Essays on Deposit Markets and Banking Competition

By

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A dissertation submitted in partial fulfillment of

the requirements for the degree of

Doctor of Philosophy

(Economics)

at the

UNIVERSITY OF WISCONSIN–MADISON

2026

Date of final oral examination: 05/05/2026

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One more book.

Acknowledgments

I am deeply grateful to my advisor, Jean-François Houde, and to the other members of my committee, Karam Kang, Jason Allen, and Lu Han. Jean-François, thank you for always having time for me, even when there was no obvious reason to, and for the patience the years required; much of how I think about industrial organization, and how I approach an empirical question, I learned from you. Karam, thank you for saying the hard things, even when they were not what I wanted to hear; this dissertation is sharper because of it, and so am I. Jason, thank you for the time and the careful comments; since you joined the project, things became clearer and somehow easier. Lu, thank you for the years of working together, and for showing me, by example, what it looks like to write a paper and do economics with care.

I thank my coauthor on Chapter 3, Evan Newell, for the work we have done together. From earlier years, I am grateful to my master's advisor, Sonia Di Giannatale, and to the other professors at CIDE—especially Kaniska Dam—who set me on this path before I knew where it would lead. I am also grateful to Ken Hendricks, Ashley Swanson, Chris Sullivan, Lorenzo Magnolfi, Martin O'Connell, Panle Jia Barwick, Dan Quint, Dean Corbae, Alan Sorensen, Mark Egan, Kevin Williams, Felipe Brugues, Robert Clark, and Andres Gonzalez-Lira for thoughtful comments and suggestions on these papers. I owe a particular thanks to John Kennan, our placement director, for steady guidance through the job market, and to Vivak Patel for his company and support during that same period. Seminar and conference participants at the IO Lunch, the Industrial Organization Workshop at Wisconsin, and the Midwest Economic Association also offered feedback that improved this work. I thank the Wisconsin School of Business for providing the data that made the empirical work possible—and for housing half of my committee. And to the UW–Madison Department of Economics: thank you for being my home through these years. Thank you also to the administrative staff—especially Becca George—who kept everything moving.

The people I leaned on along the way deserve more than fits on a page. My deepest thanks go to Anya, Andrea, and Katherine—for all the time we spent together, the long dinners and the longer talks. To Danny, Leah, and Qalbi: thank you for being our extended family in Madison. I came here for a degree, and I am leaving with a family. And to the friends I made through economics—Anna, Claire, Emily, Sarah, Arjun, Davi, Rodrigo, and the many others who suffered through this with me—thank you for making the bad days survivable and the good ones better. To the people I met outside economics, who reminded me that there is a world beyond it: thank you for keeping things normal, and often funny.

To my oldest friends—Robin, Nely, Raquel, Faridis, and the others I have not named but have not stopped missing—thank you for staying close through years when I could only be far. There are other names that should be on this page and are not; the omission is mine, and the gratitude is the same.

To my mother, thank you for believing in me before I could, and for showing me how to face difficulty—always by example, never only in words. And for the sacrifice of these years, including the visits you could not make. To my grandparents: thank you for thinking I am the best thing in the world; I have spent a long time trying to deserve it. To my father, thank you for being there throughout, in your own way. And to my younger siblings: I hope, when you grow up, you will be a little proud of me. That is the only example I have aspired to be.

To my aunt and cousin, Maritza and Lissette, to Raulito and Armando, and to the kids: thank you for being there throughout these years, and from the very first day I arrived in the United States. And to Cecilia, who was family to us in Mexico, and who walked with me through the earliest steps of my academic life: thank you for the long faith. To my husband's family, who have become mine, and especially to my mother-in-law, Antonieta: thank you for the warmth, and for taking me in as if I had always been there.

And, more importantly, to my husband, Mitch. Everything was easier with you. You alone would have been enough; somehow, with you, I learned to want more. We did this together. And now we get to hope for a better life on the other side. And to Nina, my cat—for being my comfort animal through the long years.

Abstract

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University of Wisconsin-Madison, 2026

Under the supervision of Professor Jean-François Houde

This dissertation comprises three essays studying competition in U.S. deposit markets using structural industrial organization methods. Each essay addresses a distinct dimension of how banks price deposits and how their pricing strategies shape market outcomes, financial stability, and monetary policy transmission.

Chapter 1 quantifies how segmentation and bank market power in deposit markets shape the transmission of monetary policy. Using rate data differentiated by deposit account size, I document that uninsured rates are higher than insured rates, that banks exhibit significant heterogeneity in exposure to these market segments, and that pass-through from policy rates to deposit rates is incomplete. I develop and estimate a structural model of bank competition with segmented deposit markets by insurance status and spatial competition to understand these patterns and quantify their implications for monetary transmission. I find that uninsured deposits are slightly more elastic than insured deposits, while insured deposits have higher servicing costs. In counterfactual simulations of federal funds rate increases, I find that insured deposit outflows are three times larger than uninsured outflows and pass-through is higher for uninsured rates. Banks substitute toward wholesale funding, contracting lending as monetary policy tightens. Small banks experience larger balance sheet contractions following rate increases, while competitive markets exhibit stronger

deposit pass-through. These findings demonstrate that accounting for deposit segmentation is essential for understanding monetary transmission: segmentation amplifies policy effects in competitive markets but dampens transmission in concentrated markets.

Chapter 2 examines how U.S. retail banks use zone rating—defining geographic zones with uniform deposit rates—and quantifies the implications for rate dispersion, competition, and bank profitability. I document heterogeneity in zone rating practices across banks: larger banks maintain broader zones covering expansive geographical areas and exhibit higher rate dispersion, while smaller banks employ more sophisticated zone pricing strategies relative to their geographic footprint. To understand the competitive effects of this pricing practice, I estimate a structural model of deposit competition with differentiated banks and zone rating. I develop novel instruments based on tiered zone rating structures to address endogeneity in deposit pricing, exploiting customized zone-level variation. In counterfactual experiments, moving all banks to finer zones raises average deposit rates and rate dispersion but reduces bank variable profits, with particularly large effects for smaller banks. These findings demonstrate that banking's competitive environment limits banks' ability to profit from geographic price discrimination, providing empirical evidence that market price discrimination can weaken firm profitability if competition is sufficiently intense.

