining panels examine the SAV $2.5K rates, 12M CD $10K rates, and CHECK $2.5K rates. 12M CD $10K exhibits smaller rate variation across branches and banks, whereas the other products exhibit significant rate variation, with less than 50% of the variation explained by time fixed effects. However, bank-time fixed effects still account for almost all of the rate variation, at around 94%. Overall, Table 1 shows that banks tend to set uniform rates across branches, with the majority of deposit-rate variation arising across rather than within banks.

There are various potential reasons why large banks might implement uniform rates. First, a lack of local experts and high costs, such as agency costs as in standard capital budgeting models, make it difficult for banks to analyze local markets and set deposit rates at the branch level.[22] Second, setting different rates exposes banks to potential complaints

[22]See the earlier literature on uniform deposit rates (for example, Radecki, 2000; Biehl, 2002; Heitfield,

about regional price dispersion.[23] Importantly, uniform rate setting has crucial implications for how banks compete for deposits. Large banks operating in multiple regions and setting uniform rates face limitations when responding to changes and competition in local markets, instead determining rates based on their national market conditions. Conversely, small and local banks can set rates locally, offering greater flexibility. The inability to price to the local market is a key cost of being a large bank in our model, while a key benefit is that large banks can offer superior liquidity services that entail large fixed costs. Our empirical findings are consistent with the prior empirical literature that argues that large banks leverage their extensive ATM networks and superior liquidity services technologies to operate nationally, while small banks rely on local knowledge, personalized services, and community ties to compete within their specific regions. This results in a disparity in rate-setting behavior and in the business of deposits at large vs. small banks.

We extend prior results on uniform rate setting by documenting the sources of branch-level deposit rate variation. That is, we study which local-market characteristics can explain variation in deposit rates once time fixed effects are removed. Table 2 presents results from a two-step test of the contribution of local-market characteristics to rate variation. We first regress branch-level deposit rates on time fixed effects to extract the time effects, and then regress the residuals on fixed effects of interest in the second step to evaluate their explanatory power for the remaining variation:

$$\text{Rate}_{b,t} = \alpha_t + \epsilon_{b,t}, \tag{2}$$

$$\hat{\epsilon}_{b,t} = \text{FE} + \varepsilon_{b,t}. \tag{3}$$

Table 2 explores whether the interaction of time and bank, size, or local characteristics like HHI or population fixed effects can explain the remaining variation. Column 1 shows that around 90% of the remaining rate variation can be accounted for by bank-time in all four products. Column 2 demonstrates a large $\times$ time fixed effect explains 11% of money market rates, 15.1% of savings rates, 21.9% of CD rates, and 14% of the remaining variance of checking account rates. While size explains less of the remaining variation than that explained by using bank-level effects, size explains 10 times more than local characteristics. Indeed, Columns 3 and 4 show that time-varying local HHI and local population at the county level have little explanatory power for rate variance (2% or less across all rates).[24]

1999; Heitfield and Prager, 2004; Park and Pennacchi, 2009).

[23] See the large literature on uniform pricing by chain stores and other retail outlets (for example, Anderson and Simester, 2001; Leslie, 2004; Orbach and Einav, 2007; Anderson, Jaimovich, and Simester, 2015; DellaVigna and Gentzkow, 2019) and online retailers (`https://thebillionpricesproject.com/datasets/` and Cavallo, 2018). Wenning (2024) studies national pricing by life insurers.

[24] We show in Appendix C that the relation between HHI and the sensitivity of deposit rates to the Federal

FE	(1) Bank×Time	(2) Large×Time	(3) HHI×Time	(4) Pop×Time
MM $25K				
Observations	50,355,985	49,061,246	50,355,985	49,528,298
R-squared	0.877	0.110	0.002	0.004
SAV $2.5K				
Observations	52,982,180	51,675,075	52,982,180	51,985,473
R-squared	0.894	0.151	0.015	0.009
12M CD $10K				
Observations	53,612,603	52,297,484	53,612,603	52,589,280
R-squared	0.913	0.219	0.017	0.013
CHECK $2.5K				
Observations	51,108,483	49,880,060	51,108,483	50,143,387
R-squared	0.874	0.140	0.016	0.011

Table 2: **Residual analysis.** This table tests the contribution of local market characteristics to rate variations after removing time variation. The data consist of weekly deposit rates from RateWatch, covering the period from 2001 to 2020 at the branch level. The selected deposit products include money market accounts with a balance of $25,000 (MM $25K), savings accounts with a balance of $2,500 (SAV $2.5K), 12-month CDs with a balance of $10,000 (12M CD $10K), and interest checking accounts with a balance of $2,500 (CHECK $2.5K). Fixed effects incorporated are bank-time in Column 1, Large×Time in Column 2 where Large is a dummy for the 14 large banks defined above, HHI×Time in Column 3, and Population×Time fixed effects in Column 4, where HHI and Population are calculated at the county level.

These results support the argument that variation in local market conditions doesn't explain much of the variation in deposit-rate setting behavior, while differences in bank size explain substantially more of the variation in rates.

3.2 Deposit rates for large vs. small banks

We document that small banks offer higher deposit rates than large banks in two ways. First, we compare the time series of RateWatch average deposit rates of the median large bank to the median small bank in Figure 1: small banks set higher rates for all four of the most represented product categories, namely money market accounts of $25k, savings deposits of $2.5k, 12-month CDs of $10k, and checking deposits of $2.5k from 2001 through 2020. We repeat this comparison using Call Report data in Appendix A Table A.1. The Call Report

Funds rate documented by Drechsler et al. (2017) is due to small banks.

	MM $25K	*SAV $2.5K*	*12M CD $10K*	*CHECK $2.5K*
	(1)	(2)	(3)	(4)
Large	−0.262***	−0.284***	−0.484***	−0.222***
	(0.004)	(0.003)	(0.004)	(0.003)
Observations	4,166,511	4,331,543	4,351,767	4,197,739
R-squared	0.651	0.578	0.912	0.477

Table 3: **Deposit rate differences between large and small banks.** This table estimates the average deposit rate difference between large and small banks using RateWatch data from 2001 to 2020. Branch-level deposit rates are collapsed into bank-level rates by taking the average rates weighted by branch deposit balance. The 14 large depository institutions are defined above and the dependent variables are deposit rates of money market accounts of $25,000, saving account of $2,500, 12 month CD of $10,000, and checking account of $2,500. All columns control for time fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

data also shows that large banks pay lower rates relative to small banks, in particular for the larger product categories such as savings and transaction deposits.[25]

Second, we show that large banks offer lower rates across all four products using regressions of weighted average deposit rates by bank on a large-bank dummy variable and time fixed effects. As shown in column 3 of Table 3, large banks set MM $25K rates 26 basis points lower than small banks after controlling for time fixed effects. The remaining columns show similar results for savings accounts, certificates of deposit, and checking accounts.[26]

Finally, we document the differences in the deposit rates of small banks that either do or do not co-locate with large banks. Again using RateWatch data from 2001 to 2020, Figure 2 illustrates that small banks located in areas where large banks have a higher market share set relatively lower rates. As shown in Figure 2, the deposit rates of all deposit products have a negative relationship with the deposit share of large banks. This pattern is not consistent with small banks needing to set higher rates to compete effectively against large banks when small banks co-locate with large banks. Instead, small banks co-located with larger banks charge lower rates on average relative to other small banks. This finding supports the idea that local depositor preferences are a key determinant of rate-setting behavior.

[25] Call Reports provide rates for broader categories of deposit-product types, including time deposits, savings deposits, and transactions deposits.

[26] In Appendix C, we show that the relation between rates and bank size is monotonic for all banks except for the very smallest banks. These very small banks altogether hold less than 2% of deposits.

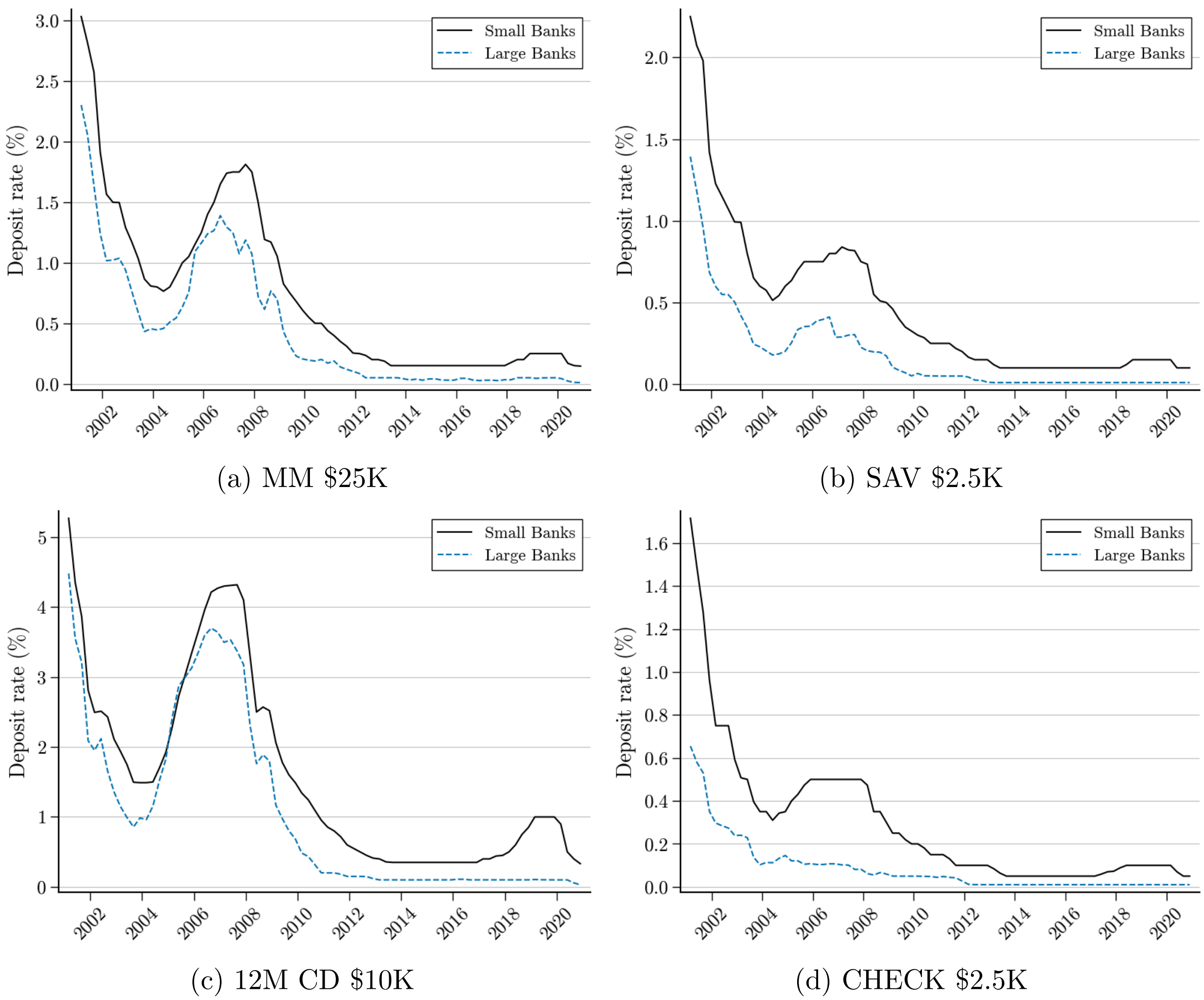
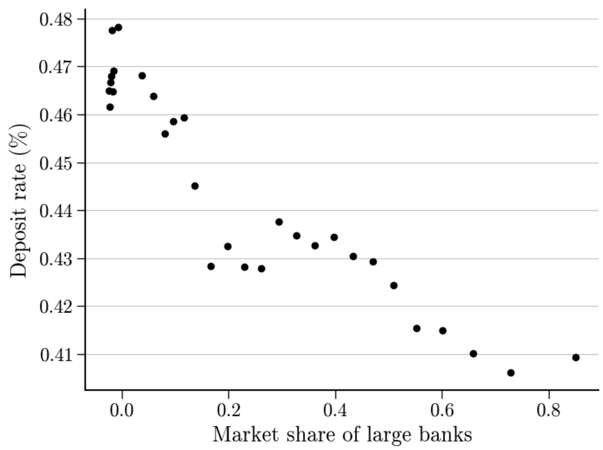
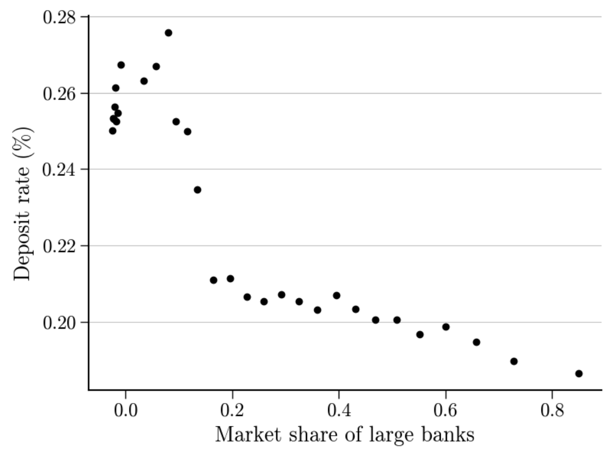


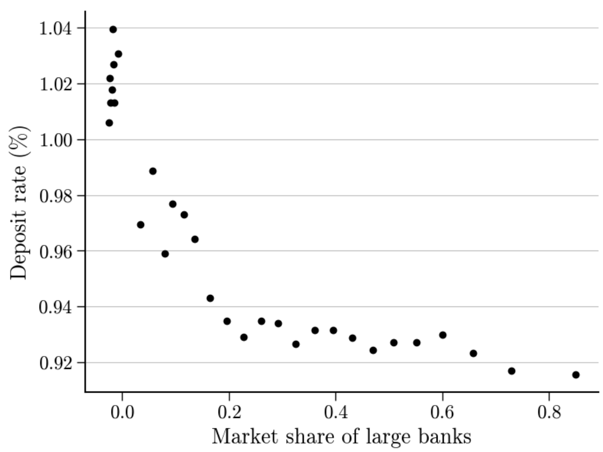
Figure 1: **Deposit rates of large vs. small banks.** The figures show the time series of weighted average deposit rates of the median large bank compared to the median small bank using the RateWatch data from 2001 to 2020. The charts display rates for money market accounts with a balance of $25,000, savings accounts with a balance of $2,500, 12-month CDs with a balance of $10,000, and checking accounts with a balance of $2,500. The black lines denote small banks and the blue lines denote large banks.



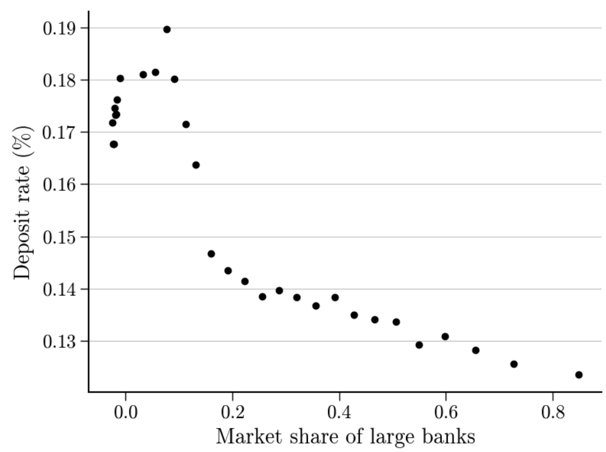
(a) MM $25K



(b) SAV $2.5K



(c) 12M CD $10K



(d) CHECK $2.5K

Figure 2: **Small-bank deposit rates vs. large-bank market share.** These figures illustrate the relationship between deposit rates of small banks and the market share of large banks in the local market where small banks operate, using RateWatch data from 2001 to 2020 at the branch level, and controlling for week fixed effects. The charts display deposit rates of money market accounts of $25,000, saving accounts of $2,500, 12 month CD of $10,000, and checking accounts of $2,500. The market share of large banks is calculated at the zipcode level by dividing the total deposits held by large banks by the total deposits within the zipcode from Summary of Deposits.

4 Market selection by large vs. small banks

In this section, we provide evidence that large and small banks tend to operate in markets with different characteristics, and have different balance-sheet compositions. These differences are consistent with large and small banks having different liquidity-services technologies, and serving customers with different preferences over the tradeoff between higher deposit rates and superior financial services.

4.1 Customer demographics

We document that large banks are located in areas with high populations, high incomes, high housing prices, and less elderly populations.

Consistent with large banks finding it costly to offer county-specific deposit rates, large banks generally operate in markets that share similar demographic characteristics. In particular, large banks are primarily found in more densely populated and more urban areas. Such urban areas may be populated with consumers with strong preferences for low-cost deposit access due to commuting and other opportunity costs. In contrast, rural areas are more likely to be served by small banks, consistent with small banks utilizing local knowledge and community connections to address county-specific needs.

Figure 3 displays the branch locations of large banks in 2019 in red, and population in shades of green, with darker green indicating a higher population. The figure clearly illustrates the concentration of large banks in more densely populated areas on the coasts and in large cities.

Figure 4 provides further detail on the distribution of large and small bank branches across the US by mapping the share of branches belonging to large and small banks. Counties are colored according to the proportion of branches held by smaller banks in 2019, with darker shades of green indicating a larger share of branches being owned by small banks. Large banks hold more shares in coastal and major cities, whereas more rural and less populated areas, such as the Midwest and Central South regions, have a higher share of branches owned by small banks.