Chapter 3 (with Evan Newell) studies how bank mergers affect deposit pricing and bank stability. We use the 2019 merger between BB&T and SunTrust, which formed Truist Financial Corporation, to identify the local competitive effects of consolidation in U.S. retail banking. Before the merger, the two banks overlapped in some counties but not others, generating variation in exposure that separates the local competition effect from the scale effect of becoming a larger institution. Difference-in-differences event-study estimates show that deposit spreads rise in overlap counties relative to counties served by only one predecessor bank after the merger, with larger effects in markets with weaker outside competition. A structural deposit-demand model implies that the merger lowered deposit rates at consummation, with the effect attenuating in post-merger years as competitors adjusted. A complementary bank-level analysis of Z-scores suggests modest short-run effects on bank stability.

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Chapter 1

Deposit Segmentation and Bank Competition: Implications for Monetary Policy Transmission

1.1 Introduction

Deposits constitute the primary funding source for U.S. banks, accounting for over 70% of bank liabilities. Yet not all deposits are created equal. The Federal Deposit Insurance Corporation (FDIC) insures deposit accounts up to $250,000 per depositor, per insured bank, creating a regulatory threshold that divides deposits into two distinct categories: those fully protected by deposit insurance (which I refer to as *insured deposits*) and those exceeding the insurance limit (which I refer to as *uninsured deposits*). This threshold creates what I call *deposit market segmentation*: a systematic division of the deposit market into segments with different pricing dynamics, depositor characteristics, and competitive pressures. The importance of understanding this segmentation became evident during the March 2023 banking crisis, which occurred during a period of rapid monetary tightening and highlighted how uninsured depositors can rapidly withdraw funds, creating funding pressures for banks.

In this paper I ask: *How does deposit market segmentation and bank market power affect the transmission of monetary policy?* When the Federal Reserve adjusts interest rates, those changes ripple through the financial system, affecting how much banks lend and ultimately influencing real economic activity. A critical channel of this transmission works through bank deposits (Drechsler, Savov, and Schnabl, 2017): when the Fed raises rates, depositors' outside options such as money market funds and Treasury bills become more attractive, forcing banks to raise deposit rates to retain funds. However, if banks have market power, they may pass through only a fraction of the policy rate increase, extracting rents by widening the spread between policy rates and deposit rates. Incomplete pass-through causes deposits to flow out of the banking system, as depositors shift to better-yielding alternatives. The resulting deposit outflows constrain bank lending and amplify the contractionary effects of monetary tightening: banks with greater market power experience larger deposit outflows and thus larger lending contractions.

Understanding the strength of this *deposit channel* is relevant for predicting how monetary policy affects credit supply and economic activity. I focus specifically on how deposit market segmentation and spatial competition shape this transmission mechanism. Banks tend to specialize in serving different types of depositors. Some banks focus primarily on households with modest balances who prioritize convenience and safety; these banks draw most of their funding from insured deposits. Other banks specialize in serving businesses and wealthy individuals who need large transaction balances and value cash management services; these banks rely more heavily on uninsured deposits. Bank specialization means that a market's competitive structure can differ substantially across the two deposit segments: even when a market appears unconcentrated overall, it may have high concentration in the uninsured segment if few banks specialize in serving commercial clients, directly affecting banks' pricing power in that segment. Segmentation also enables banks to charge different rates across deposit segments, exploiting differences in how sensitive each group is to rate changes. While bank specialization clearly increases market power by creating segment-specific concentration, the effect of charging different rates across segments is theoretically ambiguous. Segmentation can either amplify or dampen how policy rate changes pass through to depositors, depending on the competitive environment. The strength of monetary policy transmission therefore varies systematically across banks depending on their deposit composition and across markets depending on their competitive structure in each segment.

To answer how deposit segmentation and bank market power affect monetary transmission, I combine multiple proprietary and public datasets that together provide information on deposit pricing, quantities, bank characteristics, and depositor demographics. My primary data sources include advertised deposit rates from RateWatch (a commercial vendor tracking rates at over 100,000 bank branches), bank balance sheet data from FDIC Call Reports and Summary of Deposits, household financial information from the Survey of Consumer Finances, U.S. Census data on local demographics and establishments, and macroeconomic data from the Federal Reserve Economic Data (FRED) database.

These data allow me to observe deposit rates differentiated by account size, enabling measurement of segment-specific pricing. I use advertised interest rates on money market accounts with minimum balance requirements of $2,500 (MM2.5K) and $250,000 (MM250K) as proxies for insured and uninsured deposits, respectively. I observe total deposits by branch location (from Summary of Deposits) and segment-level deposits aggregated at the bank level (from Call Reports Schedule RC-O), but not their intersection at the branch-segment level. To address this data limitation, I develop a method to allocate bank-level segment totals across geographic markets using observed deposit rates, local market characteristics, and the model's economic structure, which I validate against multiple data sources including the Survey of Consumer Finances.

Using these data, I document substantial heterogeneity in banks' deposit composition. Large banks (those with assets above $100 billion) hold on average 44% uninsured deposits compared to 18% for small banks (assets under $10 billion) during the 2009–2019 period, with substantial within-category variation (standard deviation of 22% for large banks versus 13% for small banks). These segments also differ in depositor composition: households with modest balances hold most insured deposits, while businesses and wealthy individuals hold most uninsured deposits. Deposit composition varies systematically across geographic markets, reflecting differences in local depositor types and competitive structure. Reduced-form evidence reveals that banks pay a substantial premium on uninsured deposits and that monetary policy pass-through to deposit rates is incomplete and differs across segments. However, the economic mechanisms driving these patterns remain unclear: do differences arise from depositor preferences, bank pricing power, or market structure?

To interpret these facts and quantify their implications for monetary policy transmission, I develop and estimate a structural model of bank competition with segmented deposit markets. The model builds on Drechsler et al. (2017)'s Cournot framework but extends it in three ways. First, I incorporate deposit market segmentation as an additional source of market power: banks choose optimal quantities across two deposit segments—insured and uninsured—as well as wholesale funding, enabling price discrimination across segments. Second, I introduce an *asset revenue channel* through which monetary policy affects bank revenues: higher policy rates increase banks' lending rates and marginal revenue from assets, not just funding costs. Third, rather than deriving testable predictions from the theoretical model, I estimate the full structural model to recover demand elasticities, cost parameters, and competitive structure.

On the demand side, depositors choose between insured and uninsured deposit products offered by competing banks in local markets, following a spatial nested logit structure that allows for both within-segment and cross-segment substitution. On the supply side, banks choose how much to raise from each funding source to maximize profits, facing an asset revenue function with diminishing returns and segment-specific deposit demand elasticities. The interaction of demand elasticities, marginal funding costs, and asset revenue determines equilibrium deposit rates, quantities, and bank lending. An important advantage of this approach is flexibility: the model allows whether segmentation amplifies or dampens monetary transmission to be theoretically ambiguous, with the answer depending on the estimated parameters and competitive environment.

When the federal funds rate rises, it affects both the demand and supply sides simultaneously. On the demand side, since many investment products are linked to the Federal funds rate, when the Federal Reserve increases this rate, depositors' outside options improve (e.g. money market funds, Treasury bills). This forces banks to raise deposit rates to keep their depositors. On the supply side, higher policy rates affect bank funding costs and revenues through two channels: the *wholesale funding cost channel*, which directly increases the cost of non-deposit funding, and the *asset revenue channel*, which increases banks' lending rates and raises the marginal revenue earned on assets. Combined, these supply-side forces shape how much banks lend and where they get their funding. The new equilibrium deposit quantities, rates, and bank balance sheet composition are jointly determined by these demand shifts, cost shifts, and the curvature of banks' asset revenue technology. Because these demand shifts differ across insured and uninsured segments—uninsured depositors have better outside options while insured deposits face higher servicing costs—monetary policy transmission differs in magnitude across segments.

Estimation proceeds in two stages. On the demand side, I estimate a nested logit model of depositor choice across banks and segments using instrumental variables to address endogeneity of deposit rates and nest shares. I instrument for deposit rates using cost shifters (past credit losses and past balance sheet expenses) and for nest shares using shift-share instruments that exploit spatial variation in competitor characteristics. The demand estimation recovers segment-specific rate elasticities and substitution patterns across banks and segments. On the supply side, I recover cost parameters from banks' first-order conditions for optimal funding choices. I estimate the curvature of the asset revenue function using variation in bank-level assets and federal funds rates, and I back out deposit servicing costs and wholesale funding cost parameters from equilibrium conditions equating marginal revenues to marginal costs across funding sources.

To quantify how monetary policy shocks transmit through the model, I exploit variation in the estimated time fixed effects from both demand and supply estimations. The time fixed effects from asset revenue estimation capture how asset profitability responds to policy rate changes, while the time-segment fixed effects from demand estimation capture how depositor outside options shift with monetary policy. By regressing these estimated fixed effects on changes in the federal funds rate, I recover the aggregate pass-through governing transmission through both supply-side (asset revenue channel) and demand-side (outside option channel) mechanisms.

The demand estimation reveals a difference between insured and uninsured deposits: uninsured deposits are more rate-elastic, with an own-price elasticity of 0.21 compared to 0.14 for insured deposits. On the supply side, I structurally recover three parameters that govern banks' funding decisions, providing new evidence on bank funding costs (Jacewitz and Pogach, 2018; Narayanan and Ratnadiwakara, 2024). First, the asset revenue function exhibits moderate decreasing returns to scale, indicating that banks face diminishing marginal profitability when lending increases. Second, I recover non-interest deposit servicing costs averaging 1.4 cents per dollar of deposits, with insured deposits costing more to serve than uninsured deposits, likely due to FDIC insurance premiums, which range from 0.5 to 1.0 cents per dollar. These recovered marginal servicing costs allow me to quantify how the uninsured deposit premium varies with bank size, market concentration, and monetary policy stance. Third, wholesale funding exhibits modest convexity, reflecting the fact that banks face upward-sloping supply curves in wholesale markets.

The pass-through estimation from time fixed effects reveals how depositor outside options respond to policy rate changes. Higher policy rates improve depositors' outside options, creating competitive pressure on banks. This outside option effect is nearly twice as large for insured depositors, indicating their greater sensitivity to changes in alternative investment opportunities. Combined with the own-price elasticity estimates, this reveals a nuanced transmission mechanism: uninsured depositors are more responsive to bank-specific rate changes (higher elasticity of 0.21), but insured depositors experience larger shifts in their outside options when the Fed adjusts rates.

I use the estimated model to simulate the effects of a 10 basis point increase in the federal funds rate, tracing through both the supply-side mechanisms (the asset revenue channel and wholesale funding cost channel) and demand-side (depositor response) mechanisms. The counterfactual analysis directly addresses my research question: how deposit market segmentation and bank market power affect monetary policy transmission. The results reveal that segmentation creates differential transmission across deposit segments, with stronger effects flowing through the insured segment despite banks having greater market power over uninsured deposits. Specifically, when the federal funds rate rises by 10 basis points, uninsured deposit rates rise by 2.5 basis points (25% pass-through) while insured rates rise by only 1.8 basis points (18% pass-through), reflecting banks' greater pricing power in the uninsured segment. However, this incomplete pass-through generates differential quantity responses: insured deposits contract by 0.25% while uninsured deposits contract by only 0.08%, despite the smaller rate adjustment in basis points for insured deposits. Banks respond to these deposit outflows by increasing wholesale funding by 0.12%, partially offsetting the deposit contraction, but the net effect on bank balance sheets is a contraction in lending of 0.06% on average.