Figure 5 presents binned box-plots illustrating the correlations between large and small banks' location choices and geographical demographics. Each panel displays the share of branches at the county level on the y-axis and the demographic variable split in to 10 equally sized bins, on the x-axis. The blue boxes represent the interquartile range of the data, the band inside the box is the median, the diamond marker represents the average, and the whiskers represent the 10th and 90th percentiles. These figures show that small banks hold a higher market share in areas characterized by lower population density, lower

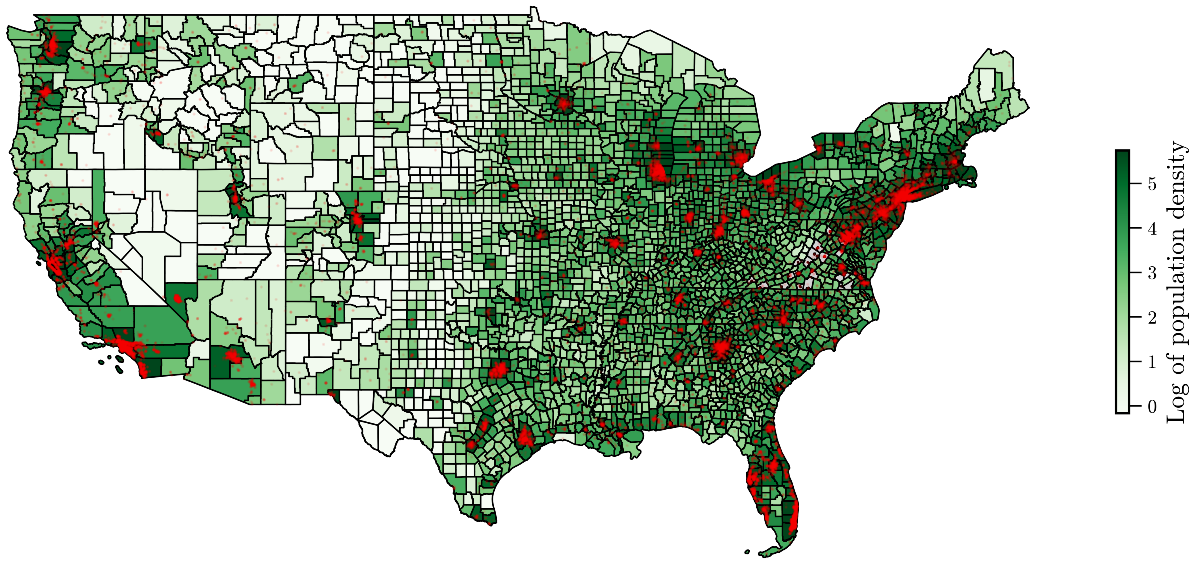


Figure 3: **Branch location of large banks and county population.** This map displays the branch locations of large banks in 2019 in red, and the log of population density in shades of green with dark green indicating a higher population density. The location data are from FDIC's Summary of Deposits.

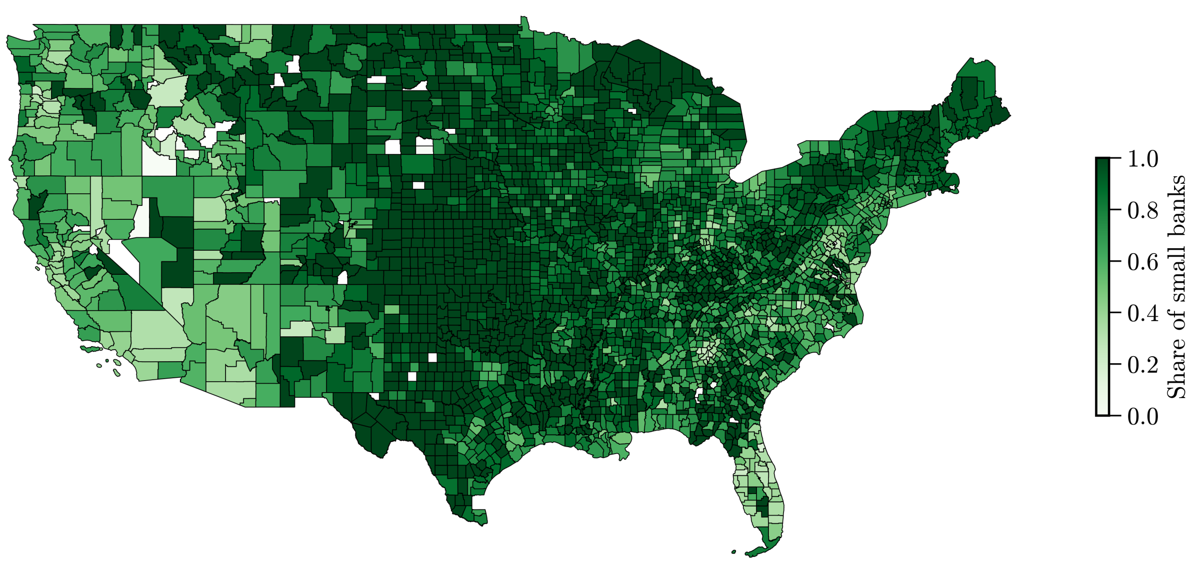


Figure 4: **Share of branches held by small banks.** This map displays the share of branches held by small banks at the county level in 2019. The share of small banks' branches is calculated by dividing the number of branches held by small banks by the total number of branches in the county. The intensity of the color represents the level of branch shares, with deeper shades indicating a higher share of small bank branches. The branch location data are from FDIC's Summary of Deposits.

household income, lower housing prices, and a higher proportion of individuals over 65 years of age.

These graphs suggest differences in the customer bases of large and small banks. Large banks target more highly populated areas with higher average incomes, higher house prices, and lower average ages. We argue that customers with these demographics, who were shown by Campbell (2006) to have higher financial sophistication, place a higher value on the superior liquidity and financial services of large banks. Small banks operate in less populated areas with lower average incomes, lower house prices, and an older demographic.[27] Although these characteristics have been shown to be associated with a lower degree of financial sophistication, and lower financial returns on average (Smith et al., 2023), it appears that within the deposit asset class these consumers actually earn higher deposit rates on average.

Why would consumers whose demographics are associated with *more* sophisticated financial decisions in other contexts receive *lower* deposit rates on average? In Section 6, we measure depositors' demands, and find that large banks' depositors have a lower sensitivity to deposit rates and a higher willingness to pay for large banks' financial services.[28] These findings are consistent with Smith et al. (2023) who document that wealthy individuals have a higher percentage allocation to higher-yield (and riskier) fixed income assets, and thereby earn a higher return overall.[29] One can consider a high-wealth portfolio with a smaller percentage allocation to deposits, along with a larger allocation to risky bonds, as a "barbell" strategy that utilizes deposits mainly for transaction and liquidity services. Large banks suit these depositors because they offer superior liquidity, as well as a broad array of financial services. Thus, deposits serve different purposes for customers with different demographics due to differences in associated household income and wealth.

We note the connection between the different customer bases of large vs. small banks, and banks' uniform rate-setting policies. If large banks were to expand into rural areas dominated by small banks, they would find it costly to offer county-specific rates. Since customers in small-bank markets are sensitive to deposit rates, large banks cannot compete effectively with small banks offering better rates. Alternatively, large banks could raise rates to compete, but they would lose profits in urban areas since customers there are inelastic to deposit rates. Consequently, neither approach to expanding into rural areas may be profitable for large banks. Similarly, in urban areas, superior liquidity-service technologies

[27] Jiang, Yu, and Zhang (2023) show that older individuals tend to exhibit lower elasticity in their demand than younger individuals, so the presence of old customers is unlikely to be driving the higher elasticities at small banks.

[28] See Haendler (2023) for evidence regarding the superiority of large banks deposit technology offerings, and Koont (2023) and Sarkisyan (2024) who study recent improvements in digital banking at smaller banks.

[29] See, for example, `https://www.federalreserve.gov/econres/scfindex.htm`.

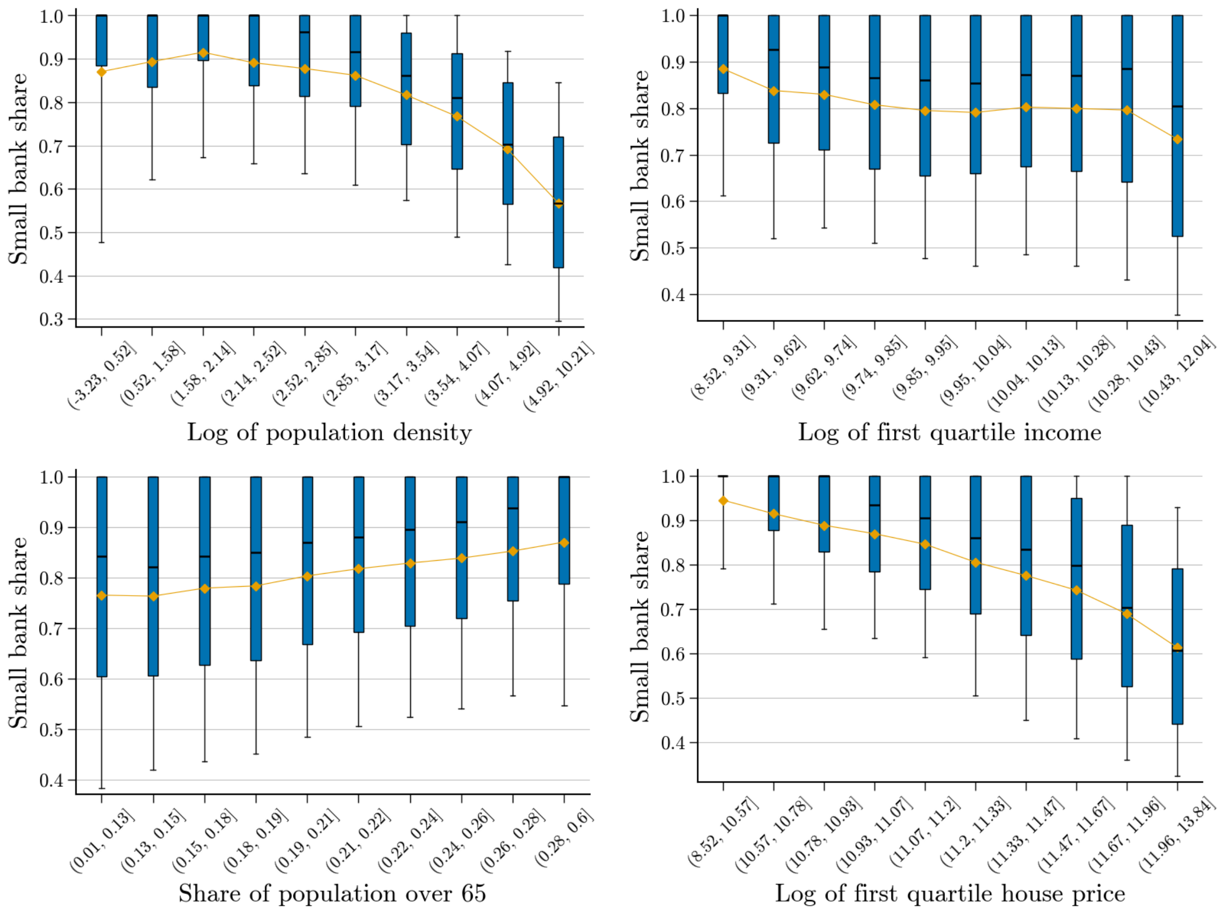
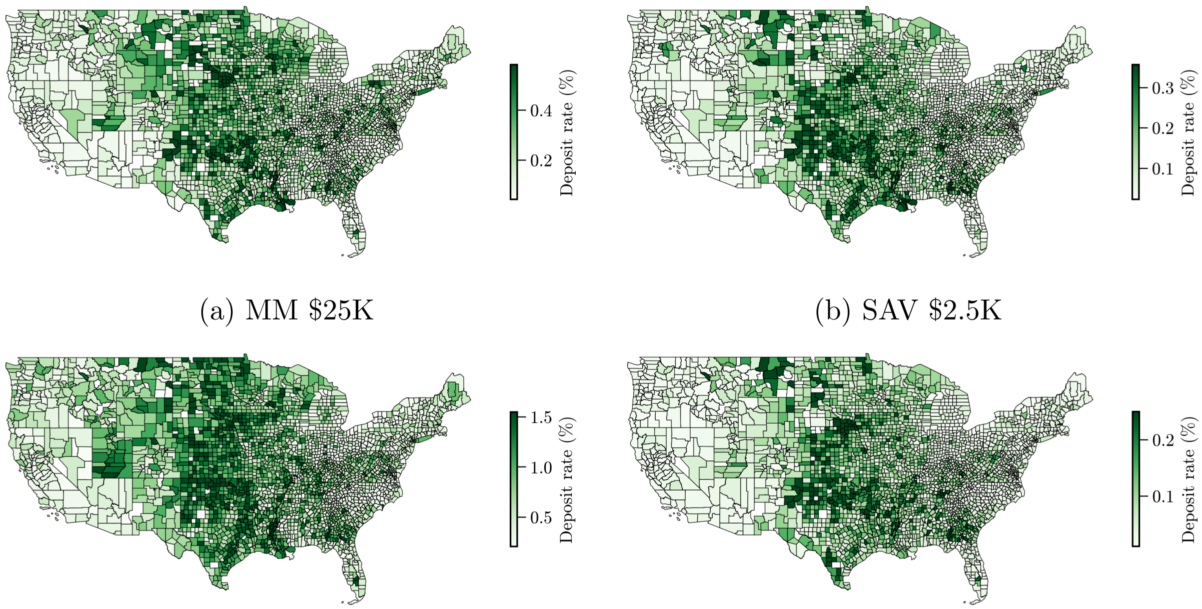


Figure 5: **Small bank share and demographics.** These figures examine the relationship between the share of small bank branches and local population, income, elderly population, and housing prices from 2006 to 2020. The blue boxes represent the interquartile range of the data, the band inside the box is the median, the diamond marker represents the average, and the whiskers represent the 10th and 90th percentiles. Demographic data are sourced from Data Axle at the county level. Income and housing prices represent the 25% quantile of the respective measures. The Small bank share data are derived from FDIC's Summary of Deposits. The two datasets are merged using County FIPS codes.



(a) MM \$25K

(b) SAV \$2.5K

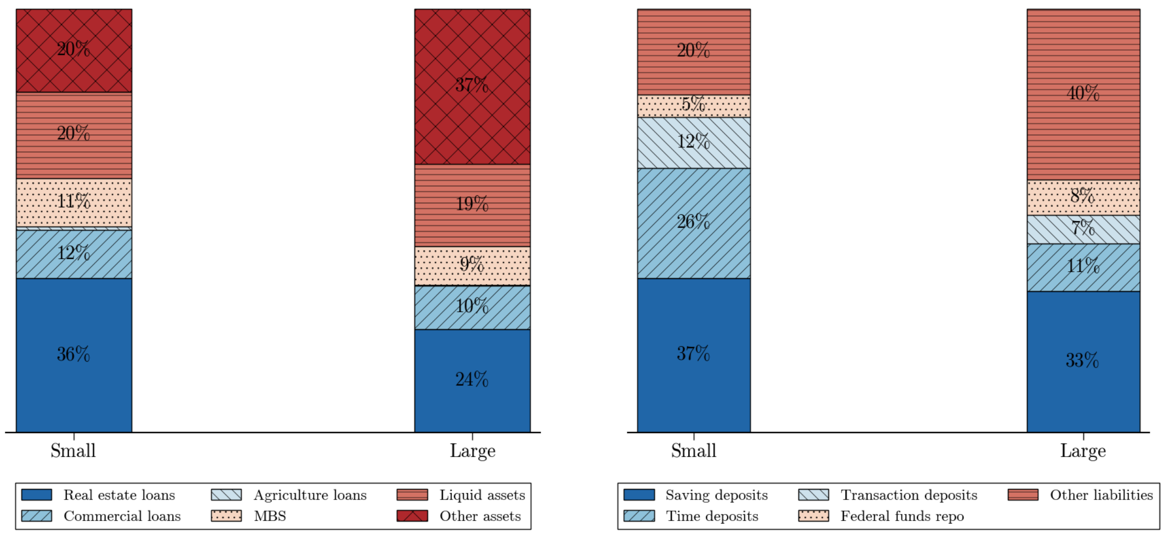
(c) 12M CD \$10K

(d) CHECK \$2.5K

Figure 6: **Geographic distribution of deposit rates.** These maps display the deposit rates of Money Market Accounts of \$25,000, Saving accounts of \$2,500, 12 Month CDs of \$10,000, and Checking accounts of \$2,500 in 2019 using RateWatch data. The deposit rates are collapsed at county level weighted by branch deposit balance. The rates are winsorized at the 95th Percentile. The intensity of the color represents the level of deposit rates, with deeper shades indicating a higher county-level rate. The location data are from FDIC's Summary of Deposits.

are more highly valued than superior deposit rates, making it challenging for small banks to compete in urban areas served by large banks.

The geographic distribution of large vs. small banks, along with the rate differences between them, results in observable deposit rate differences across distinct geographic areas. Figure 6 displays the average deposit rates weighted by branches' deposit shares by county using RateWatch data from 2019. This figure can be compared with Figure 4, depicting the geographic distribution of small banks, indicating that areas with a higher share of small banks exhibit higher average deposit rates for Money Market Accounts, Savings, Checking, and CDs. Rural and less-populated area populations benefit from higher deposit rates, while urban populations appear to value the compensating differential of the superior liquidity services of large banks.



(a) Asset structure

(b) Liability structure

Figure 7: **Asset and liability structure.** These figures illustrate the asset and liability structures of large and small banks, based on quarterly Call Report data from 2001 to 2020. For each asset or liability class, the annual share is calculated by dividing the total amount of that specific asset or liability class held by all banks by the total assets or liabilities held by all banks, and then averaging these ratios over the years. Figures are plotted separately for large and small banks, with the left bar in each group representing data for small banks and the right bar for the 14 large banks.

4.2 Balance sheet composition

In addition to serving distinct geographic areas and demographic populations, large and small banks vary in the composition of their balance sheets. This variation is indicative of the different business models of large and small banks, and the different liquidity services and financial services they offer to cater to the specific needs and preferences of their respective clients.

Figures 7a and 7b display the asset and liability structures of small banks vs. large banks, highlighting substantial differences in the assets and liabilities of their respective business models. Large banks tend to hold more other assets other than loans or liquid assets, such as trading assets, accounting for about 37% of their total assets. Small banks allocate more of their assets to real estate loans, commercial loans, and MBS. They also hold more agriculture loans than large banks. This aligns with the idea that small banks focus more on traditional lending and provide greater support to farmers and rural communities, while large banks engage in more sophisticated financial activities.

While deposits constitute the majority of liabilities for both types of banks, large banks have substantially more “other liabilities,” which includes alternative funding sources such as commercial paper and longer term bonds. In general, large banks have more diverse funding sources beyond deposits. Large banks also borrow more from Federal funds repos than small banks, making them less dependent on deposit funding. Large and small banks also have different deposit compositions. While both large and small banks have a majority of deposits from savings accounts, time deposits are relatively more important for small banks. Note also that large banks have a higher share of uninsured deposits than small banks (see, for example, Jiang et al., 2024b). A higher uninsured share is unlikely to drive large banks to offer lower deposit rates, and indeed, all else equal, would be expected to lead to higher deposit rates.[30]

5 Model

The previous sections offer evidence that banks tend to set uniform rates across branches, and that bank size, not local market conditions, explains deposit rate variation. Furthermore, small banks consistently set higher rates than large banks, and deposit rates have a negative relationship with the local-market deposit share of large banks. Finally, small and large banks run different business models and operate in different markets. Building on these observations, we develop a parsimonious model of the deposit business of large and small banks with heterogeneous markets.