The counterfactual analysis reveals substantial heterogeneity in monetary transmission across banks and markets. Small banks experience larger balance sheet contractions (0.09%) compared to large banks (0.03%), reflecting their greater reliance on deposit funding, particularly insured deposits. More competitive markets exhibit stronger pass-through to deposit rates and smaller lending contractions, while concentrated markets with greater bank market power show more muted transmission. However, interpreting these patterns is challenging because differences in market concentration and bank characteristics may reflect factors beyond market power alone. These findings extend the deposit channel of monetary policy established by Drechsler et al. (2017) by showing how deposit market segmentation creates differential depositor responses that interact with banks' pricing strategies. While Drechsler et al. (2017) demonstrate that banks with market power extract rents by widening deposit spreads when rates rise, I show that segmentation between insured and uninsured deposits enables banks to price discriminate across segments, generating nuanced effects on equilibrium pass-through that depend on the composition of banks' deposit base. This demonstrates that accounting for deposit insurance segmentation is essential for understanding bank market power in deposit markets. Measuring market power based on aggregate deposit spreads can be misleading when banks exercise differential pricing power across segments.

The remainder of the paper is organized as follows. Section 1.1 provides a detailed review of the related literature on the deposit channel of monetary transmission, structural banking models, and deposit market competition. Section 1.2 describes the data sources and key variable construction. Section 1.3 presents the four empirical facts about deposit segmentation, pricing, and pass-through. Section 1.4 develops the structural model of segmented deposit competition. Section 1.5 outlines the empirical implementation of the model. Section 1.6 presents the estimation strategy and parameter estimates. Section 1.7 analyzes counterfactual monetary policy experiments. Section 1.8 concludes.

Related Literature

This paper contributes to the literature on monetary policy transmission through bank funding and to the structural estimation of bank competition. I extend the deposit channel framework by showing how segmentation by insurance coverage creates differential pass-through across insured and uninsured deposits, and I develop a spatial model that jointly estimates demand and supply to recover segment-specific costs and competitive dynamics.

This paper builds most directly on Drechsler et al. (2017), who establish the "deposit channel" of monetary transmission: banks with market power pass through only a fraction of policy rate changes to depositors, extracting rents that vary with the level of interest rates. When the Fed raises rates, depositors' outside options become more attractive, shifting deposit demand inward. Banks respond by raising deposit rates, but the extent of pass-through depends on their market power. In concentrated markets where banks face less competition, they pass through less of the rate increase, widening the spread between policy rates and deposit rates. This incomplete pass-through causes deposits to flow out as depositors move funds to better-paying alternatives, with outflows concentrated in markets where banks have more market power and adjust rates less aggressively.

Begenau and Stafford (2022) explore how uniform rate-setting across branches affects the deposit channel; and Granja and Paixao (2019) examine deposit competition and uniform pricing in bank mergers. My paper extends this framework in two ways. First, I decompose the aggregate deposit channel into separate insured and uninsured components, showing that pass-through differs across these segments despite facing the same policy shock. Second, I structurally estimate a model that separately identifies demand-side (depositor preferences) and supply-side (bank pricing power) forces. This decomposition reveals that the heterogeneous pass-through arises from an interaction between rate sensitivity and deposit elasticities: uninsured depositors are more sensitive to policy rates but less elastic with respect to bank-specific rates, giving banks more pricing power in this segment. An important methodological distinction is that I employ general functional forms for asset revenue and wholesale funding costs, rather than the specific linear and quadratic forms in Drechsler et al. (2017). This generalization allows me to characterize the broader conditions under which policy rate changes lead to deposit outflows, asset contractions, and funding composition shifts, yielding predictions that are theoretically more ambiguous but empirically more flexible and robust to alternative banking technologies. Related work on sticky deposit rates and monetary transmission includes Driscoll and Judson (2013) and Xiao (2020); for a critical review of the deposit channel see Repullo (2020).

Recent work has further explored monetary transmission through bank funding, emphasizing the role of bank market power and deposit composition. Wang, Whited, Wu, and Xiao (2022) develop a dynamic structural model comparing bank market power to capital regulation as dampening forces on monetary transmission, jointly modeling multiple channels. Abrams (2019) shows that traditional market power measures can be biased when consumers have limited consideration sets. Brissimis, Delis, and Iosifidi (2018) examines how bank market power affects lending responses to monetary shocks in the U.S. Albertazzi, Burlon, Jankauskas, and Pavanini (2022) develop a structural model of imperfect competition in euro area banking with insured and uninsured deposits, focusing on how ECB unconventional policies (funding facilities) reduce bank fragility and prevent runs. My paper differs in examining conventional monetary policy transmission in the U.S., emphasizing how deposit market segmentation creates differential pass-through across insured and uninsured segments and across spatially heterogeneous local markets. Recent reduced-form work documents patterns during the 2022-2023 tightening cycle: Narayanan and Ratnadiwakara (2024) show that banks with more financially sophisticated depositors experienced greater outflows, while Jiang, Matvos, Piskorski, and Seru (2023) identify banks vulnerable to uninsured depositor runs. The March 2023 failures of Silicon Valley Bank and First Republic Bank, analyzed by Acharya, Richardson, Van Nieuwerburgh, and White (2023) and Jiang et al. (2023), highlighted how uninsured deposit concentration interacts with monetary transmission and financial stability. Related work includes Drechsler, Savov, and Schnabl (2021) on deposit spreads and monetary policy, and Hanson, Shleifer, Stein, and Vishny (2015) on maturity transformation and interest rate risk. Relative to this literature, my structural approach decomposes the deposit channel into insured and uninsured segments, exploiting spatial variation in branch networks to separately identify demand-side preferences from supply-side strategic pricing across deposit segments.

My estimation strategy builds on the literature using discrete choice models to estimate deposit demand. Ho and Ishii (2011a) and Dick (2008a) pioneered this approach, using branch-level data to show that consumers value branch proximity and face switching costs. Egan, Hortaçsu, and Matvos (2017) extend this framework to study deposit insurance and bank risk, developing a dynamic model of deposit competition among the 16 largest U.S. banks. They show that the deposit insurance safety net affects market discipline: uninsured depositors are more sensitive to bank risk, and reducing capital requirements below 18% destabilizes the banking system. Relative to Egan et al. (2017), who aggregate to the national level and focus on systemic banks, I exploit local market variation across approximately 200 banks operating in multiple markets to identify how deposit segmentation interacts with geographic market structure. This allows me to separately estimate how banks' strategic funding choices between insured and uninsured deposit segments vary across markets with different competitive conditions.

More recent structural work has examined specific dimensions of deposit market competition. Ho and Ishii (2011a) analyze the role of branch networks in deposit competition. Aguirregabiria, Clark, and Wang (2020) study bank diversification and geographic expansion decisions. Allen, Clark, and Houde (2009) examine how market structure affects the diffusion of e-commerce in retail banking. Related, Koont (2023) study how digital banking platforms affect deposit competition, showing that digital adoption by mid-sized banks reduces concentration but increases reliance on uninsured deposits. d'Avernas, Eisfeldt, Huang, Stanton, and Wallace (2023) examine differences in deposit pricing and business models between large and small banks, while Asil and Kastl (2023) develop a dynamic model of bank competition and regulation. Relative to these papers, my contribution is to jointly model insured and uninsured deposit segments within a unified spatial competition framework, allowing me to quantify how deposit market segmentation by insurance coverage shapes both competitive dynamics. Other work applying structural estimation to banking includes Egan, Hortaçsu, and Matvos (2021), Egan, Lewellen, and Sunderam (2022), Kuehn (2018), and Kim (2021).

A related strand of literature examines how bank size affects funding costs. Jacewitz and Pogach (2018) document that larger banks pay less for uninsured deposits. My structural approach decomposes the size-cost relationship into components attributable to scale economies in deposit servicing, market power, and risk premia. I find that recovered marginal costs decline with bank size, consistent with scale economies. See Kroszner (2016) for a literature review on bank funding costs. Other work examining deposit insurance, bank risk, and deposit pricing includes Park (1995), Acharya et al. (2023), and Pancost and Robatto (2023).

1.2 Data and Institutional Background

This section provides the institutional context for deposit markets and describes the data sources used in the analysis. I begin by explaining the structure of the U.S. banking system, the role of deposits in bank funding, and the regulatory environment linking monetary policy to deposit pricing. I then describe the primary data sources and provide summary statistics for the estimation sample.

Institutional Background

The FDIC insures deposits up to $250,000 per depositor, per insured bank, creating a regulatory threshold that divides deposits into insured and uninsured segments.[1] Deposits below this limit are fully protected against bank failure, eliminating default risk for insured depositors. For deposits exceeding $250,000, only the first $250,000 is insured, leaving the remainder uninsured and exposing depositors to potential losses if their bank fails. This creates a natural segmentation

[1] The insurance limit was $100,000 from 1980 to 2008, was temporarily raised to $250,000 in October 2008 during the financial crisis, and was made permanent in 2010 under the Dodd-Frank Act.

in deposit markets: insured depositors face minimal incentive to monitor bank risk and may prioritize convenience factors like branch access and service quality, while uninsured depositors have stronger incentives to monitor bank financial health and may demand higher interest rates. Banks pay FDIC insurance premiums ranging from 3 to 45 basis points of insured deposits, with rates determined by the bank's capital adequacy and supervisory ratings. Banks pay assessment fees only on insured deposits, creating a direct cost differential that provides banks with incentives to attract uninsured deposits.

Deposits are held by two primary types of depositors: households (retail depositors) and businesses (commercial depositors). According to the Survey of Consumer Finances (SCF), approximately 93% of U.S. households held transaction or savings deposits in 2019.[2] The median household holds approximately $4,600 in deposits, but the distribution is extremely skewed: the top 10% of households by wealth hold over 60% of all household deposits. Business deposits are even more concentrated, with large corporations and institutional clients holding substantial balances that frequently exceed FDIC insurance limits. This extreme concentration has important implications for deposit market segmentation: a relatively small share of depositors account for the majority of deposit balances and are thus most likely to hold uninsured deposits. Throughout this paper, I classify banks into three size categories based on their total assets: small banks (assets under $10 billion), medium banks ($10 billion to $100 billion), and large banks (above $100 billion). Additional details on the deposit size distribution are provided in Appendix E.

Data Sources

My analysis combines several proprietary and public datasets that together provide information on deposit rates, quantities, bank characteristics, and depositor demographics. The integrated dataset spans 2009–2019 and covers approximately 200 commercial banks operating across multiple geographic markets.

My primary source for deposit interest rates is RateWatch, a commercial vendor that collects weekly advertised rates and annual percentage yields (APY) for deposit products from over 100,000 branches representing more than 7,000 FDIC-insured depository institutions. RateWatch data

[2]The SCF is conducted triennially by the Federal Reserve Board and provides the most comprehensive data on household financial holdings in the United States.

captures the rates that banks publicly offer to attract deposits, providing detailed information including FDIC branch and owner identifiers, service type (retail vs. business), account types, and minimum balance requirements. RateWatch records the specific branch setting each rate, enabling analysis of geographic price variation even within the same banking organization. I focus on Money Market Deposit Accounts (MMDAs) with minimum deposits of $2,500 (MM2.5K) and $250,000 (MM250K), which serve as proxies for insured and uninsured deposits, respectively.[3] These account types are well-populated in the data, though for branches that do not advertise rates for these specific products, I impute rates from the closest branch within the same bank.[4]

The FDIC's Summary of Deposits (SOD) provides annual branch-level data on all FDIC-insured deposit institutions from 1994 to the present. While SOD does not report deposit quantities disaggregated by product type or insurance status, it supplies reliable information on total deposits held at each branch and precise branch locations (address, county, MSA). This geographic information is essential for defining local deposit markets and measuring bank presence across markets. I merge SOD data with RateWatch using FDIC branch identifiers to link deposit rates to deposit quantities at the branch-market level.