Customers have heterogeneous preferences for deposits and their characteristics, and banks choose locations, business models, and rates based on the observed differences in preferences across markets. Taking uniform rate setting as a given constraint for multi-market banks, we derive equilibrium predictions for bank location and business-model choices, as well as deposit rates by bank type and location. Finally, we derive predictions for the distribution of market-specific deposit rate elasticities faced by large and small banks. We specify our model to align with our elasticity estimation in Section 6, in particular incorporating classic Industrial Organization considerations such as product differentiation and consumer heterogeneity (see Berry, Levinsohn, and Pakes, 1995).

Depositors The economy is divided into local markets, each indexed by $k \in \{1, \ldots, K\}$ and with a mass M_k of depositors. Each depositor is endowed with one dollar and makes a discrete choice among bank deposits. Each option j is characterized by the deposit rate r_j and by the liquidity services $x_j \in \{0, 1\}$ offered by the bank to its depositors. Depositor i in

[30] See Egan et al. (2017) for a study of deposit rates within the set of large banks as a function of their uninsured deposit share and relative credit risk.

market k maximizes the utility function:

$$\max_{j \in \mathcal{B}_k} u_{ijk} = -\alpha_k s_j + \beta_k x_j + \epsilon_{ijk}, \tag{4}$$

where r^f is the competitive risk-free rate; s_j is the deposit spread, $s_j \equiv r^f - r_j$; and ϵ_{ijk} is an idiosyncratic utility shock for depositor i if choosing bank j, which follows the extreme value distribution $F(\epsilon) = \exp(-\exp(-\epsilon))$. The choice set $\mathcal{B}_k$ contains the index of each bank with a branch in market k. The parameters α_k and β_k are depositors' sensitivity to a bank's deposit spreads (s_j) and superior liquidity and financial services ($x_j \in \{0, 1\}$) in market k.[31] This is a simplified version of the utility function that we estimate in Section 6, allowing us to obtain closed-form solutions.

In Section 6, we estimate α_k and β_k for different markets as a function of income. Our hypothesis is that the underlying utility function for deposits are not homethetic with respect to income. In particular, wealthy households may have a lower rate sensitivity because they hold a smaller proportion of their wealth in deposits. We test this hypothesis in Section 6 and show that rate elasticities indeed decline significantly and substantially with income. Consistent with work on limited participation (see Vissing-Jørgensen, 2002; Smith et al., 2023), beyond a certain income threshold, it becomes profitable to pay a participation cost to access stock and bond markets, reducing the fraction of wealth that higher-income households keep in deposit accounts. Given this portfolio allocation, higher-income households then have a higher willingness to pay for large banks' superior liquidity services, and are less sensitive to deposit rates. The superior liquidity services offered by large banks include larger branch networks, higher quality banking apps, and broader menus of financial services.[32] By contrast, lower-income households rely more on deposits as a saving vehicle and tend not to invest in other financial products (Smith et al., 2023).

In Equation (4), we constrained banks to set a uniform interest rate across all of their branches, $r_{jk} = r_j$. Section 3 confirmed empirical support for this assumption. Given the extreme value distribution, the market share for the deposits of bank j in market k is then given by

$$d_{jk} = \frac{\exp(-\alpha_k s_j + \beta_k x_j)}{\sum_{i \in \mathcal{B}_k} \exp(-\alpha_k s_i + \beta_k x_i)}, \tag{5}$$

and the total demand is $D_{jk} = M_k d_{jk}$.

[31] Without loss of generality, no two markets have the same values for both α_k and β_k.

[32] See Haendler (2023), Koont (2023), and Sarkisyan (2024) for studies of the recent effects of digital offerings by small vs. large banks.

Banks Banks earn profits by raising deposits and investing in bonds, earning the risk-free rate r^f. Each bank chooses which markets to open branches in and whether to offer superior liquidity services. Both opening branches and providing superior liquidity services require fixed investment costs.

We can write the profit maximization problem of bank j as

$$\max_{x_j, s_j, b_{jk}} \sum_{k \in \mathcal{M}_j}^{K} \left((s_j - c) D_{jk} - \kappa_k \right) b_{jk} - \chi x_j, \tag{6}$$

where c is the per-unit cost of servicing deposits; $b_{jk} \in \{0, 1\}$ indicates whether bank j opens a branch in market k (at fixed cost κ_k); $\mathcal{M}_j \equiv \{k : b_{jk} = 1\}$ is the set of markets where bank j opens a branch; and $x_j \in \{0, 1\}$ indicates whether bank j provides superior liquidity services to its customers (at cost χ). To streamline our analysis, we make two assumptions:

$$\beta_k < \log\left(1 + \frac{\chi}{\kappa_k}\right)\left(1 + \frac{\kappa_k \alpha_k}{M_k}\right) \quad \text{and} \quad \frac{1}{\alpha_k} + \frac{\kappa_k}{M_k} \neq \frac{1}{\alpha_\ell} + \frac{\kappa_\ell}{M_\ell} \quad \forall k, \ell. \tag{7}$$

The first assumption implies that the costs of the technology can only be recouped if the bank operates in more than one market.The second assumption ensures that each market has a different optimal deposit spread for single-market banks.

The deposit rate is set to maximize the bank's profits, which gives the first order condition

$$\sum_{k \in \mathcal{M}_j} D_{jk} + (s_j - c) \sum_{k \in \mathcal{M}_j} \frac{\partial D_{jk}}{\partial s_j} = 0. \tag{8}$$

Given households' preferences, solving for the optimal deposit spread for a given bank j yields

$$s_j - c = -(\eta_j^s)^{-1} \tag{9}$$

where η_j^s is the deposit-weighted average semi-elasticity of deposit spreads faced by bank j,

$$\eta_j^s \equiv \frac{\sum_{k \in \mathcal{M}_j} \partial D_{jk} / \partial s_j}{\sum_{k \in \mathcal{M}_j} D_{jk}} = -\frac{\sum_{k \in \mathcal{M}_j} D_{jk} \alpha_k (1 - d_{jk})}{\sum_{k \in \mathcal{M}_j} D_{jk}}. \tag{10}$$

Equation (9) equates the marginal benefit of wider spreads net of variable costs to the marginal cost of lower deposit demand.

Finally, a free-entry condition for banks pins down the quantity of banks entering each market.

Equilibrium Given the set of parameters $\{\chi, c, M_k, \kappa_k, \alpha_k, \beta_k\}_{k=1}^{K}$, a pure-strategy Nash equilibrium is a set of decision rules for depositors j_{ik}, and for banks b_{jk}, x_j, s_j, that solves depositors' and banks' maximization problems and such that the market for deposits clears and the free-entry condition is satisfied. Note that there might exist several equilibria, but the results below hold for any pure-strategy Nash equilibrium.

Analysis We first derive the number of single-market banks entering every market in Proposition 1.

Proposition 1. *(Free-entry condition) Denote the deposit spread and liquidity services of single-market banks entering market k as s_k^S and x_k^S. The free-entry condition in market k is such that the number of single-market banks entering market k is given by*

$$N_k^S = \left\lfloor \frac{M_k}{\kappa_k \alpha_k} - \Omega_k e^{\alpha_k s_k^S - \beta_k x_k^S} + 1 \right\rfloor = \frac{M_k}{\kappa_k \alpha_k} - \Omega_k e^{\alpha_k s_k^S - \beta_k x_k^S} + 1 - \phi_k \quad \text{if} \quad N_k^S > 0, \tag{11}$$

where $\phi_k \in [0, 1)$, $\Omega_k = \sum_{i \in \mathcal{L}_k} \exp(-\alpha_k s_i + \beta_k x_i)$, and $\mathcal{L}_k \equiv \{j : b_{jk} = 1 \text{ and } |\mathcal{M}_j| > 1\}$ is the set of multi-market banks entering market k.

The term $\phi_k \in [0, 1)$ arises from the fact that N_k^S needs to be a natural number. The profit of a single-market bank could be above the entry cost κ_k, but not sufficiently high to warrant the entry of an additional bank and have $N_k^S + 1$ banks compete for deposits. This residual ϕ_k could have an impact on bank j's market share d_{jk} in very small markets, but becomes vanishingly small as M_k increases. To ease the exposition of our results, we now assume $\phi_k = 0$ and $N_k^S > 0$.

Given the free-entry condition, we can then derive the equilibrium bank j's deposit share for a bank entering market k:

$$d_{jk} = \frac{1}{\frac{M_k}{\kappa_k \alpha_k} + 1} \frac{\exp(-\alpha_k s_j + \beta x_j)}{\exp(-\alpha_k s_k^S + \beta_k x_k^S)} \tag{12}$$

where s_k^S is the spread and liquidity service of a single-market bank operating only in market k.

Proposition 2 provides a first characterization of our equilibrium: In equilibrium, two types of banks emerge. We have large banks (L) that invest in liquidity services and operate across various markets by opening multiple branches, and small banks (S) that do not invest in liquidity services and only open a branch in a single market. We now use the superscript S or L to denote choice variables pertaining to small or large banks, respectively.

Proposition 2 (Small banks operate in one market)**.** *If and only if $x_j = 0$, then $|\mathcal{M}_j| = 1$.*

These results highlight the trade-off between bearing the cost of liquidity-service technologies, which is profitable only when operating at a large scale across multiple markets, and the capacity of small banks to set rates fine-tuned to individual markets. A bank constrained by uniform pricing cannot compete with single-branch banks, who can offer the market's optimal deposit rate, unless it also offers superior liquidity services.

The model offers strong predictions regarding the distinction between markets where large banks operate and markets with only small banks. For these propositions, we define *colocation* markets to be the set of markets $\mathcal{C}$ where both small and large banks operate, $\mathcal{C} = \{k : \exists j, b_{jk} = 1 \text{ and } |\mathcal{M}_j > 1|\}$. Small banks operate in all markets, while large banks select only a set of markets, thus colocation markets are, equivalently, markets where large banks locate. Proposition 3 provides a condition for such markets.

Proposition 3 (Colocation markets' demand)**.** *If market k has both large and small banks—that is, if $k \in \mathcal{C}$, the ratio of deposits supplied by small and large banks is given by*

$$\log\left(\frac{D_k^S}{D_{jk}^L}\right) = \alpha\left(s_j^L - s_k^S\right) - \beta_k. \tag{13}$$

Proposition 3 illustrates that in colocation markets, the share of small banks' deposits is increasing in depositors' price sensitivity and the gap between large and small-bank deposit spreads, and decreasing in market k's willingness to pay for superior liquidity services. Thus, in colocation markets, small banks engage in competition for deposits by offering lower deposit spreads, while large banks benefit from the preference for liquidity services β_k. Note, however, that while colocated small banks may offer *higher* rates than large banks in their markets, colocated small banks might offer *lower* rates than their counterparts in markets with only small banks, depending on the distribution of depositor preferences.

Proposition 4 demonstrates that deposit spreads of banks are uniquely driven by their average spread semi-elasticity. Thus, if the deposit spread of small banks is smaller than that of large banks, as observed in the data, it is because these large banks operate in markets with lower elasticities on average. In our model, the primary driver of the rate gap between large and small banks is that they strategically select different markets to operate in.

Proposition 4 (Deposit spreads and average spread semi-elasticity)**.** *Given the first-order condition (9), $s_i < s_j$ if and only if $|\eta_i^s| > |\eta_j^s|$.*

Although small banks establish branches in all markets, large banks avoid markets with spread semi-elasticities that differ significantly from the deposit-weighted average of the markets they serve. Instead, large banks gravitate towards the largest clusters of markets with similar elasticities. The constraint to maintain uniform deposit rates across all branches, combined with the fixed cost of opening a branch, makes markets with more extreme elasticities unprofitable for large banks. Indeed, Proposition 5 shows that large banks never establish branches in markets where the rate sensitivity α_k is sufficiently different from their deposit-weighted spread semi-elasticity η_j^s. (Inequality (14) is never satisfied for small banks.)

Proposition 5 (Large banks' location)**.** *If*

$$\frac{\alpha_k}{|\eta_j^s|} - \log\left(\frac{\alpha_k}{|\eta_j^s|}\right) > \beta_k + 1 + \frac{\kappa_k \alpha_k}{M_k} - \log\left(1 + \frac{\kappa_k \alpha_k}{M_k}\right), \tag{14}$$

then bank j does not locate in market k.

Similarly, Proposition 6 demonstrates that if we observe two markets—one where a large bank locates and another where it does not locate—then the latter market must have a rate sensitivity that is further away from its deposit-weighted average semi-elasticity η^s.

Proposition 6 (Colocation markets)**.** *Assume $\kappa_k/M_k = \kappa_\ell/M_\ell \approx 0$ and $\beta_k \leq \beta_\ell$. If $k \in \mathcal{M}_j$ and $\ell \notin \mathcal{M}_j$, then*

$$\frac{\alpha_k}{|\eta_j^s|} - \log\left(\frac{\alpha_k}{|\eta_j^s|}\right) < \frac{\alpha_\ell}{|\eta_j^s|} - \log\left(\frac{\alpha_\ell}{|\eta_j^s|}\right). \tag{15}$$

Figure 8 shows an example of the equilibrium banks' rates and profits given a distribution of αs and βs across markets, keeping other parameters constant. To maximize profits, large banks choose to locate where the mass of markets with similar price-sensitivities is the largest, close to the median. Following condition (14), they do not locate in markets with extreme αs (see top left panel). Thus, markets where large banks enter are characterized by relatively low elasticities and are also markets where small banks charge higher spreads (see bottom left panel). In our model, the presence of large banks does not necessarily indicate heightened price competition for small banks. Instead the presence of large banks indicates a market that displays a spread-sensitivity that is "prevalent," in the sense that it has a high representation among depositors and is similar to many other markets with larger numbers of depositors (see top left and right panels). In the data, we show that, in the U.S., low price sensitivities with high preference for financial services are prevalent. This is consistent with the U.S. having a fairly well-developed financial system outside of the banking system, and depositors using banks for their superior liquidity services. This example yields the empirical finding in Figure 2 that the *average* small bank rate is negatively correlated with the market share of large banks (see bottom right panel).

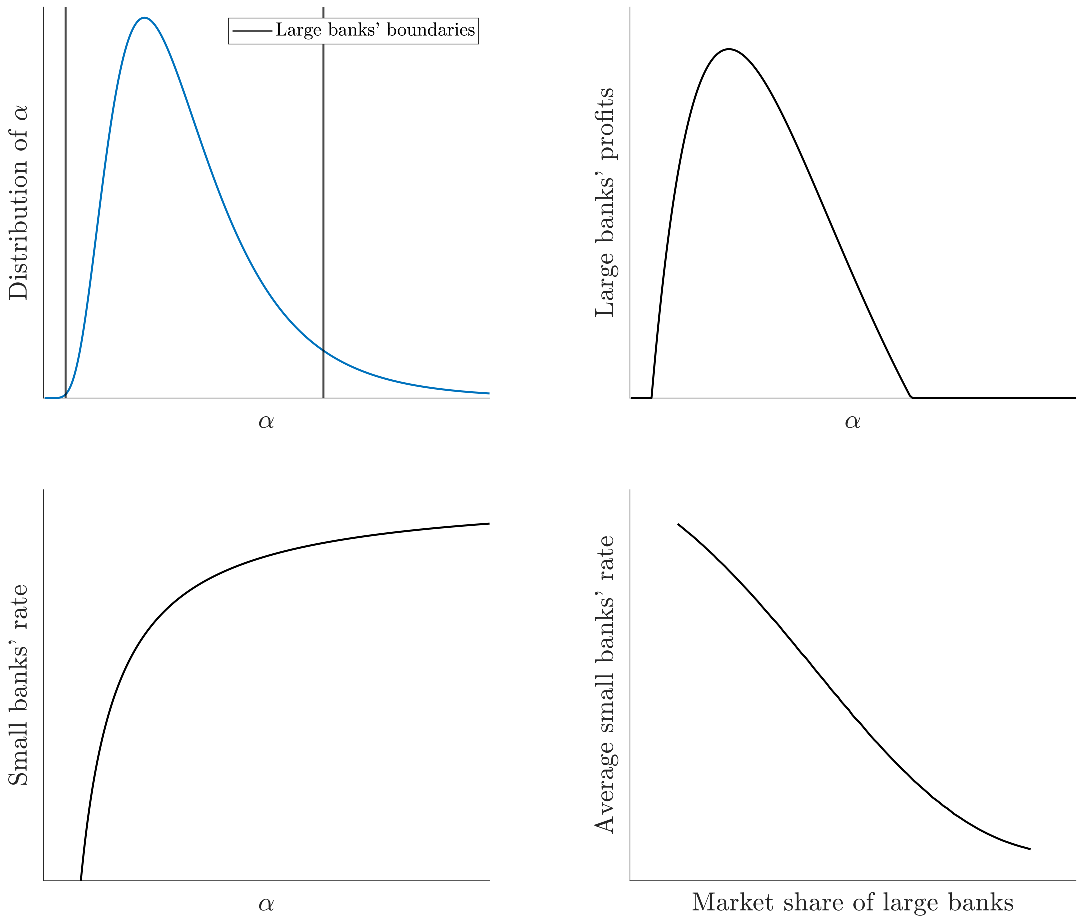


Figure 8: **Symmetric equilibrium rates.** This figure shows the equilibrium variable given a distribution of αs and βs. We solve for the symmetric equilibrium where all large banks enter in the same markets. We use a lognormal distribution for α_k and $\beta_k = ((10-\alpha_k)/10)^3$. Top left shows the distribution of αs and the corresponding boundaries beyond which large banks do not open branches. Top right shows the profits of large banks. Bottom left shows the deposit spread of small banks as a function of α. Bottom right shows the mapping between the average deposit spread of small banks and the market share of large banks. We provide details regarding the parametrization of this illustrative example in Appendix E.

Proposition 7 demonstrates the pitfall associated with equating HHI with the level of market-level competition. The intuition for this proposition offers a general insight into how the causes of market concentration impact the interpretation of the relationship between concentration and the level of market competition. In particular, we study how the implications of market *concentration* for *market competition* is starkly different depending on whether differences in concentration are driven by differences in entry costs or differences in rate sensitivities.

For simplicity, consider a market with only small banks. If the cost of opening a branch κ_k increases, then net profits decrease, fewer banks enter, and competition, measured by deposit spreads or the Herfindahl–Hirschman index (HHI), worsen. If, instead, rate sensitivity α_k increases, we also have that net profits decrease and fewer banks enter. However competition, as measured by deposit spreads, improves! From the perspective of a bank, a market with higher rate semi-elasticity is a more competitive environment, while a market with a higher entry cost is less competitive. However, HHI only depends on the number of banks, which decreases in both cases. Thus, the correlation between HHI and deposit spread is ambiguous, while the correlation between rate sensitivity and deposit spread is always negative. In the next section, we find that α_k explains more variation in deposit spreads than HHI.