Every quarter, all FDIC-insured commercial banks file Consolidated Reports of Condition and Income, commonly known as Call Reports. These reports provide detailed financial information for each bank, including the composition of their balance sheets, income statements, and regulatory capital ratios. Call Reports are the only publicly available source reporting insured versus uninsured deposit quantities, reported in Schedule RC-O. Banks report total domestic deposits separated into amounts less than or equal to the FDIC insurance limit ($250,000) versus amounts exceeding this threshold, aggregated at the bank holding company level.[5] This bank-level split is essential for my imputation procedure that estimates segment-specific deposits at the local market level. For many bank-level variables such as assets, equity, loan portfolios, and other balance sheet items, I use the FDIC's Summary of Deposits and Income (SDI) database, which aggregates quarterly Call Report

[3]Money market accounts are interest-bearing deposit accounts insured by the FDIC that typically offer higher rates than regular savings accounts while allowing limited check-writing privileges. They are among the most popular deposit products for customers with substantial balances. As a robustness check, I also estimate key results using accounts with a $25,000 minimum deposit threshold in place of $2,500; results are qualitatively similar and available upon request.

[4]RateWatch data quality improved substantially after 2004, with more consistent coverage and fewer missing observations. Data quality improved further after 2010, which constitutes the majority of my sample.

[5]Specifically, banks report estimated insured deposits, uninsured deposits, and preferred deposits on Schedule RC-O of the Call Report. Insured amounts include deposits in accounts where the balance is within FDIC coverage limits after considering depositor ownership categories and account titling.

data at the institution level. I obtain Call Report and SDI data from the FDIC's publicly available databases.

I complement bank-level supply data with demand-side information from the Survey of Consumer Finances (SCF), a triennial household survey conducted by the Federal Reserve Board. The SCF provides detailed information on household demographics, income, wealth, and financial account holdings including deposit account balances and the number of deposit accounts held at different institutions. The SCF is particularly valuable for two purposes: (1) understanding the distribution of deposit account sizes across households, which informs how I model the insured/uninsured split in depositor populations, and (2) validating my imputed local market quantities by comparing aggregate patterns to survey-based estimates. Appendix E provides detailed analysis of depositor heterogeneity using SCF microdata.

I employ the American Community Survey (ACS) from the U.S. Census Bureau, which provides annual demographic and economic information at the county and census tract level. It includes median household income, population, age distribution, educational attainment, and homeownership rates. These local-level characteristics serve as controls in estimation and help explain spatial variation in deposit demand. To capture the business side of the deposit market, I use County Business Patterns (CBP) data containing establishment counts, employment, and payroll by industry and county.[6] I further supplement this with industry-level gross output data from the Bureau of Economic Analysis's (BEA) KLEMS database to refine estimates of business deposit demand.

Finally, federal funds rates, and other macroeconomic indicators are obtained from the Federal Reserve Economic Data (FRED) database maintained by the Federal Reserve Bank of St. Louis.

Geographic Market Definition

I define deposit markets as county clusters rather than individual counties to reduce measurement error in market shares and improve computational feasibility. This definition is motivated by two empirical regularities documented in the banking literature. First, depositors exhibit strong preferences for geographic proximity when choosing banks: Dick (2008a) and Ho and Ishii (2011a) find that branch proximity is a primary determinant of bank choice, with households willing to

[6]CBP data exclude government employees, self-employed individuals, and farm workers, and cover around 75% of private sector employment. I use payroll as a proxy for business deposit balances, following the approach that businesses hold deposits proportional to operating expenses.

travel only short distances for banking services. Second, large banks manage deposit pricing across broad geographic zones rather than setting rates branch-by-branch: in Labrador-Badia (2025), I document that multi-market banks typically set uniform deposit rates across entire states or regions, reflecting administrative constraints and competitive considerations that operate at scales larger than individual counties.

Given these institutional features, the clustering algorithm aggregates contiguous counties based on commuting patterns and deposit market integration, following d'Avernas et al. (2023). The procedure iteratively merges lower-population counties that are adjacent, with limited consideration of similarity in characteristics such as population and deposit concentrations, until reaching a target number of economically meaningful markets. The final sample consists of approximately 450 geographic markets, which include clusters of large MSAs with nearby counties as well as grouped rural counties. This approach balances geographic granularity with data reliability, as market shares measured at the county level can be noisy in sparsely populated areas or markets with few bank branches. Appendix K provides the complete clustering algorithm and resulting market definitions.

Sample Construction

For the structural estimation, I restrict the sample to banks for which I observe *both* MM2.5K *and* MM250K rates in at least one branch, ensuring that I observe pricing behavior across both segments for each bank in the analysis. This restriction focuses the analysis on banks that actively compete in both the insured and uninsured deposit markets. For county clusters where a bank has branches but no observed rates for a particular product, I impute the missing rate using the observed rate at the geographically closest branch within the same bank, where distance is measured as geodesic distance. This spatial imputation affects less than 15% of bank-county cluster observations in most years.

I further restrict the sample to the 200 largest banks by total assets, which account for the majority of deposits and assets held in commercial retail banking. I exclude online-only and hybrid banks, which represent less than 10% of total market share in all years, because these institutions do not fit the spatial competition framework central to my identification strategy. This restriction helps balance the computational demands of the estimation with the need for broad market coverage. By focusing on the largest banks with physical branch networks, I capture institutions that operate in multiple markets and account for a substantial share of deposits. As a robustness check, I also estimate key results using samples of the largest 250 and 300 banks, which encompass banks of all sizes; results are qualitatively similar and available upon request. The sample period from 2009 to 2019 covers both the zero lower bound era and the subsequent monetary policy normalization cycle, during which rates gradually increased. This period provides substantial variation in the federal funds rate, which is essential for identifying how monetary policy affects deposit pricing.

1.3 Deposit Market Facts

This section presents four stylized facts about U.S. deposit markets that motivate the central research questions and guide the structural model specification. First, banks systematically pay higher interest rates on uninsured deposits relative to insured deposits. Second, monetary policy pass-through to deposit rates is incomplete and differs across segments, with uninsured deposits exhibiting stronger pass-through. Third, banks with high uninsured deposit shares are geographically concentrated in competitive urban markets. Fourth, uninsured deposit shares increase systematically with bank size. Together, these facts establish that deposit markets are segmented along the insurance dimension, that this segmentation has implications for monetary transmission, and that both demand-side preferences and supply-side competition vary across segments and geography. These patterns motivate a structural framework that models insured and uninsured deposits as distinct products with segment-specific demand elasticities, allows for spatial competition across heterogeneous local markets, and incorporates bank-level strategic choices over deposit composition.

Banks Pay a Segmentation Premium on Uninsured Deposits

I define the *segmentation premium* as the difference in interest rates offered on uninsured versus insured deposits: Segmentation Premium $= r_{\text{uninsured}} - r_{\text{insured}}$. To measure this premium empirically, I follow the approach in Egan et al. (2017) and Jagtiani, Jacewitz, and Pogach (2017), using deposit rates on accounts with *large* minimum deposit requirements as a proxy for uninsured deposits and rates on accounts with *small* minimum deposit requirements as a proxy for insured deposits.

Figure 1.1 shows that banks consistently pay higher rates on uninsured deposits compared to insured deposits. During the period 2009–2019, using money market account data, banks paid on average 12.8 basis points more on accounts requiring $250,000 minimum deposits (proxy for uninsured) compared to accounts requiring $2,500 minimum deposits (proxy for insured), approximately three times the rate level paid on insured deposits. The median premium is 9.7 basis points with a standard deviation of 18.2 basis points. As a percentage of the insured rate, the segmentation premium averages 196.7% (median: 118.8%), meaning uninsured rates are approximately three times higher than insured rates. These statistics are computed at the bank-year-market level, which gives greater weight to large multi-market banks.[7]

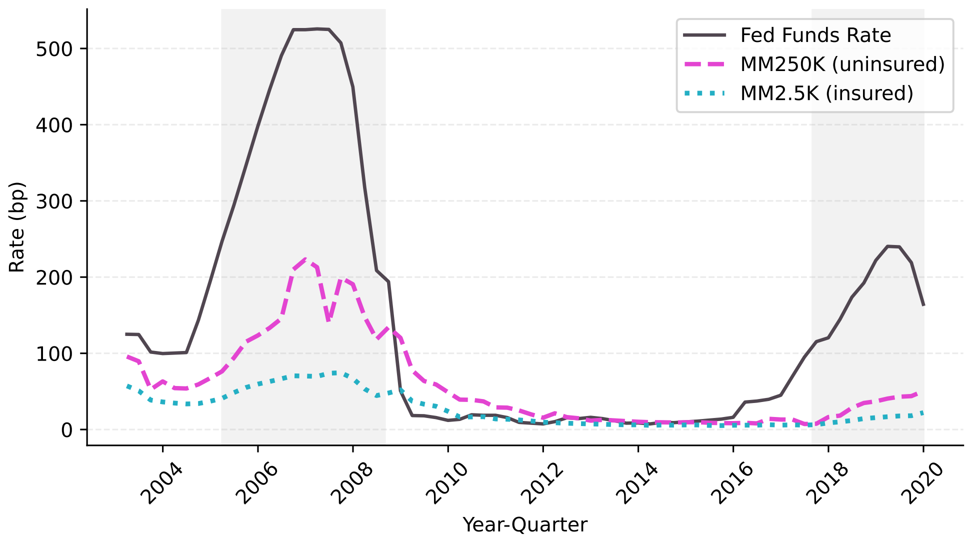
Segmentation Premium Determinants: Preliminary Evidence

Banks offering higher interest rates on uninsured deposits are likely to attract more customers opting for such deposits, potentially increasing their share of uninsured funds. However, the higher premiums also increase funding costs, which could exacerbate financial distress at riskier institutions. This might lead customers to move their insured deposits to less financially distressed banks, prioritizing stability over higher returns. Hence, a simple reduced-form analysis of the relationship between the share of uninsured deposits and the segmentation premium might not be sufficient to capture the nuances of this relationship.

Instead, I take a hedonic pricing approach to decompose the segmentation premium into its underlying determinants. By regressing the premium on observable bank characteristics (particularly measures of bank riskiness and size) while controlling for bank, market, and time fixed effects, I can identify which bank attributes systematically affect the price differential between insured and uninsured deposits. This provides preliminary evidence on whether the segmentation premium reflects risk compensation (market discipline), scale economies in serving different depositor types, or other structural features of deposit competition. To implement this, I estimate

[7] Because the bank-market-level weighting scheme gives more weight to banks operating in more markets, and larger banks tend to offer lower rates, these averages may understate the typical rates paid by smaller institutions. An alternative bank-level aggregation (weighting each bank equally regardless of market presence) yields qualitatively similar patterns with somewhat higher average rate levels.

Figure 1.1: Deposit rates by segment and monetary policy



Notes: Quarterly time series (2003–2020) showing the federal funds rate (black line), insured deposit rates for MM2.5K accounts (lower series, labeled "Insured"), and uninsured deposit rates for MM250K accounts (upper series, labeled "Uninsured"). Both deposit rate series are consistently below the federal funds rate — pass-through is incomplete, with deposit rates typically less than half the federal funds rate level. The uninsured series sits above the insured series throughout, reflecting the segmentation premium documented in the text. Both series track the federal funds rate cycle qualitatively but attenuate its magnitude. Shaded areas indicate periods of elevated policy rates. Rates are weighted by national insured and uninsured deposit shares respectively. Data source: RateWatch and FRED.

the following model:

$$\ln(r^U_{jmt}) - \ln(r^I_{jmt}) = \alpha_0 + \gamma\rho_{jm} + X_{jmt}\beta + \tau_t + \eta_m + \tau_{tm} + \epsilon_{jmt} \quad (1.1)$$

where t is the year, m is the county cluster (local market), j is the bank, r^U_{jmt} is the interest rate for MM250K, r^I_{jmt} is the interest rate for MM2.5K, and the dependent variable $\ln(r^U_{jmt}) - \ln(r^I_{jmt})$ is the log segmentation premium.[8] The variable ρ_{jm} represents the bank's riskiness, measured by the lagged z-score (the sum of return on assets and equity-to-assets ratio, divided by the standard deviation of return on assets). Higher z-scores indicate lower risk, so a negative coefficient implies riskier banks pay higher segmentation premiums. The vector X_{jmt} includes lagged bank characteristics: number of branches, number of counties, number of employees, total assets, and log bank age.