Proposition 7 (Herfindahl–Hirschman index)**.** *If $k \notin \mathcal{C}$, then*

$$d_k^S = \frac{1}{1 + \frac{M_k}{\kappa_k \alpha_k}}, \quad s_k^S = c + \frac{1}{\alpha_k} + \frac{\kappa_k}{M_k}, \quad \textit{and} \quad \mathrm{HHI}_k = \frac{1}{1 + \frac{M_k}{\kappa_k \alpha_k}}. \tag{16}$$

Thus,

$$\frac{\partial s_k^S}{\partial \alpha_k} \frac{\partial \alpha_k}{\partial \, \mathrm{HHI}_k} < 0 \quad \textit{and} \quad \frac{\partial s_k^S}{\partial \kappa_k} \frac{\partial \kappa_k}{\partial \, \mathrm{HHI}_k} > 0. \tag{17}$$

6 Large vs. small banks: rate semi-elasticities

In this section, we provide evidence that rate semi-elasticities vary systematically across large vs. small banks due to a difference in the distribution of elasticities to which large vs. small banks cater. We test our model's prediction that large banks tend to offer lower deposit rates and locate in areas in which the rate semi-elasticity is closer to the median of the empirical distribution. We also provide evidence that higher income depositors have lower rate elasticities and a higher willingness to pay for superior liquidity services. Finally, we show that our semi-elastcity estimates can explain more of the residual variation in deposit rates after controlling for time fixed effects than other local variables, such as HHI, can.

Our results support that geographical variation in deposit rates is driven by local market preferences, while variation across banks is driven by variation in location decisions by large vs. small banks.

To estimate rate semi-elasticities, we employ methods from the industrial organization literature following Egan et al. (2017), Xiao (2020), and Wang et al. (2022). Egan et al. (2017) study deposit pricing at the 16 largest banks, and show that estimated demand for uninsured deposits declines with bank credit risk. In general, for both insured and uninsured deposits at these large banks, they find that demand is inelastic, a fact that our estimation strongly confirms. Xiao (2020) finds that the rate elasticity for banks is a lot lower than that of non-banks. Wang et al. (2022) develops a large-scale DSGE model in order to study both supply of and demand for deposits. Their emphasis on market concentration is distinct to our focus on product differentiation between large vs. small banks.

6.1 Estimating rate semi-elasticities

Defining markets We define markets based on counties to capture local-branch customer preferences. The idea is that customers choose banks based on their local availability and accessibility, with households in San Francisco being more likely to opt for banks with branches in San Francisco relative to banks operating exclusively in New York.

The distribution of the US population across counties is highly skewed, with some very large counties and a long tail of very small counties. Given our interest in the differences across banks of different sizes and technologies, and counties with different demographics and preferences, we aim to retain all counties in our analysis. To this end, we utilize a clustering approach for small counties. Our approach allows us to retain the small banks that operate in these areas rather than dropping them from the sample or grouping them in another way.[33]

We employ the breadth-first search algorithm (see Even and Even, 2011; Zhou and Hansen, 2006) to construct county clusters for low-population counties. Our algorithm systematically searches through the county network to identify suitable county groupings. We first identify counties with populations below the 95$^{\text{th}}$ percentile as candidates to be grouped with contiguous neighboring counties. Starting with the smallest county as the "target" county, we identify neighboring counties and prioritize merges to candidate contiguous counties that afford the shortest centroid distance between the two counties and have similar population density. The process is iterative, and continues merging counties until the total

[33] For example, given that their focus is not on differences between small and large banks, Wang et al. (2022) combine all banks with market shares below 0.001% or with less than 10 branches into one bank.

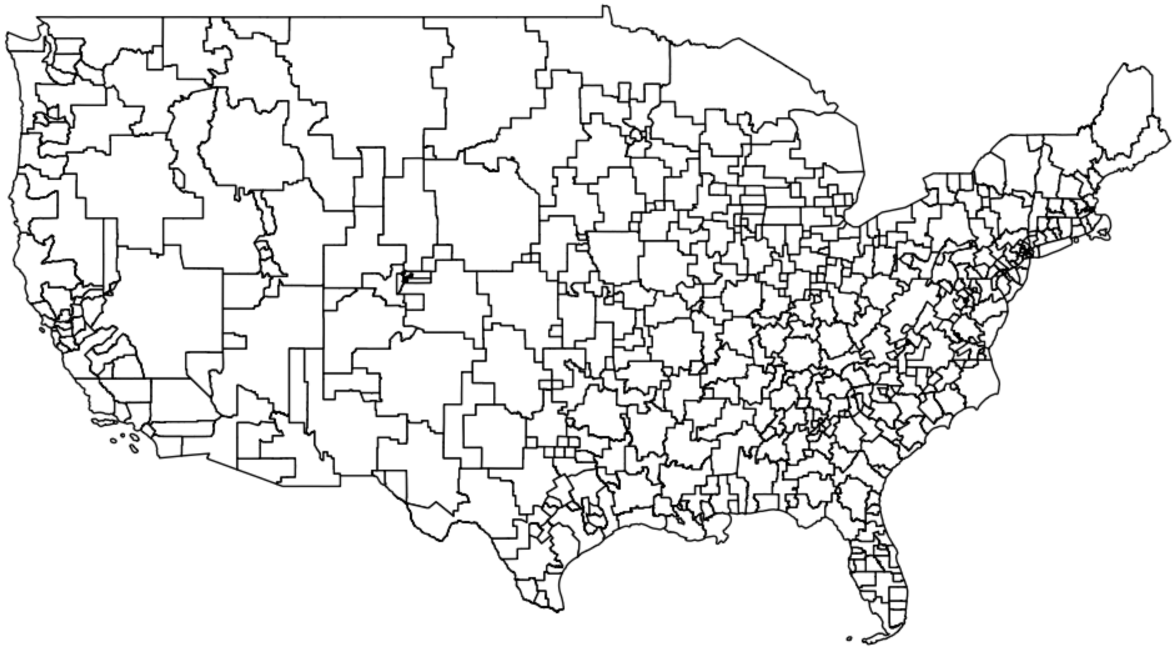


Figure 9: **County cluster map.** This map shows the boundary of the county clusters.

population of the created cluster surpasses the 95th percentile threshold or the total land area of the cluster exceeds area of the largest U.S. county (San Bernardino County).

Our procedure results in 3,088 counties being organized into 520 clusters. Figure 9 shows the boundary of county clusters. We define a county cluster k in year t as a market k, t. We aggregate branches at the bank level.

Estimation model setup We extend the estimation methods used in the prior literature based on our theoretical model to study depositor preferences across markets and product differentiation across large vs. small banks. Following Wang et al. (2022), there is measure one of customers in each county-cluster year. In each cluster-year market (denoted by k, t), each customer i is endowed with one dollar, and can make a discrete choice to allocate this dollar to bonds (denoted by $j = 0$ and used as the outside good or numeraire), deposits in one of the banks (denoted by $j = 1, \ldots, J$) that are available in their (cluster-year) market, or cash (denoted by $j = J + 1$). We set bonds as the outside option, whose return is the federal funds rate. The deposit spread at bank j in county cluster k in year t is the deposit spread $s_{j,k,t} \equiv r_t^f - r_{j,k,t}$, where we use the the federal funds rate as a proxy for the risk-free rate. Customers allocate funds to deposits based on bank-cluster-year characteristics $X_{j,k,t}$ and the deposit spread $s_{j,k,t}$. The customer chooses their allocation to cash, bonds and deposits to maximize their indirect utility,

$$U_{i,j,k,t} = -\alpha_i s_{j,k,t} + \beta X_{j,k,t} + \xi_{j,k,t} + \epsilon_{i,j,k,t},$$

where $\xi_{j,k,t} = \xi_j + \xi_{k,t} + \Delta\xi_{j,k,t}$ consists of bank fixed effects ξ_j, market fixed effects $\xi_{k,t}$, and unobserved product characteristics $\Delta\xi_{j,k,t}$, where $\Delta\xi_{j,k,t} = \xi_{j,k,t} - \xi_j - \xi_{k,t}$. We also extend the standard model to allow customers to have heterogeneous rate sensitivities, α_i, that depend on customer demographics D_i. Specifically, we let $\alpha_i = \alpha + \Pi D_i + \sigma\nu_i$, where $\nu_i \sim N(0, 1)$. The shock term $\epsilon_{i,j,k,t}$ is a stochastic term capturing customer-product specific shocks, which we assume follows a Type I extreme-value distribution with $F(x) = e^{-e^{-x}}$.

The full utility specification is

$$\begin{aligned} U_{i,j,k,t} &= -\alpha s_{j,k,t} - (\Pi D_i + \sigma\nu_i)s_{j,k,t} + \beta X_{j,k,t} + \xi_{j,k,t} + \epsilon_{i,j,k,t} \\ &= \delta_{j,k,t} - (\Pi D_i + \sigma\nu_i)s_{j,k,t} + \epsilon_{i,j,k,t}, \end{aligned} \tag{18}$$

where $\delta_{j,k,t} = \alpha s_{j,k,t} + \beta X_{j,k,t} + \xi_{j,k,t}$ is the mean utility of product j across all customers in market k, t and $\xi_{j,k,t}$ is the common unobserved demand shock to all customers for product j.

The logit choice probability that a customer i selects product j in market k, t is expressed as follows:

$$\begin{aligned} d_{i,j,k,t} &= \int_i \mathbb{1}_{i,j,k,t} \, dF(\epsilon_{i,j,k,t}) \\ &= \frac{\exp(\delta_{j,k,t} + (\Pi D_i + \sigma\nu_i)s_{j,k,t})}{1 + \sum_{l=1}^{J+1} \exp(\delta_{l,k,t} + (\Pi D_i + \sigma\nu_i)s_{l,k,t})}, \end{aligned} \tag{19}$$

where the indicator variable takes a value of one if bank j's deposits in market k during year t provides the highest utility to customer i compared to all other products. The second line is derived from the indirect utility defined in Equation (18) and the distribution of $\epsilon_{i,j,k,t}$. Therefore, the market share of product j in a county cluster k at time t can be represented as

$$\begin{aligned} d_{j,k,t}(X_{j,k,t}, s_{j,k,t}; \alpha, \Pi, \beta, \sigma) &= \int d_{i,j,k,t} \, dF_D(D) \, dF_\nu(\nu) \\ &= \frac{1}{N} \sum_{i=1}^{N} \frac{\exp(\delta_{j,k,t} + (\Pi D_i + \sigma\nu_i)s_{j,k,t})}{1 + \sum_{l=1}^{J+1} \exp(\delta_{l,k,t} + (\Pi D_i + \sigma\nu_i)s_{l,k,t})}, \end{aligned} \tag{20}$$

where $F_D(D)$ denotes the distribution function of observed demographics D_i, $F_\nu(\nu)$ denotes the distribution function of unobserved heterogeneous rate sensitivity ν_i, and σ captures the size of dispersion. The second line of Equation (20) serves as an approximation of the integral. D_i and ν_i, $i = 1, \ldots, N$, are N draws from $F_D(D)$ and $F_\nu(\nu)$, respectively.

Identification A standard identification challenge in demand estimation is the endogenous determination of the price, in this case the deposit rate. Due to this endogeneity, biased estimates will result from regressing market shares directly on deposit rates. To address the endogeneity problem, we employ supply shocks $Z_{j,k,t}$ as instrumental variables. We utilize three instrument variables. The first instrument, following Wang et al. (2022), is the ratio of non-interest expenses on fixed assets to total assets from the prior year. This captures the notion that, as the cost of fixed assets increases, banks may respond by raising deposit rates to compensate for the higher expenses. The second instrument measures the labor cost facing the bank, based on Dick (2008). We use county-level wages in the commercial banking industry, obtained from the Bureau of Labor Statistics, to calculate a deposit-weighted average of annual industry wages across the counties where a bank operates. This instrument reflects labor cost shocks from local markets, reducing the likelihood of capturing bank-specific labor costs that might correlate with unobserved quality aspects of bank products. The third instrument, inspired by Egan et al. (2022) and following the traditional instrument construction from Berry et al. (1995), captures the average characteristics of competitors' products. The intuition is that when competitors offer products with better characteristics, a bank may raise its deposit rates to stay competitive. We use the number of employees per branch as the product characteristic. We first calculate the average characteristics provided by each bank's competitors within each market, and then we compute a weighted average of these competitor characteristics across all markets where the bank operates.

The fundamental assumption supporting this IV strategy is that while banks should adjust rates in response to changes in their marginal costs, customers are unlikely to modify their demand in response to these cost changes. Because our estimation includes fixed effects for each market/year and for each bank, any concerns that the exclusion restriction is not satisfied must be due to a cost change that is correlated with unobserved product characteristics that are not absorbed by bank fixed effects (i.e., it affects a single bank differently across county/year), or by county/year fixed effects (i.e., it affects only a particular bank in that county/year). Any such unobserved characteristics must also be orthogonal to the bank characteristics we include, namely, the interaction between the large bank dummy variable and the average personal income in the market, the logarithm of the number of branches the bank owns, and the logarithm of the number of employees per branch. To ensure the robustness of our results, we present estimation outcomes using the same instrumental variables as Wang et al. (2022) in Appendix C, and the main findings remain consistent.

We estimate $\theta \equiv (\alpha, \beta, \Pi, \sigma)$ following Nevo (2000) and Conlon and Gortmaker (2020). For given values of (Π, σ), we numerically solve $\delta_{j,k,t}(\Pi, \sigma)$ by contraction mapping, using the method introduced by Berry et al. (1995). Upon obtaining $\delta_{j,k,t}$, we utilize linear IV GMM regression of the mean utility equation,

$$\delta_{j,k,t}(\Pi, \sigma) = \alpha(r_{j,k,t} - r_t^f) + \beta X_{j,k,t} + \xi_j + \xi_{k,t} + \Delta\xi_{j,k,t}. \tag{21}$$

The moment condition of the mean utility equation is derived from the exclusion restriction that the supply shocks are expected to be orthogonal to the unobserved product characteristics in Equation (21):

$$E[Z_{j,k,t}\, \Delta\xi_{j,k,t}(\theta)] = 0. \tag{22}$$

With W as a consistent estimate of $E[Z'\, \Delta\xi\, \Delta\xi'\, Z]$, the GMM estimator is

$$\hat{\theta} = \underset{\theta}{\operatorname{argmin}}\, \Delta\xi(\theta)' Z W^{-1} Z' \Delta\xi(\theta). \tag{23}$$

Bank entry decisions might generate an endogeneity problem if such decisions were correlated with the unobservable demand factor, $\Delta\xi_{j,k,t}$. However, in our setting, banks decide whether to enter a market based solely on observable factors, without any prior knowledge or signals about $\Delta\xi_{j,k,t}$. Once all information is revealed, including $\Delta\xi_{j,k,t}$, banks that have entered the market set their prices simultaneously. This structure ensures that a bank's entry decision is driven only by observable factors $X_{j,k,t}$ and not correlated with $\Delta\xi_{j,k,t}$. Therefore, the critical identification assumption, $E[Z_{j,k,t}\Delta\xi_{j,k,t}(\theta)|\text{Bank } j \text{ enters market } (k,t)] = 0$, holds in our framework, allowing the use of standard demand estimation methods with reduced concerns about potential endogeneity in entry decisions.

Based on the estimation, we calculate the rate semi-elasticity of bank j in market k, t by

$$\hat{\eta}^r_{j,k,t} \equiv \frac{\%\Delta \hat{d}_{j,k,t}}{\Delta r_{j,k,t}} = \frac{\partial \hat{d}_{j,k,t}}{\partial r_{j,k,t}} \cdot \frac{1}{\hat{d}_{j,k,t}} = \frac{1}{\hat{d}_{j,k,t}} \int \hat{\alpha}_i \hat{d}_{i,j,k,t}(1 - \hat{d}_{i,j,k,t})\, dF_D(D)\, dF_\nu(\nu), \tag{24}$$

where $\hat{d}_{i,j,k,t}$ is the fitted value of Equation (19) and $\hat{d}_{j,c,t}$ is the fitted market share of bank j in market k, t. Note that we use *rate* semi-elasticity here for clarity, which is equivalent to the negative of the *spread* semi-elasticity used in the model.

Estimation data We estimate rate semi-elasticities using deposit rates data from the Call Reports spanning 2001 to 2020. These rates are determined at the bank-year level by dividing the deposit interest expense by the total deposits. We assume the bank applies uniform rates across all its branches, an assumption that is consistent with our model assumption $r_{j,k} = r_j$

	N	Mean	Std	25%	50%	75%
Deposit rates (%)	292,940	1.219	1.065	0.372	0.854	1.866
Market income ($thousand)	292,940	41.390	14.000	32.362	38.916	46.754
Log(Employee per branch)	292,940	2.602	0.757	2.297	2.619	2.955
Log(Branch number)	292,940	3.280	2.499	1.386	2.565	5.075
Local labor cost (%)	292,940	10.484	2.035	10.589	10.831	11.089
Fixed asset expenses (%)	292,940	0.428	0.225	0.300	0.393	0.515
Competitors' employees per branch	292,940	17.843	5.801	14.476	17.724	21.538
Log(Income)	5,177,500	3.749	0.919	3.178	3.850	4.407

Table 4: **Summary statistics.** This table reports the summary statistics of the data used in the estimation.

and supported by the empirical findings detailed in Section 3. We assume that total customer wealth is composed of cash, investments in Treasury securities, money market funds, and deposits. Following the prior literature, we utilize macro aggregates from FRED (Federal Reserve Economic Data) to proxy for the share of cash, bonds, and overall deposits in customers' portfolios over time. To allocate aggregate holdings across counties, we assume that non-deposit wealth at the market level is proportional to total personal income in the market obtained from the Bureau of Economic Analysis.

Our measure for customers' demographic D_i is household income, randomly drawn from Data Axle's U.S. Consumer database. The unobserved heterogeneous rate sensitivity ν_i is drawn from a standard normal distribution. For each market k, t we draw 500 households, i.e., $N = 500$ in Equation (20). The bank characteristics $X_{j,k,t}$ include the interaction between the large banks dummy variable and the average personal income in the market, the logarithm of the number of branches the bank owns and the logarithm of the number of employees per branch. The average personal income data is from Bureau of Economic Analysis. Table 4 shows the summary statistics of the data used in the estimation. In the estimation, we demean the log of household income, so that the estimated α reflects the rate sensitivity of a household with the average of the log of income.

Estimation results Table 5 displays our estimation results. The mean rate sensitivity is 1.202, which indicates that a 1 percentage point increase in the deposit rate leads to a 1.202% increase in the market share of bank j in a market comprising households with average income, assuming other factors remain constant. Furthermore, Table 5 corroborates our earlier findings by demonstrating that households with higher incomes exhibit lower sensitivity to changes in deposit rates. Specifically, a one standard deviation increase in household income corresponds to a 0.990 decline in α_i. Additionally, the estimated β coefficients underscore

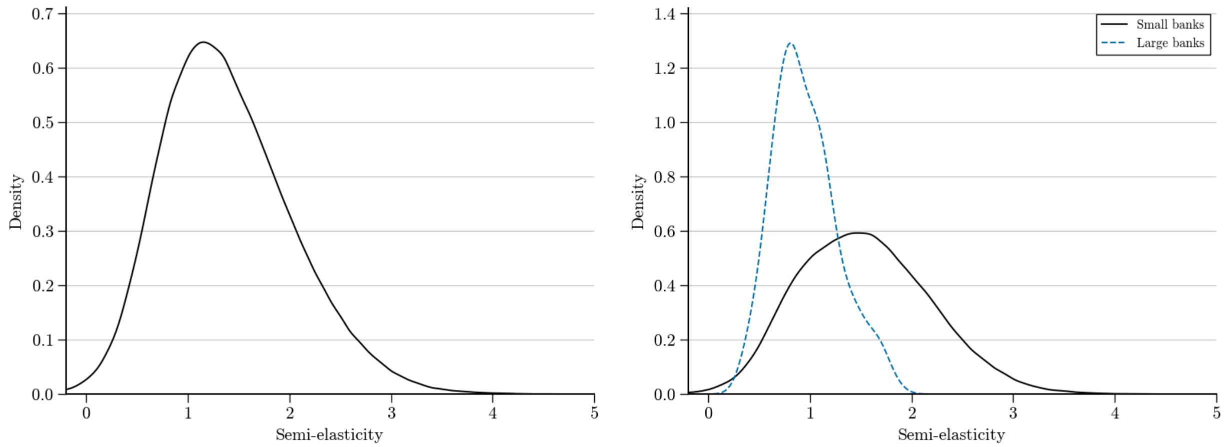
Parameter	Symbol	Estimate	SE
Preference parameters			
Deposit rate	α	1.202	0.059
Large $\times$ Market average income	β_1	0.014	0.001
Log(Employee per branch)	β_2	0.505	0.021
Log(Branch number)	β_3	0.161	0.018
Heterogeneity parameters			
Household log-income	Π	-1.077	0.042
Rate sensitivity dispersion	σ	0.760	0.041
Observations		292,940	
Adjusted R-squared		0.547	

Table 5: **Demand estimation.** This table reports the estimates of demand parameters. The sample includes all U.S. commercial banks from 2001 to 2020. The data is from the Call Reports, the Summary of Deposits, Data Axle, Bureau of Economic Analysis, and Bureau of Labor Statistics. Large $\times$ Market Average Income is the interaction between the large banks dummy variable and the average personal income in the market, Log(Branch Number) is the logarithm of total number of branches held by the bank, and Log(Employee per Branch) is the logarithm of average number of employees per branch.

the importance of liquidity services for customers. β_1 indicates that in markets with higher average income, households appreciate the customer support and superior liquidity services that large banks provide, placing greater value on large banks. Specifically, holding other features constant, large banks in San Francisco (with an average income of \$135,000 in 2020) can offer a deposit rate that is 0.99% lower than large banks in Champaign (with an average income of \$50,000 in 2020) to achieve the same level of customer satisfaction. The estimation also indicates that customers place higher value on banks with more employees per branch and a larger number of branches.

6.2 Rate semi-elasticities: large vs. small banks

With our parameter estimates in hand, we generate rate semi-elasticity estimates using Equation (24). Figure 10 presents the distributions of rate semi-elasticities $\hat{\eta}^r_{j,k,t}$ for each bank j, market k, year t. The left panel illustrates the distribution of semi-elasticities for all banks across all markets. The distribution is skewed, with most of the mass around lower elasticities but with a fat right tail. The right panel separates the distribution of average semi-elasticities for large and small banks. For most large banks, semi-elasticity estimates cluster around 1, which is close to the median of the overall semi-elasticity distribution in the left panel. This observation aligns with our model's prediction that large banks operate in



(a) Full sample (b) Large vs. small

Figure 10: **Density of rate semi-elasticities.** This figure plots the density of estimated rate semi-elasticities $\hat{\eta}^r_{j,k,t}$. The left figure shows the distribution of semi-elasticities of all banks in all markets. The right figure shows the distribution of deposit-weighted average semi-elasticity of large and small banks. The solid line denotes large banks, and the dash line denotes small banks.

markets with median, or "predominant," semi-elasticity values. In contrast, the distribution for small banks shows a wider range and a notable amount of mass in the right tail, centering around 1.5 with high dispersion. This implies that customers at small banks exhibit higher (and more variable) rate elasticities, meaning their deposit balances are more sensitive to changes in deposit rates. These findings support our model's prediction that small banks serve the markets with higher, and more disperse, semi-elasticities.

Table 6 displays the summary of rate semi-elasticities generated by our IV estimation and Equation (24). We calculate the *average* semi-elasticity $\hat{\eta}_{j,t}$ for each bank j at year t, weighted by the deposits in the markets where the bank operates. That is, for a bank j with N branches in a given year t, the average elasticity $\hat{\eta}^r_{j,t} = \sum_{k \in \mathcal{M}_j} \frac{d_{k,j,t}}{D_{j,t}} \cdot \hat{\eta}^r_{j,k,t}$, where $\hat{\eta}^r_{j,k,t}$ denotes the rate semi-elasticity of bank j located in cluster k at time t. Table 6 documents substantial differences across large vs. small banks. Small banks have higher average semi-elasticities, with deposit increases of 1.537% corresponding to a 1% relative increase in deposit rates, while at large banks the deposit increase associated with a 1% increase in rates is 0.957%. The semi-elasticity for small banks is higher than that for large banks, indicating that customers of small banks are more sensitive to changes in deposit rates. Additionally, small banks exhibit more extreme values in their semi-elasticity estimates. The empirical difference between the semi-elasticity estimates for large and small banks match the prediction in Proposition 4 that large banks do not cater to markets with the more extreme rate semi-elasticities.

	N	Mean	Std	10%	25%	50%	75%	90%
Small	99,497	1.537	0.646	0.733	1.065	1.504	1.966	2.390
Large	234	0.957	0.314	0.592	0.739	0.907	1.148	1.421
All	99,731	1.536	0.646	0.732	1.064	1.503	1.965	2.389

Table 6: **Rate semi-elasticity.** This table presents summary statistics for the calculated average rate semi-elasticity at the bank level, separated by small banks, large banks, and the overall sample.

Figure 11 plots the relationship between the average rate semi-elasticities, and the market share of large banks within each county cluster. A clear correlation emerges, showing that in areas with a higher concentration of large banks, demand tends to be more inelastic, which supports Proposition 6 and consistent with Figure 2.

Our evidence documenting differences in rate semi-elasticities between large and small banks provides support for the key results from our model. The higher rate semi-elasticities at small banks is consistent with these banks serving a different customer base than that of large banks, and operating a different deposit business model as a result.

6.3 Deposit demand estimation: further analysis

In this subsection, we present further analysis on the deposit demand estimation. We show that semi-elasticity has more explanatory power for rate variation than local variables the prior literature has focused on.

Semi-elasticity and rate variation Since our model indicates that banks set deposit rates based on households' local-market rate semi-elasticities, we carry out a residual analysis in Table 7, similar to the analysis reported in Table 2 but for the average rate semi-elasticity estimates and other variables. We run regressions of the first stage residuals on an indicator for the 14 large banks in Column 1, on the deposit-weighted average rate semi-elasticity in Column 2, on deposit-weighted average income in Column 3, and on deposit-weighted average HHI in Column 4. The data consist of weekly deposit rates for the four RateWatch deposit products MM $25K, SAV $2.5, 12M CD $10K, and INT $2.5K over the period from 2001 to 2020. As shown, the semi-elasticity-time fixed effects consistently account for the largest amount of variation in deposit rates. This table provides further support for our model result that banks set deposit rates according to the average rate semi-elasticity they face and the importance of uniform rates. We also note that deposit-weighted average HHI outperform local HHI to explain deposit rates (see Table 7) by a factor of ten, which emphasizes the

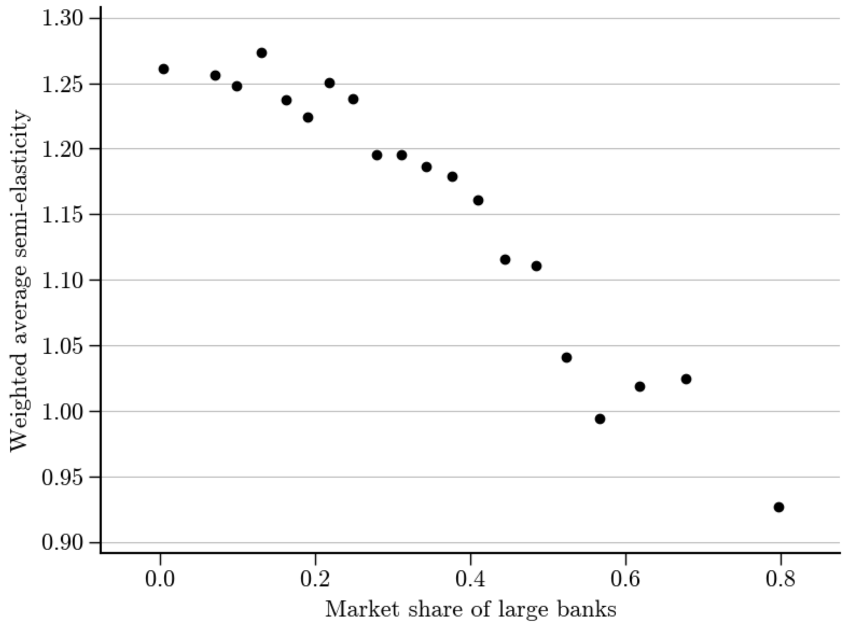


Figure 11: **Rate semi-elasticity and large bank local share.** This figure presents the relationship between *average* rate semi-elasticity and market share of large banks from the BLP estimation data using Call Report data, controlling for year fixed effects. The semi-elasticities are cluster-year averages, weighted by bank deposits.

importance of uniform pricing. Finally, average HHI explains only half as much variation in deposit rates as average rate semi-elasticity, which corrborates Proposition 7. This suggests that relying solely on income or HHI is insufficient to fully capture the factors driving rate variation.

7 Conclusion

A comprehensive understanding of how banks set deposit rates is essential for researchers and policymakers. Prior work has emphasized market concentration and de-emphasized differences in customer preferences and the deposit-business technologies of banks. We argue that product differentiation is a key consideration in deposit market competition, as is standard in Industrial Organization studies in other markets. Large and small banks serve customers with different preferences over deposit rates and liquidity services, and thus operate different production functions, in different locations, for their deposit franchises. We provide a parsimonious model illustrating these ideas and extensive empirical evidence supporting the idea that much of the variation in deposit pricing behavior across banks may be due to variation in preferences and technologies, as opposed to being driven purely by pricing power

FE	(1) Large×Time	(2) $\hat{\zeta}$×Time	(3) Income×Time	(4) HHI×Time
MM $25K				
Observations	47,683,906	47,683,906	47,683,906	47,683,906
R-squared	0.111	0.133	0.020	0.041
SAV $2.5K				
Observations	50,239,052	50,239,052	50,239,052	50,239,052
R-squared	0.150	0.247	0.065	0.149
12M CD $10K				
Observations	50,848,875	50,848,875	50,848,875	50,848,875
R-squared	0.219	0.256	0.064	0.157
CHECK $2.5K				
Observations	48,498,227	48,498,227	48,498,227	48,498,227
R-squared	0.141	0.215	0.088	0.129

Table 7: **Residual analysis.** This table tests the contribution of semi-elasticity to rate variations after removing time variation, implementing a two-step analysis and reporting the results of the second stage. The data consist of weekly deposit rates from RateWatch, covering the period from 2001 to 2020 at the branch level. The selected deposit products include money market accounts with a balance of $25,000, savings accounts with a balance of $2,500, 12-month CDs with a balance of $10,000, and checking accounts with a balance of $2,500. The incorporated fixed effects are a large bank indicator (with "Large" as a dummy for the 14 large banks defined above), the estimated semi-elasticity $\hat{\eta}^r$, bank-level weighted average county-income, and HHI all interacted with week fixed effects.

derived from the large observed degree of concentration in the banking industry. Indeed, such concentration may be the result of large fixed costs required for large banks to offer superior liquidity-service technologies, such as ATM networks and consumer-facing software solutions, tailored to customers who highly value these services.

References

Anderson, Eric, Nir Jaimovich, and Duncan Simester, 2015, Price stickiness: Empirical evidence of the menu cost channel, *Review of Economics and Statistics* 97, 813–826.

Anderson, Eric T., and Duncan I. Simester, 2001, Does demand fall when customers perceive that prices are unfair? The case of premium pricing for large sizes, *Marketing Science* 27, 492–500.

Atkeson, Andrew G., Adrien d'Avernas, Andrea L. Eisfeldt, and Pierre-Olivier Weill, 2018, Government guarantees and the valuation of American banks, in Martin Eichenbaum, and Jonathan A. Parker, eds., *NBER Macroeconomics Annual 2018*, volume 33, 81–145 (University of Chicago Press).

Bassett, William F., and Thomas F. Brady, 2002, What drives the persistent competitiveness of small banks?, Working Paper, Federal Reserve Board.

Begenau, Juliane, Monika Piazzesi, and Martin Schneider, 2015, Banks' risk exposures, Working Paper 21334, NBER.

Begenau, Juliane, and Erik Stafford, 2023, Uniform rate setting and the deposit channel, Working Paper, Stanford University.

Benmelech, Efraim, Jun Yang, and Michal Zator, 2024, Bank branch density and bank runs, Working Paper 31462, NBER.

Berger, Allen N., and Timothy H. Hannan, 1989, The price-concentration relationship in banking, *Review of Economics and Statistics* 71, 292–299.

Berger, Allen N., Anil K Kashyap, and Joseph M. Scalise, 1995, The transformation of the U.S. banking industry: What a long, strange trip it's been, *Brookings Papers on Economic Activity* 1995, 55–218.

Berger, Allen N., Nathan H. Miller, Mitchell A. Petersen, Raghuram G. Rajan, and Jeremy C. Stein, 2005, Does function follow organizational form? Evidence from the lending practices of large and small banks, *Journal of Financial Economics* 76, 237–269.

Berndt, Antje, Darrell Duffie, and Yichao Zhu, 2024, The decline of too big to fail, Working Paper, Stanford University.

Berry, Steven, James Levinsohn, and Ariel Pakes, 1995, Automobile prices in market equilibrium, *Econometrica* 63, 841–890.

Bianchi, Javier, and Saki Bigio, 2022, Banks, liquidity management, and monetary policy, *Econometrica* 90, 391–454.

Biehl, Andrew R., 2002, The extent of the market for retail banking deposits, *Antitrust Bulletin* 47, 91–106.

Bolton, Patrick, Ye Li, Neng Wang, and Jinqiang Yang, 2024, Dynamic banking and the value of deposits, *Journal of Finance* (forthcoming).

Buchak, Greg, Gregor Matvos, Tomasz Piskorski, and Amit Seru, 2024, Beyond the balance sheet model of banking: Implications for bank regulation and monetary policy, *Journal of Political Economy* 132, 616–693.

Calem, Paul S., and Leonard I. Nakamura, 1998, Branch banking and the geography of bank pricing, *Review of Economics and Statistics* 80, 600–610.

Calomiris, Charles W., and Doron Nissim, 2014, Crisis-related shifts in the market valuation of banking activities, *Journal of Financial Intermediation* 23, 400–435.

Campbell, John Y., 2006, Household finance, *Journal of Finance* 61, 1553–1604.

Cavallo, Alberto, 2018, More Amazon effects: Online competition and pricing behaviors, in *Jackson Hole Economic Symposium Conference Proceedings* (Federal Reserve Bank of Kansas City).

Chang, Briana, Ing-Haw Cheng, and Harrison G. Hong, 2023, The fundamental role of uninsured depositors in the regional banking crisis, Working Paper, University of Wisconsin, Madison.

Cole, Rebel A., Lawrence G. Goldberg, and Lawrence J. White, 2004, Cookie-cutter versus character: The micro structure of small business lending by large and small banks, *Journal of Financial and Quantitative Analysis* 39, 227–251.

Conlon, Christopher, and Jeff Gortmaker, 2020, Best practices for differentiated products demand estimation with PyBLP, *The RAND Journal of Economics* 51, 1108–1161.

Corbae, Dean, and Pablo D'Erasmo, 2013, A quantitative model of banking industry dynamics, Working Paper, Federal Reserve Bank of Philadelphia.

Corbae, Dean, and Pablo D'Erasmo, 2020, Rising bank concentration, *Journal of Economic Dynamics and Control* 115, 103877.

Corbae, Dean, and Pablo D'Erasmo, 2021, Capital buffers in a quantitative model of banking industry dynamics, *Econometrica* 89, 2975–3023.

DellaVigna, Stefano, and Matthew Gentzkow, 2019, Uniform pricing in U.S. retail chains, *Quarterly Journal of Economics* 134, 2011–2084.

Demyanyk, Yuliya, Charlotte Ostergaard, and Bent E. Sørensen, 2007, U.S. banking deregulation, small businesses, and interstate insurance of personal income, *Journal of Finance* 62, 2763–2801.

Dick, Astrid A., 2008, Demand estimation and consumer welfare in the banking industry, *Journal of Banking & Finance* 32, 1661–1676.

Drechsler, Itamar, Alexi Savov, and Philipp Schnabl, 2017, The deposits channel of monetary policy, *Quarterly Journal of Economics* 132, 1819–1876.

Drechsler, Itamar, Alexi Savov, and Philipp Schnabl, 2021, Banking on deposits: Maturity transformation without interest rate risk, *Journal of Finance* 76, 1091–1143.

Drechsler, Itamar, Alexi Savov, Philipp Schnabl, and Olivier Wang, 2024, Deposit franchise runs, Working Paper 31138, NBER.

Egan, Mark, Ali Hortaçsu, and Gregor Matvos, 2017, Deposit competition and financial fragility: Evidence from the US banking sector, *American Economic Review* 107, 169–216.

Egan, Mark, Stefan Lewellen, and Adi Sunderam, 2022, The cross-section of bank value, *Review of Financial Studies* 35, 2101–2143.

Even, Shimon, and Guy Even, 2011, *Graph Algorithms*, second edition (Cambridge University Press, Cambridge).

Fleckenstein, Matthias, and Francis A. Longstaff, 2024, Is maturity-transformation risk priced into bank deposit rates?, Working Paper 32724, NBER.

Gordon, Myron J., and Eli Shapiro, 1956, Capital equipment analysis: The required rate of profit, *Management Science* 13, 102–110.

Granja, João, and Nuno Paixão, 2024, Bank consolidation and uniform pricing, Working Paper, University of Chicago.

Haddad, Valentin, Barney Hartman-Glaser, and Tyler Muir, 2023, Bank fragility when depositors are the asset, Working Paper, University of California, Los Angeles.

Haendler, Charlotte, 2023, Keeping up in the digital era: How mobile technology is reshaping the banking sector, Working Paper, Boston College.

Hannan, Timothy H., 1991, Bank commercial loan markets and the role of market structure: Evidence from the surveys of commercial lending, *Journal of Banking and Finance* 15, 133–149.

Hannan, Timothy H., 1997, Market share inequality, the number of competitors, and the HHI: An examination of bank pricing, *Review of Industrial Organization* 12, 23–35.

Hannan, Timothy H., and Allen N. Berger, 1991, The rigidity of prices: Evidence from the banking industry, *American Economic Review* 81, 938–945.

Haynes, George W., Charles Ou, and Robert Berney, 1999, Small business borrowing from large and small banks, in *Proceedings 776*, 287–327 (Federal Reserve Bank of Chicago).

Heitfield, Erik, and Robin A. Prager, 2004, The geographic scope of retail deposit markets, *Journal of Financial Services Research* 25, 37–55.

Heitfield, Erik A., 1999, What do interest rate data say about the geography of retail banking markets?, *Antitrust Bulletin* 44, 333–347.

Huang, Can, 2023, *Essays in Venture Capital and Banking*, Ph.D. thesis, University of California, Berkeley.

Jermann, Urban J., and Haotian Xiang, 2023, Dynamic banking with non-maturing deposits, *Journal of Economic Theory* 209, 105644.

Jiang, Erica, Gregor Matvos, Tomasz Piskorski, and Amit Seru, 2024a, Which banks are (over) levered? Insights from shadow banks and uninsured leverage, Working Paper 26903, NBER.

Jiang, Erica Xuewei, Gregor Matvos, Tomasz Piskorski, and Amit Seru, 2024b, Monetary tightening and U.S. bank fragility in 2023: Mark-to-market losses and uninsured depositor runs?, *Journal of Financial Economics* 159, 103899.

Jiang, Erica Xuewei, Gloria Yang Yu, and Jinyuan Zhang, 2023, Bank competition amid digital disruption: Implications for financial inclusion, Working Paper, University of Southern California.

Koont, Naz, 2023, The digital banking revolution: Effects on competition and stability, Working Paper, Stanford GSB.

Leslie, Phillip, 2004, Price discrimination in Broadway theater, *RAND Journal of Economics* 35, 520–541.

Ma, Yueran, and José A. Scheinkman, 2021, Going-concern debt of financial intermediaries, Working Paper, University of Chicago.

Mester, Loretta J., 1987, Multiple market contact between savings and loans, *Journal of Money, Credit, and Banking* 19, 538–549.

Minton, Bernadette A., René M. Stulz, and Alvaro G. Taboada, 2019, Are the largest banks valued more highly?, *Review of Financial Studies* 32, 4604–4652.

Neumark, David, and Steven A. Sharpe, 1992, Market structure and the nature of price rigidity: Evidence from the market for consumer deposits, *Quarterly Journal of Economics* 107, 657–680.

Nevo, Aviv, 2000, A practitioner's guide to estimation of random-coefficients logit models of demand, *Journal of Economics & Management Strategy* 9, 513–548.

Oberfield, Ezra, Esteban Rossi-Hansberg, Nicholas Trachter, and Derek T. Wenning, 2024, Banks in space, Working Paper 32256, NBER.

Orbach, Barak Y., and Liran Einav, 2007, Uniform goods: The case of the movie-theater industry, *International Review of Law and Economics* 27, 129–153.

Park, Abraham, 2009, Private vs. public real estate markets: How are these markets related in terms of risk and return?, *Graziado Business Review* 12.

Park, Kwangwoo, and George Pennacchi, 2009, Harming depositors and helping borrowers: The disparate impact of bank consolidation, *Review of Financial Studies* 22, 1–40.

Radecki, Lawrence J., 1998, The expanding geographic reach of retail banking markets, *FRBNY Economic Policy Review* 4, 15–34.

Radecki, Lawrence J., 2000, Competition in shifting product and geographic markets, *Antitrust Bulletin* 45, 553–833.

Rhoades, Stephen A., 1992, Evidence on the size of banking markets from mortgage loan rates in twenty cities, Staff Study 162, Federal Reserve Board.

Sarkisyan, Sergey, 2024, Instant payment systems and competition for deposits, Working Paper, Ohio State University.

Sharpe, Steven A., 1997, The effect of consumer switching costs on prices: A theory and its application to the bank deposit market, *Review of Industrial Organization* 12, 79–94.

Smith, Matthew, Owen Zidar, and Eric Zwick, 2023, Top wealth in America: New estimates under heterogeneous returns, *Quarterly Journal of Economics* 138, 515–573.

Vissing-Jørgensen, Annette, 2002, Limited asset market participation and the elasticity of intertemporal substitution, *Journal of Political Economy* 110, 825–853.

Wang, Yifei, Toni M. Whited, Yufeng Wu, and Kairong Xiao, 2022, Bank market power and monetary policy transmission: Evidence from a structural estimation, *Journal of Finance* 77, 2093–2141.

Wenning, Derek, 2024, National pricing and the geography of US life insurers, Working Paper, Indiana University.

Xiao, Kairong, 2020, Monetary transmission through shadow banks, *Review of Financial Studies* 33, 2379–2420.

Yankov, Vladimir, 2024, In search of a risk-free asset: Search costs and sticky deposit rates, *Journal of Money, Credit and Banking* 56, 1053–1098.

Zhou, Rong, and Eric A. Hansen, 2006, Breadth-first heuristic search, *Artificial Intelligence* 170, 385–408.

	TOT	SAV	TIME	TRANS
	(1)	(2)	(3)	(4)
Large	-0.390^{***}	-0.243^{***}	-0.003	0.006
	(0.031)	(0.032)	(0.028)	(0.021)
Observations	120,134	119,287	119,678	118,937
R-squared	0.795	0.679	0.902	0.291

Table A.1: **Deposit rate differences between large and small banks (Call Report data).** This table estimates the average deposit rate difference between large and small banks using Call Report data from 2001 to 2020. The 14 large depository institutions are defined above and the dependent variables are the implied deposit rates for total deposits, savings deposits, time deposits, and transaction deposits. All columns control for time fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendices

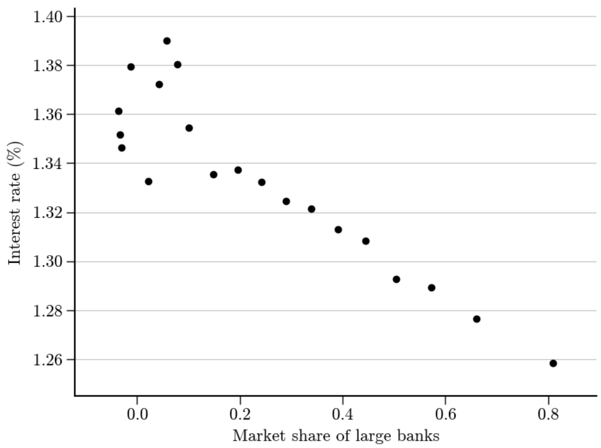
A Call Report corroboration of RateWatch results

To corroborate the RateWatch deposit-pricing differentials between large and small banks that are reported in the body of paper, we carry out a similar analysis using bank-level deposit rates from Bank Call Reports, calculated by dividing interest expense on deposit products by their balance. Similar to Table 3, Table A.1 regresses the implied deposit rates from Call Report data on the large-bank indicator variable and year fixed effects from 2001 to 2020. On average, the total deposit rates of large banks are 0.390% lower than those of small banks. In terms of individual products, large banks set statistically significantly lower deposit rates on saving deposits, which are the largest deposit product category. However, we find no statistically significant difference for time and transaction deposits.

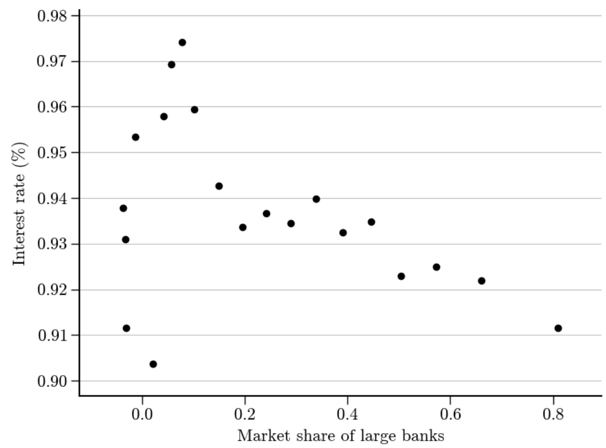
Similar to Figure 2, Figure A.1 examines the relationship between the deposit rates of branches owned by small banks and the market share of large banks in those markets, but this time using Call Report and Summary of Deposits data from 2001 to 2020. Figure A.1 confirms that small banks in markets dominated by large banks set lower deposit rates, with this pattern holding across different types of deposits.

B Large banks as top 1% of assets

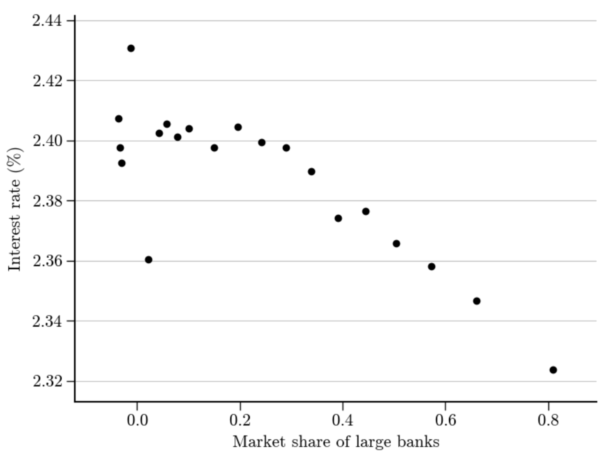
For robustness, we present results using an alternative definition of large banks, characterized as those in the top 1% of asset size. Figure B.1 replicates Figure 1 using this alternative



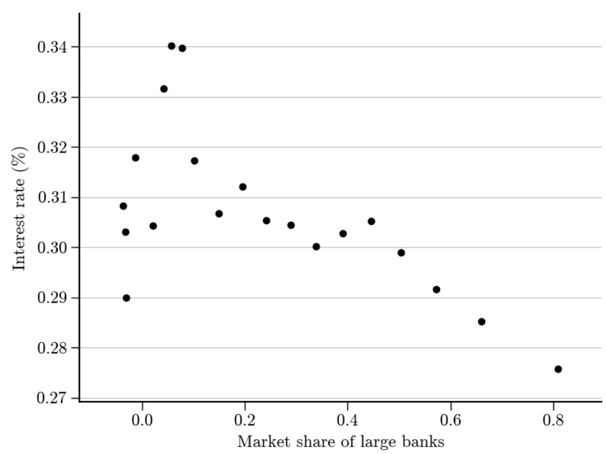
(a) Total deposits



(b) Savings deposits

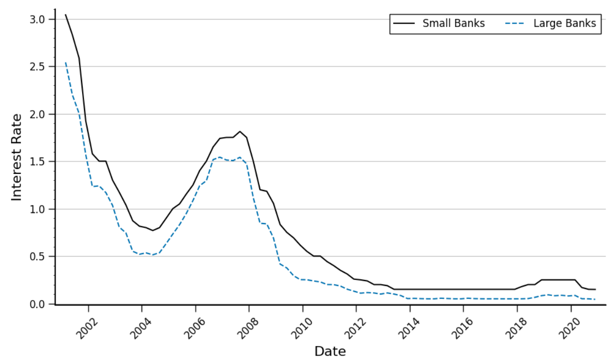


(c) Time deposits

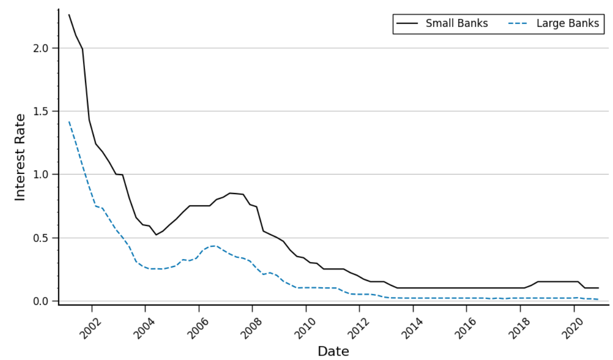


(d) Transaction deposits

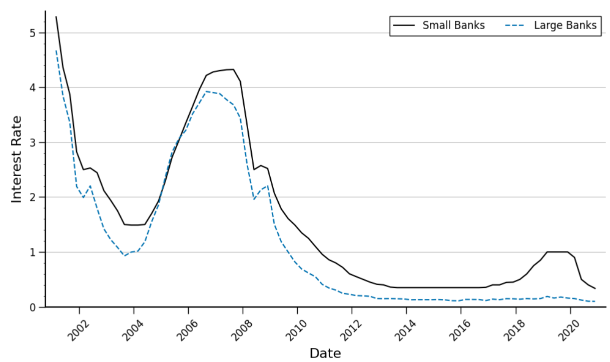
Figure A.1: **Small-bank deposit rates vs. large-bank market share (Call Report and Summary of Deposits data).** These figures illustrate the relationship between deposit rates of small banks and the market share of large banks in the local market where small banks operate, using Call Report data from 2001 to 2020 at the branch level, and controlling for time fixed effects. The charts display the implied deposit rates for total deposits, savings deposits, time deposits, and transaction deposits. The market share of large banks is calculated at the zipcode level by dividing the total deposits held by large banks by the total deposits within the zipcode from Summary of Deposits.



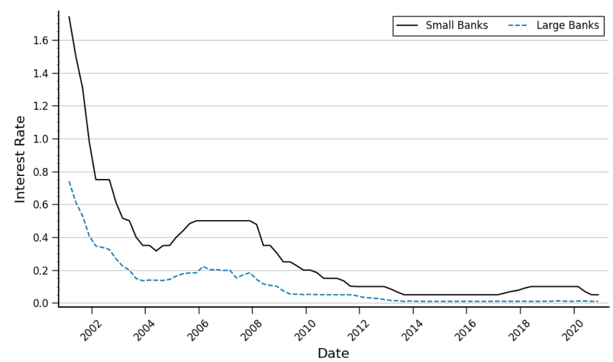
(a) MM $25K



(b) SAV $2.5K



(c) 12M CD $10K



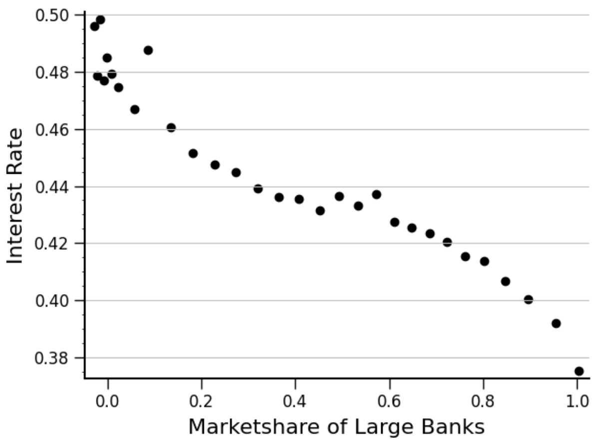
(d) CHECK $2.5K

Figure B.1: **Deposit rates of large vs. small banks (RateWatch data).** The figures show the time series of weighted average deposit rates of the median large bank compared to the median small bank using the RateWatch data from 2001 to 2020. The charts display rates for money market accounts with a balance of $25,000 (MM $25K), savings accounts with a balance of $2,500 (SAV $2.5K), 12-month CDs with a balance of $10,000 (12M CD $10K), and checking accounts with a balance of $2,500 (CHECK $2.5K). Large banks are defined as those with asset sizes in the top 1%. The black lines denote small banks and the blue lines denote large banks.

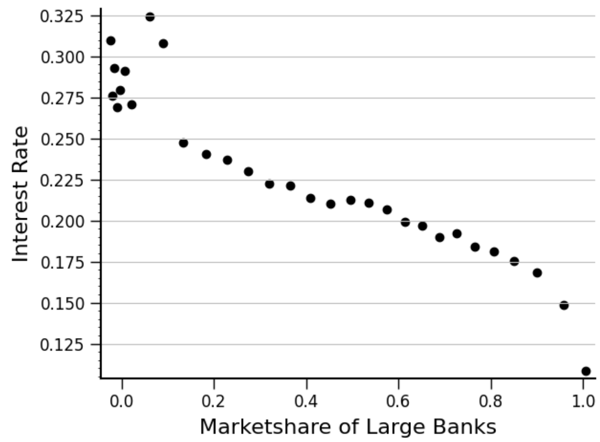
size definition, while Table B.1 replicates the findings from Table 3. Both confirm similar results, indicating that large banks tend to set lower rates compared to small banks.

Figure B.2 replicates Figure 2, illustrating the relationship between small bank rates and the local market share of large banks. Consistent with Figure 2, Figure B.2 shows that small banks in areas where large banks have a higher market share tend to set lower rates compared to small banks in areas with a smaller presence of large banks.

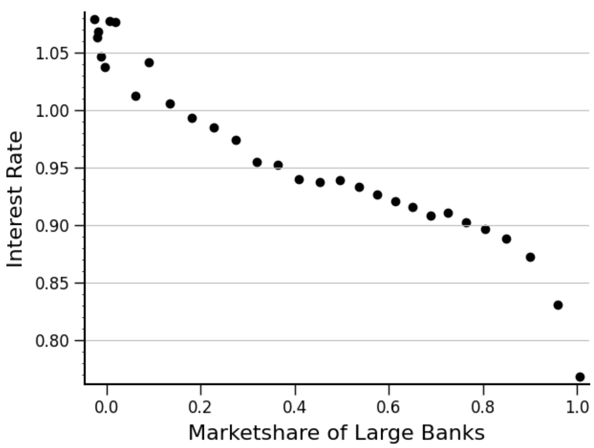
We also conduct the demand estimation using the alternative large bank definition. Table B.2 shows the estimation results, with similar estimates with Table 5. The mean rate sensitivity is 1.236, close to the estimates of Table 5 of 1.202. We also find higher income households tend to have lower rate sensitivity, and markets with higher average income value



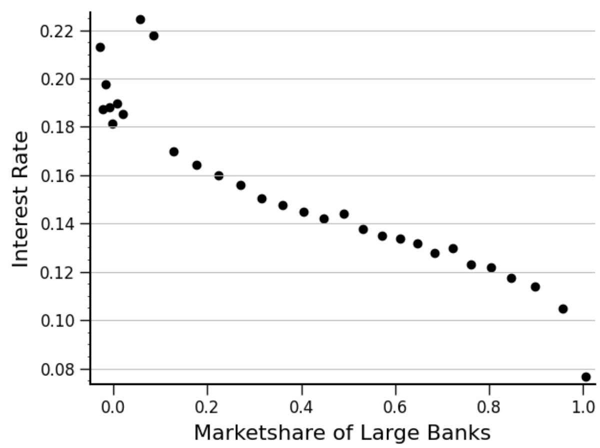
(a) MM $25K



(b) SAV $2.5K



(c) 12M CD $10K



(d) CHECK $2.5K

Figure B.2: **Small-bank deposit rates vs. large-bank market share (RateWatch and Summary of Deposits data).** These figures illustrate the relationship between deposit rates of small banks and the market share of large banks in the local market where small banks operate, using RateWatch data from 2001 to 2020 at the branch level, and controlling for week fixed effects. The charts display deposit rates of money market accounts of $25,000, saving accounts of $2,500, 12 month CD of $10,000, and checking accounts of $2,500. The market share of large banks is calculated at the zipcode level by dividing the total deposits held by large banks by the total deposits within the zipcode from Summary of Deposits.

	MM \$25K	SAV \$2.5K	12M CD \$10K	CHECK \$2.5K
	(1)	(2)	(3)	(4)
Large	-0.217^{***}	-0.289^{***}	-0.370^{***}	-0.217^{***}
	(0.002)	(0.002)	(0.002)	(0.001)
Observations	4,166,511	4,331,543	4,351,767	4,197,739
R-squared	0.652	0.581	0.912	0.480

Table B.1: **Deposit rate differences between large and small banks (RateWatch data).** This table estimates the average deposit rate difference between large and small banks using RateWatch data from 2001 to 2020. Branch-level deposit rates are collapsed into bank-level rates by taking the average rates weighted by branch deposit balance. Large banks are defined as those with asset sizes in the top 1%, and the dependent variables are deposit rates of money market accounts of \$25,000, saving account of \$2,500, 12 month CD of \$10,000, and checking account of \$2,500. All columns control for time fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

large banks more. Figure B.3 depicts the semi-elasticity distribution, illustrating that, similar to Figure 10, small bank elasticities under the alternative size definition also have a fatter left tail. The shape of the distribution for large banks is also relatively unaffected by the alternative definition of a large bank.

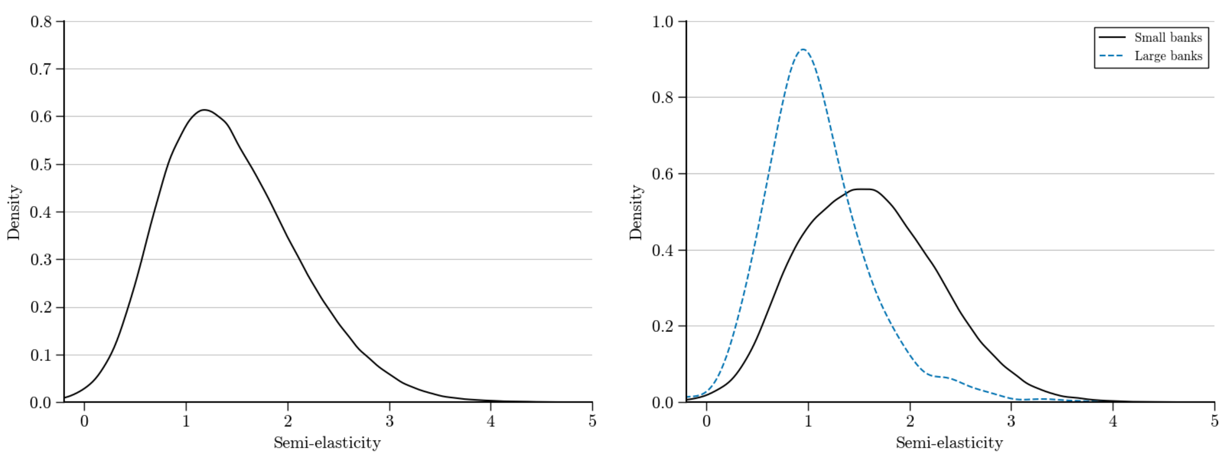
Figure B.4 illustrates the correlation between the average semi-elasticity within a cluster and the market share of large banks for each cluster, echoing the findings presented in Figure 11. Regions dominated by a higher proportion of large banks typically exhibit less elastic deposit rate elasticities. Together, these results indicate that altering the definition of large banks does not significantly affect the overall analysis.

C Additional robustness checks

Deposit rates and bank sizes We present additional analyses to further document the relationship between deposit rates and bank size. Figure C.1 presents a scatter plot of deposit rates against the log of bank assets, using bank-quarter-level Call Report data from 2001 to 2020, controlling for time fixed effects. There is a hump-shaped relationship between rate and bank size. However, importantly, the positive portion of this relationship only holds for very small banks. These very small banks collectively hold only 2% of the total deposit share. For the banks representing the remaining 95% of deposit share, the relationship between deposit rates and size is negative, aligning with our main findings comparing large vs. small banks. Indeed, while a subset of very small banks, with very few deposits, may exhibit lower

Parameter	Symbol	Estimate	SE
Preference parameters			
Deposit rate	α	1.236	0.059
Large $\times$ Market average income	β_1	0.005	0.001
Log(Employee per branch)	β_2	0.500	0.021
Log(Branch number)	β_3	0.154	0.019
Heterogeneity parameters			
Household log-income	Π	-1.103	0.041
Rate sensitivity dispersion	σ	0.810	0.040
Observations		292,940	
Adjusted R-squared		0.547	

Table B.2: **Demand estimation.** This table reports the estimates of demand parameters. The sample includes all U.S. commercial banks from 2001 to 2020. The data is from the Call Reports, the Summary of Deposits, Data Axle, Bureau of Economic Analysis, and Bureau of Labor Statistics. Large $\times$ Market Average Income is the interaction between the large banks dummy variable and the average personal income in the market, Log(Branch Number) is the logarithm of total number of branches held by the bank, and Log(Employee per Branch) is the logarithm of average number of employees per branch.



(a) Full sample

(b) Large vs. small

Figure B.3: **Density of rate semi-elasticities.** This figure plots the density of estimated rate semi-elasticities. The left figure shows the distribution of semi-elasticities of all banks in all markets. The right figure shows the distribution of deposit-weighted average semi-elasticity of large and small banks. The solid line denotes large banks, and the dash line denotes small banks.

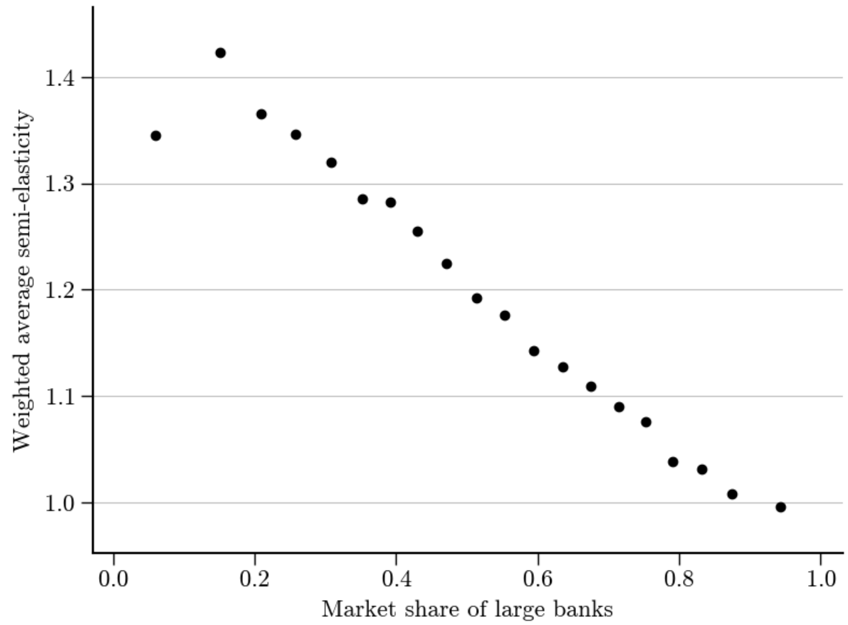


Figure B.4: **Rate semi-elasticity and large bank local share.** This figure presents the relationship between rate semi-elasticity and market share of large banks from the BLP estimation data using Call Report data, controlling for year fixed effects. The semi-elasticities are cluster-year averages, weighted by bank deposits.

rates than other small banks, the overall trend across a more continuous view of bank size supports our conclusion that larger banks set lower deposit rates.

Replication of Drechsler et al. (2017) Table 2 Table C.1 replicates the results in Table 2 of Drechsler et al. (2017), utilizing RateWatch data from 2001 to 2020 to examine the relationship between the Herfindahl-Hirschman Index (HHI) and bank rates. The main regression is

$$\Delta y_{it} = \alpha_i + \eta_{c(i)} + \lambda_{s(i)t} + \delta_{j(i)t} + \gamma \, \Delta \mathrm{FF}_t \times \mathrm{HHI}_i + \epsilon_{it},$$

where Δy_{it} represents the changes in deposit spreads of money market accounts of \$25,000, $\Delta \mathrm{FF}_t$ denotes the changes in Federal Funds rate, and HHI is the rate-family-level HHI. Following the methodology laid out in Drechsler et al. (2017), we calculate HHI by aggregating the square of deposit-market shares of all banks within a specific county for each year, followed by averaging the results over the entirety of the years.

Column 1 replicates and confirms the main result of Table 2 of Drechsler et al. (2017). Columns 2 through 5 explore potential factors contributing to rate variation, serving as supplementary analyses to Table 1 in the main text. Column 2 reveals that variation in the Federal Funds Rates can account for over half of the variation of observed rate changes.

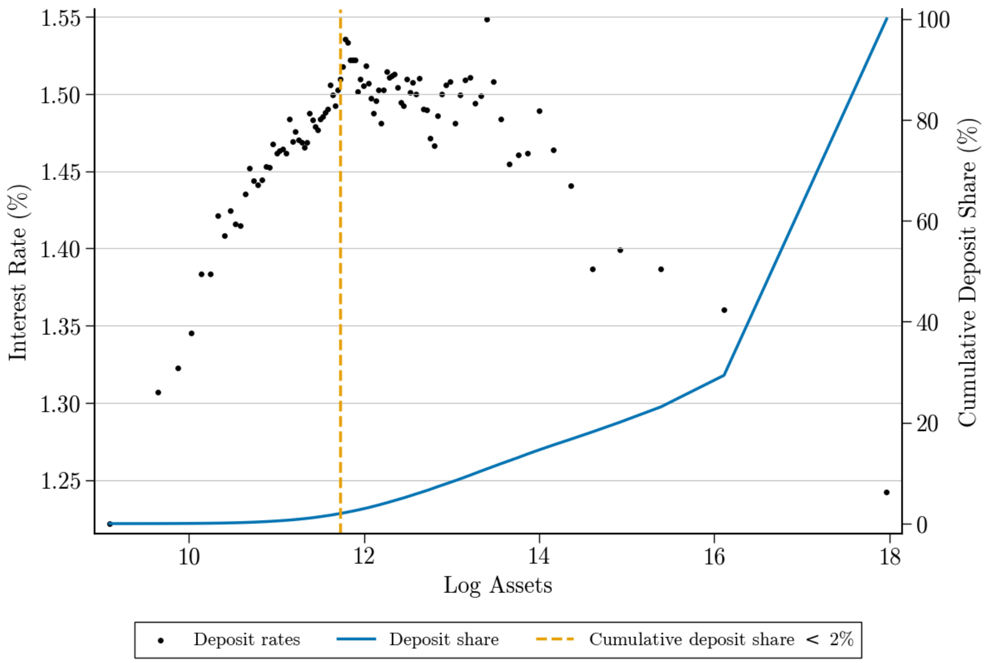


Figure C.1: **Deposit rates, bank size, and cumulative deposit share.** This figure presents the relationship between total deposit rates and log assets, using bank-quarter-level Call Report data from 2001 to 2020, with time fixed effects controlled. The orange line represents the cumulative deposit share of banks within each asset bin. The vertical line marks the cutoff point, indicating that banks with assets below this line collectively hold 2% of the total deposit share.

Incorporating HHI into the third column does not change the R^2 of the regression, suggesting that HHI plays a relatively minor role in explaining the variation in deposit rate changes, however the coefficient on the interaction of HHI and the change in the Federal Funds rate retains its economic and statistical significance. Columns 4 and 5 respectively include all fixed effects (Column 4) and only bank-time fixed effects (Column 5). Comparing these last two columns shows that bank-time fixed effects account for most of the variation in rate settings, indicating minimal rate variation within banks as shown in the main text.

Lastly, Column 6 examines the rate-setting by large vs. small banks in the context of variation in HHI. The sensitivity of large bank deposit rates does not seem to vary significantly with HHI. This is important because large banks own the majority of deposits. The sensitivity of rates to HHI appears to be driven by small banks, which are much greater in number, but jointly own a minority of deposits. Depending on the research question, regressions with equal weighting may place undue weight on the large number of quite small banks.

Alternative instrument variables Wang et al. (2022) employs three instruments: the ratio of non-interest expenses on fixed assets to total assets from the prior year, salary expenses to total assets from the prior year, and local labor cost. However, since a bank's salary expenses may be positively correlated with the unobserved quality of its deposit products, using salary expenses to total assets as an instrument could violate the exclusion restriction. Therefore, in our main estimation, we replace this instrument with competitors' product characteristics following Egan et al. (2022).

To verify the robustness of our estimation results to different sets of instrumental variables, we also present the results using the original three instruments from Wang et al. (2022) in Table C.2. These results are consistent with the main findings presented in Table 5, demonstrating the robustness of our conclusions.

D Data construction

This appendix summarizes the data cleaning and construction procedures. We first describe how we access the data, followed by steps for creating a consistent Bank Holding Company (BHC)-level dataset from Call Reports and FR Y-9C reports. Finally, we outline the construction of the panels used in demand estimation and empirical analysis.

	Dependent Variable: Δ Spread					
	(1)	(2)	(3)	(4)	(5)	(6)
	Replication	No FE	No FE	All FE	Bank×T	Add Size
ΔFF × HHI	0.0644***		0.0752***			
	(0.0212)		(0.0098)			
ΔFF		0.765***	0.749***			
		(0.0010)	(0.0023)			
ΔFF × HHI × Small						0.0819***
						(0.0236)
ΔFF × HHI × Large						−0.0331
						(0.0432)
Bank × quarter FE	Yes	No	No	Yes	Yes	Yes
Quarter FE	Yes	No	No	Yes	Yes	Yes
Bank FE	Yes	No	No	Yes	Yes	Yes
Family FE	Yes	No	No	Yes	No	Yes
Observations	198,710	198,710	198,710	198,710	198,710	193,989
R^2	0.906	0.736	0.736	0.906	0.899	0.905

Table C.1: **Replication of Drechsler et al. (2017) Table 2.** This table replicates Table 2 in Drechsler et al. (2017) using RateWatch data from 2001 to 2019. The main regression is

$$\Delta y_{it} = \alpha_i + \eta_{c(i)} + \lambda_{s(i)t} + \delta_{j(i)t} + \gamma\, \Delta \mathrm{FF}_t \times \mathrm{HHI}_i + \epsilon_{it},$$

where Δy_{it} is changes in deposit spreads of money market accounts of \$25,000, $\Delta \mathrm{FF}_t$ is changes in Federal Funds rate. HHI measures market concentration at the *rate-family* level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D.1 Accessing the data

Most of the data is retrieved automatically by running the scripts provided in the replication package. This includes using the Federal Deposit Insurance Corporation (FDIC) API to obtain Summary of Deposits data, Compustat data, the Federal Reserve Economic Data (FRED) API to retrieve macroeconomic series, the U.S. Bureau of Economic Analysis (BEA) API for county-level income and population data, and U.S. Census Bureau data for population estimates and geographic shapefiles.

Some datasets are retrieved manually. County-level wage data, for instance, is obtained from the Bureau of Labor Statistics' Quarterly Census of Employment and Wages (QCEW), specifically the NAICS-based annual average files for the years 2000–2020. Call Report and FR Y-9C data are accessed through Wharton Research Data Services (WRDS) by executing SAS scripts, included in the replication package, on the WRDS Cloud platform. Proprietary

Parameter	Symbol	Estimate	SE
Preference parameters			
Deposit rate	α	1.121	0.050
Large x Market average income	β_1	0.015	0.001
Log(Employee per branch)	β_2	0.505	0.020
Log(Branch number)	β_3	0.150	0.018
Heterogeneity parameters			
Household log-income	Π	-0.584	0.018
Rate sensitivity dispersion	σ	0.965	0.044
Observations		292,940	
Adjusted R-squared		0.542	

Table C.2: **Demand estimation.** This table reports the estimates of demand parameters using the same instrument variables as Wang et al. (2022). The sample includes all U.S. commercial banks from 2001 to 2020. The data is from the Call Reports, the Summary of Deposits, Data Axle, Bureau of Economic Analysis, and Bureau of Labor Statistics. Large $\times$ Market Average Income is the interaction between the large banks dummy variable and the average personal income in the market, Log(Branch Number) is the logarithm of total number of branches held by the bank, and Log(Employee per Branch) is the logarithm of average number of employees per branch.

datasets such as RateWatch and Data Axle were purchased and sourced directly from the respective data providers.

D.2 Constructing a BHC-level dataset

BHCs report their financial data through the FR Y-9C form, which is only filed by BHCs with consolidated assets of \$3 billion or more (this threshold has varied over time). To ensure data consistency[34] and complete coverage of the U.S. banking sector, we supplement the FR Y-9C data with Call Report data (FFIEC 031/041), which is filed at consolidated bank level.

Data cleaning and merging steps for the FR Y-9C and Call Report datasets are outlined below.

Call Reports We identify the parent BHC of the consolidated bank by the identifier of the top regulatory bank holding company (RSSDHCR), and assign the bank identifier as its BHC identifier if banks are not held by a BHC. Several key accounting variables are cleaned to ensure consistency, following the steps outlined by Drechsler et al. (2017). The

[34] If a bank drops out of the sample due to reporting thresholds, this could introduce measurement error in local market share calculations.

data is filtered by charter type to retain relevant institutions.[35] For duplicate entries, the row with the largest assets is retained. Observations with non-positive domestic deposits or total assets are dropped.

FR Y-9C We only include top regulatory bank holding company. Key variables are matched to those in Call Reports, and equivalent cleaning steps are performed. Observations with non-positive domestic deposits or total assets are removed.

FDIC Summary of Deposit Data adjustments To address cases where a large share of deposits is assigned to a single branch (e.g., for online deposits), we follow Granja and Paixão (2024) by removing branch observations where deposits exceed ten standard deviations of the branch-level mean.

Consolidating the data We begin by defining large banks according to the criteria outlined in Section 2 of the paper. Mergers and acquisitions during the sample period may cause a single bank to be identified by multiple identifiers (RSSD ID) over time. We carefully trace the relevant RSSD IDs for each large bank using the FFIEC-NIC website.

Next, we aggregate Call Report data to the BHC level by RSSDHCR identifier and merge it with the FR Y-9C data. To identify relevant BHC-year observations for our sample, we use the FDIC Summary of Deposits data, excluding BHCs without branches. In cases where BHC report in both Call Reports and FR Y-9C, FR Y-9C data is prioritized. Large banks' missing values for assets, employee counts ,salaries, and premises expenses are filled to ensure coverage, with any missing years filled using Compustat data. For small banks, missing FR Y-9C values are filled using Call Report data. Additionally, we create an indicator variable set to one whenever data are derived from Call Reports, allowing us to distinguish the data source and utilize this indicator in subsequent demand estimation analyses.

D.3 BLP panel construction

The data used for BLP estimation is structured at the BHC-County Cluster-Year level. County clusters are defined via a breadth-first search algorithm (Section 6.1 of the main paper). BHC-level variables are winsorized at the 1st and 99th percentiles to account for outliers. To convert the sample from quarterly to yearly frequency, we employ the following

[35] This includes Commercial Banks, Savings Banks, Savings & Loan Associations, Cooperative Banks, Industrial Banks, Edge or Agreement Corporations, and Holding Companies. Commercial and Savings Banks comprise approximately 93% of the total sample, with 99% of branches chartered as Commercial or Savings Banks.

approach. Expense variables, such as Salaries and Expenses on Premises, are recorded as quarterly flows. We aggregate these by summing the quarterly observations and retain only those entries with data available for all four quarters to ensure completeness. Balance sheet or snapshot variables, including Assets, Deposits, and Number of Employees, are averaged across the four quarters to produce an annual figure. The annual count of branches per bank is derived from the FDIC Summary of Deposits data.

Using the county-cluster definitions, we then calculate each BHC's market share within a given cluster for each year. The market share denominator includes local cash holdings (BOGZ1FL713125005Q), Treasury holdings (HNOTSAQ027S), and money market holdings (MMMFFAQ027S), with Treasury holdings and money market holdings being the outside option. These components are adjusted for each county-cluster by weighting the national accounting series according to the cluster's share of aggregate personal income. The market share of cash are calculated in a similar manner. We retain only observations with non-zero market shares.

The demographic variable, household income, is sourced from Data Axle's U.S. Consumer database. For each market and year, we randomly draw a sample of 500 households with replacement. Since the database covers only the years 2006–2020, the 2006 dataset is used to create household samples for the years 2001–2005. Additionally, because 2009 was a year of financial crisis and the income data for that year exhibit large number of outliers and abnormal income patterns, the 2008 dataset is used to create household samples for 2009. This approach ensures consistency and mitigates the impact of anomalies in the income data during the crisis period.

Instrument variables construction As discussed in Section 6, the three instruments used in the BLP estimation are non-interest expenses on fixed expenditures (Wang et al., 2022), local labor costs (Dick, 2008), and competitors' number of employees per branch (Egan et al., 2022).

Non-interest expenses on fixed assets (RIAD4217 in Call Reports, BHCK4217 in FR Y-9C) encompasses all non-interest expenses related to the use of premises, equipment, furniture, and fixtures, such as expenses on lease payments, depreciation, utilities, building maintenance, legal fees, insurance, amortization of assets, and ordinary repairs. We divide the instrument by the bank's lagged total assets (RCFD2170).

Local labor cost is constructed by merging the FDIC Summary of Deposits branch-level data with the QCEW county-level wage data, and compute each BHC's deposit-weighted average annual pay (avg_annual_pay) in the banking industry (NAICS 522110). Branch deposits are defined by the variable 'depsumbr'.

The number of employees per branch is calculated by dividing the total number of employees, obtained from consolidated bank data (RIAD4150 in Call Reports and BHCK4150 in FR Y-9C), by the total number of branches reported in the FDIC Summary of Deposits data. To calculate the competitors' number of employees per branch, we first calculate the average number of employees per branch among competitors in the same market, and then a deposit-weighted average of these competitor characteristics is calculated across all markets where the bank operates.

D.4 RateWatch data

For data storage purposes, RateWatch groups branches with identical interest rates into "rate families" and designates one branch in each family as the "rate setter branch." However, this designation does not imply that the flagged branch actively sets rates for other branches. RateWatch provides a file that documents the connections between "rate setters" and "followers" within each family. We utilize this file to apply the rates of the rate setter to all branches within the same rate family. We then compute branch-level interest rates for the respective products as the weekly mean-level rates.

To link each branch to its parent BHC, we merge the RateWatch data with FDIC branch data using the FDIC unique branch identifier (UNINUMBR). Additionally, we merge this data with county-level population statistics and Herfindahl-Hirschman Index (HHI) measures to capture local market conditions. Finally, bank-average rates are calculated as deposit-weighted averages, providing a comprehensive measure of interest rates at the bank level.

E Proofs

E.1 Proofs of Propositions 1 and 3

In equilibrium, all single-market banks—denoted with superscript S—solve the same first-order condition within each market. Therefore, within a market k, they have the same deposit spread and market share, denoted by s_k^S and d_k^S. Thus, the profit raised by a small (single-market) bank in market k is given by

$$\frac{M_k}{\alpha_k}\frac{d_k^S}{1-d_k^S}, \tag{25}$$

where

$$s_k^S = c + \frac{1}{\alpha_k(1-d_k^S)}, \quad d_k^S = \frac{\exp(-\alpha_k s_k^S + \beta_k x_k^S)}{N_k^S \exp(-\alpha_k s_k^S + \beta_k x_k^S) + \Omega_k}, \tag{26}$$

N_k^S is the number of small banks entering market k, $\Omega_k = \sum_{i \in \mathcal{L}_k} \exp(-\alpha_k s_i + \beta_k x_i)$, and $\mathcal{L}_k \equiv \{j : b_{jk} = 1 \text{ and } |\mathcal{M}_j| > 1\}$ is the set of multi-market banks entering market k. The free entry condition for small banks is such that N_k^S, the number of small banks entering market k, solves:

$$N_k^S = \max N \in \mathbb{N} \tag{27}$$

such that

$$(s_k^S - c)D_k^S \geq \kappa_k. \tag{28}$$

Thus,

$$N_k^S = \left\lfloor \frac{M_k}{\kappa_k \alpha_k} - \Omega_k e^{\alpha_k s_k^S - \beta_k x_k^S} + 1 \right\rfloor = \frac{M_k}{\kappa_k \alpha_k} - \Omega_k \exp\left(\alpha_k s_k^S - \beta_k x_k^S\right) + 1 - \theta_k, \tag{29}$$

where $\theta_k \in [0, 1)$. Assuming $N_k^S > 0$ and $\theta_k = 0$, we can then derive the equilibrium deposit demand for bank j in market k:

$$d_{jk} = \frac{1}{\frac{M_k}{\kappa_k \alpha_k} + 1} \frac{\exp(-\alpha_k s_j + \beta x_j)}{\exp(-\alpha_k s_k^S + \beta_k x_k^S)}. \tag{30}$$

Because the equilibrium demand does not depend on the strategy of other multi-market banks, and the maximization problem of banks is concave, the pure-strategy Nash equilibrium is unique.

E.2 Proof of Proposition 2

For this section, we first define the profit function of a small bank j in market k with N other small banks:

$$\pi^S(s_j, x_j, N; k) = (s_j - c)M_k \frac{\exp(-\alpha_k s_j + \beta_k x_j)}{\exp(-\alpha_k s_j + \beta_k x_j) + (N-1)\exp(-\alpha_k s_k^S + \beta_k x_k^S) + \Omega_k}. \tag{31}$$

That bank sets the deposit spread s_j and invests in liquidity services according to x_j. Similarly, for a large bank j, we can define

$$\pi^L(s_j, x_j, N; k, j) = (s_j - c)M_k \frac{\exp(-\alpha_k s_j + \beta_k x_j)}{\exp(-\alpha_k s_j + \beta_k x_j) + N\exp(-\alpha_k s_k^S + \beta_k x_k^S) + \Omega_{k\setminus j}}, \quad (32)$$

where $\Omega_{k\setminus j} = \sum_{i\in\mathcal{L}_k\setminus j} \exp(-\alpha_k s_i + \beta_k x_i)$. From the free-entry condition and the assumption that $\theta_k \approx 0$, in equilibrium we have that

$$\max_s \pi^S(s, 0, N_k^S; k) = \kappa. \quad (33)$$

We proceed in two steps. First, we prove that if $|\mathcal{M}_j| = 1$ then $x_j = 0$, which follows from our assumption on the size of the cost χ in Equation (7). Second, we prove that if $|\mathcal{M}_j| > 1$ then $x_j = 1$.

If $|\mathcal{M}_j| = 1$, then $x_j = 0$ We first show that, in equilibrium, a small bank has no incentives to invest in liquidity services. That is,

$$\max_s \pi^S(s, 0, N_k^S; k) = \kappa_k > \max_s \pi^S(s, 1, N_k^S; k). \quad (34)$$

The first-order conditions for the optimal deposit spreads, given $x_{jk} = 1$ and $x_k^S = 0$, yield

$$s_{jk} = c + \frac{1}{\alpha_k}\left(1 + \frac{\kappa_k\alpha_k}{M_k}\exp\left(-\alpha_k(s_{jk} - s_k^S) + \beta_k\right)\right) \quad (35)$$

and

$$s_k^S = c + \frac{1}{\alpha_k}\left(1 + \frac{\kappa_k\alpha_k}{M_k}\right). \quad (36)$$

We can compute the difference between Equation (35) and (36) as

$$-\alpha_k(s_{jk} - s_k^S) = \frac{\kappa_k\alpha_k}{M_k}\left(1 - \exp\left(-\alpha_k(s_{jk} - s_k^S) + \beta_k\right)\right). \quad (37)$$

Let us define the function of $\Delta \equiv \alpha_k(s_{jk} - s_k^S)$ as

$$f(\Delta) = \Delta + \frac{\kappa_k\alpha_k}{M_k}\left(1 - \exp(-\Delta + \beta_k)\right). \quad (38)$$

Note that $f'(\Delta) > 0$, $f(0) \leq 0$. Define $\Delta^\star$ such that $f(\Delta^\star) = 0$. Thus, $0 \leq \Delta^\star \leq \beta_k$. Therefore,

$$\Delta^\star + \frac{\kappa_k \alpha_k}{M_k} = \frac{\kappa_k \alpha_k}{M_k} \exp\left(-\Delta^\star + \beta_k\right) \geq \frac{\kappa_k \alpha_k}{M_k} \left(1 - \Delta^\star + \beta_k\right). \tag{39}$$

Thus,

$$-\alpha_k (s_{jk} - s_k^S) + \beta_k \leq \frac{\beta_k}{1 + \frac{\kappa_k \alpha_k}{M_k}}. \tag{40}$$

After some algebra, we can rewrite condition (34) as

$$-\alpha_k (s_{jk} - s_k^S) + \beta_k < \log\left(1 + \frac{\chi}{\kappa_k}\right). \tag{41}$$

Thus, if

$$\beta_k < \left(1 + \frac{\kappa_k \alpha_k}{M_k}\right) \log\left(1 + \frac{\chi}{\kappa_k}\right), \tag{42}$$

as assumed in (7), then condition (34) is satisfied and a small bank has no incentives to invest in liquidity services.

If $|\mathcal{M}_j| > 1$, then $x_j = 1$ Here, we verify that a multi-market bank ($|\mathcal{M}_j| > 1$) that does not invest in liquidity services ($x_j = 0$) cannot exist in equilibrium. We do so by showing that such a bank has no incentives to stay in any market.

For this section, we define $s_j^L(\mathcal{M})$ as

$$s_j^L(\mathcal{M}) = \arg\max_s \sum_{k \in \mathcal{M}_j} \pi^L(s, 0, N_k^S; k, j). \tag{43}$$

Note that by definition, $s_k^S = s_j^L(k)$. Furthermore, we assumed in (7) that there does not exist $k, \ell \in \{1, \ldots, K\}$ such that $\frac{1}{\alpha_k} + \frac{\kappa_k}{M_k} = \frac{1}{\alpha_\ell} + \frac{\kappa_\ell}{M_\ell}$. This assumption guarantees that $s^L(k) \neq s^L(\ell)$ for all $k, \ell \in \{1, \ldots, K\}$. Consider $k \in \mathcal{M}_j$. Since $s_j^L(\mathcal{M}_j) \neq s_j^L(k)$ and large bank j has incentives to leave market k, we get:

$$\pi^L(s_j^L(\mathcal{M}_j), 0, N_k^S; k) < \pi^L(s_j^L(k), 0, N_k^S; k) = \kappa. \tag{44}$$

Furthermore,

$$\max_s \sum_{\ell \in \mathcal{M}_j \setminus k} \pi^L(s, 0, N_\ell^S; \ell, j) > \sum_{k \in \mathcal{M}_j} \pi^L(s_j^L(\mathcal{M}_j), 0, N_k^S; k, j), \tag{45}$$

since leaving market k relaxes the uniform pricing constraint. Thus, leaving any market k is beneficial, until bank j becomes a small bank.

E.3 Proof of Proposition 5

In this section, we verify that, if the condition in Proposition 5 is satisfied for market k, there cannot be an equilibrium with $b_{jk} = 1$ where j is a large bank ($|\mathcal{M}_j| > 1$). Thus, we aim to show that in an equilibrium where $b_k^L = 1$, any large bank j has incentives to deviate to $b_{jk} = 0$. This is the case if

$$\frac{M_k}{|\eta_j^s|} \frac{\exp(-\alpha_k(s_{jk} - s_k^S) + \beta_k)}{\frac{M_k}{\kappa_k \alpha_k} + 1} < \kappa_k. \tag{46}$$

Further algebra yields

$$\alpha_k(s_{jk} - s_k^S) > \beta_k - \log\left(\frac{|\eta_j^s|}{\alpha_k} + \frac{\kappa_k |\eta_j^s|}{M_k}\right). \tag{47}$$

Since

$$s_{jk} - s_k^S = \frac{1}{|\eta_j^s|} - \frac{1}{\alpha_k}\frac{1}{1 - d_k^S} = \frac{1}{|\eta_j^s|} - \frac{1}{\alpha_k}\left(1 + \frac{\kappa_k \alpha_k}{M_k}\right), \tag{48}$$

we get

$$\frac{\alpha_k}{|\eta_j^s|} - \log\left(\frac{\alpha_k}{|\eta_j^s|}\right) > \beta_k + 1 + \frac{\kappa_k \alpha_k}{M_k} - \log\left(1 + \frac{\kappa_k \alpha_k}{M_k}\right), \tag{49}$$

concluding the proof.

E.4 Proof of Proposition 6

If $k \in \mathcal{M}_j$, $\ell \notin \mathcal{M}_j$, $\kappa_k/M_k = \kappa_\ell/M_\ell \approx 0$, and $\beta_k \leq \beta_\ell$, then

$$\frac{\alpha_k}{\eta_j^s} - \log\left(\frac{\alpha_k}{\eta_j^s}\right) \leq \beta_k + 1 \tag{50}$$

and

$$\frac{\alpha_\ell}{\eta_j^s} - \log\left(\frac{\alpha_\ell}{\eta_j^s}\right) > \beta_\ell + 1. \tag{51}$$

Thus,

$$\frac{\alpha_k}{\eta_j^s} - \log\left(\frac{\alpha_k}{\eta_j^s}\right) \leq \beta_k + 1 \leq \beta_\ell + 1 < \frac{\alpha_\ell}{\eta_j^s} - \log\left(\frac{\alpha_\ell}{\eta_j^s}\right). \tag{52}$$

E.5 Proof of Proposition 7

In any market k with only small banks,

$$d_k^S = \frac{1}{N_k^S} = \frac{1}{1 + \frac{M_k}{\kappa_k \alpha_k}}. \tag{53}$$

Thus, the Herfindahl-Hirschman index in market k is given by

$$\mathrm{HHI}_k = N_k^S \left(\frac{1}{N_k^S}\right)^2 = \frac{1}{1 + \frac{M_k}{\kappa_k \alpha_k}}. \tag{54}$$

The deposit spread is given by

$$s_k^S = c + \frac{1}{\alpha_k(1 - d_k^S)} = c + \frac{1}{\alpha_k} + \frac{\kappa_k}{M_k}. \tag{55}$$

Thus,

$$\frac{\partial s_k^S}{\partial \alpha_k} = -\frac{1}{\alpha_k^2} < 0, \quad \frac{\partial s_k^S}{\partial \kappa_k} = \frac{1}{M_k} > 0 \tag{56}$$

and

$$\frac{\partial \mathrm{HHI}_k}{\partial \alpha_k} = \frac{\mathrm{HHI}_k}{1 + \frac{M_k}{\kappa_k \alpha_k}} \frac{M_k}{\kappa_k \alpha_k^2} > 0, \quad \frac{\partial \mathrm{HHI}_k}{\partial \kappa_k} = \frac{\mathrm{HHI}_k}{1 + \frac{M_k}{\kappa_k \alpha_k}} \frac{M_k}{\kappa_k^2 \alpha_k} > 0. \tag{57}$$

E.6 Calibration

We use the set of parameters $\{M, \kappa\} = \{1, 1/100\}$, constant across all locations. The distribution of α is lognormal with mean 0.15 and volatility 0.5. The other parameters $\{\chi, c\}$ are not necessary for the figures we produce.