I estimate this specification with progressively saturated fixed effects. Column (5) includes

[8] I use log differences rather than level differences because the segmentation premium naturally scales with the rate level. Results are qualitatively similar using the level difference $r^U_{jmt} - r^I_{jmt}$ or the ratio r^U_{jmt}/r^I_{jmt} as the dependent variable; see Appendix Tables 1.30 and 1.31.

Table 1.1: Determinants of the log segmentation premium

	(1)	(2)	(3)	(4)	(5)
	Segmentation Premium (log)				
L.Z-Score	-1.445***	-1.299***	-1.677***	-1.691***	-1.674***
	(0.345)	(0.349)	(0.354)	(0.361)	(0.375)
L.Assets (100 millions)	-0.140***	-0.159***	-0.139***	-0.145***	-0.154***
	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)
L.Number Counties (tens)	-0.037***	-0.041***	-0.037***	-0.038***	-0.040***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
L.Branches (hundreds)	0.049***	0.056***	0.049***	0.050***	0.054***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
L.Employees (thousands)	0.008***	0.009***	0.007***	0.007***	0.008***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log Bank Age	0.229***	0.225***	0.233***	0.234***	0.235***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Constant	-0.056	-0.039	-0.062	-0.065	-0.068
	(0.057)	(0.058)	(0.058)	(0.059)	(0.061)
Year FE	–	✓	–	✓	–
County Cluster FE	–	–	✓	✓	–
Year × County Cluster FE	–	–	–	–	✓
Observations	58754	58754	58754	58754	58753
Adjusted R^2	0.129	0.139	0.155	0.164	0.179

Notes: This table presents the results from estimating equation (1.1), regressing the log segmentation premium (log difference between MM250K and MM2.5K rates) on lagged bank characteristics. The z-score measures bank financial health (higher values indicate lower risk): $z\text{-score} = (ROA + \text{Equity}/\text{Assets})/\sigma(ROA)$, where $\sigma(ROA)$ is the standard deviation of return on assets. All bank characteristics are lagged one period to mitigate simultaneity concerns. The sample includes banks operating in county clusters from 2009 to 2019, using county-level deposit rates from the structural demand estimation. Column (1) has no fixed effects, column (2) includes year fixed effects, column (3) includes county cluster fixed effects, column (4) includes both year and county cluster fixed effects separately, and column (5) includes year-by-county cluster fixed effects (interaction) to absorb all time-varying local market shocks. Standard errors are two-way clustered by bank and county cluster. Standard errors in parentheses, clustered by bank and county cluster. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

year-by-county cluster fixed effects (τ_{tm}), the preferred specification, which absorbs all time-varying local market shocks so that identification comes purely from comparing banks within the same market in the same year.

Table 1.1 presents the estimation results. The z-score coefficient is negative and highly significant across all specifications, ranging from -1.299 to -1.691. Since higher z-scores indicate lower risk, the negative coefficient implies that riskier banks pay *higher* segmentation premiums. Using the preferred specification in column (5), a one-standard-deviation decrease in the z-score is associated with approximately a 15% increase in the segmentation premium.[9] This finding is consistent with uninsured depositors exercising market discipline, demanding higher rates at riskier banks to compensate for uninsured default risk, as documented by Egan et al. (2017) using CDS spreads.

Larger banks pay lower segmentation premiums (negative coefficient on assets), consistent with Jacewitz and Pogach (2018). Older banks pay higher premiums, potentially reflecting legacy depositor relationships. The core result remains stable across specifications, with the most saturated specification (column 5) including year-by-county cluster fixed effects to control for time-varying local market conditions.

Appendix Table 1.30 presents robustness checks using alternative dependent variables: the ratio r^U/r^I and the adjusted premium $(r^U - r^I)/r^I$. Appendix Table 1.31 shows results using contemporaneous (non-lagged) bank characteristics. The negative relationship between bank risk and the segmentation premium is robust across all specifications. Appendix Table 1.22 supplements these results by adding a large-bank indicator directly to the specification, confirming that large banks (assets $>$ \$100 billion) pay lower segmentation premiums controlling for risk and other bank characteristics.

Differential Monetary Policy Pass-Through by Segment

A second feature of deposit markets is that the pass-through of monetary policy to deposit rates is incomplete and differs across segments. Figure 1.1 illustrates this, showing that uninsured deposit rates track the federal funds rate more closely than insured rates. To quantify this, I estimate the pass-through coefficients by regressing the change in deposit rates on the change in the federal funds rate for each segment.

Table 1.2 presents the results, showing that the pass-through coefficient for uninsured deposits is approximately 0.10, while for insured deposits, it is 0.08. Both estimates are statistically significant. The difference between them is also statistically significant at the 1 percent level ($p < 0.01$). This confirms that a 1 percentage point increase in the federal funds rate leads to a 10 basis point increase in uninsured deposit rates, compared to an 8 basis point increase for insured rates, a differential of 2 basis points that is economically meaningful and precisely estimated. This differential pass-through

[9] The average z-score in the sample is approximately 8.5 with a standard deviation of 9.2. A coefficient of -1.674 implies that a one-standard-deviation decrease ($\Delta z = -9.2$) increases the log premium by $1.674 \times 9.2 \approx 15.4$ percentage points.

is a key motivation for the segmented model in this paper, as it suggests that the transmission of monetary policy varies systematically with a bank's deposit composition.

Several factors can explain this differential pass-through. The outside options available to depositors vary significantly across segments: uninsured depositors, often businesses or wealthy households, have easier access to alternatives like money market funds or Treasury bills and are thus more sensitive to the widening spread between policy rates and deposit rates. Demand elasticities may differ across segments. If uninsured depositors are more rate-sensitive, banks optimally pass through more of the policy rate increase to this segment. Supply-side costs may also respond differently to monetary policy across segments, as FDIC deposit insurance assessment fees vary with bank risk and could adjust as monetary policy affects bank balance sheets. Additionally, geographic differences in competitive intensity and variation in how banks serve different depositor types could generate heterogeneous pass-through across markets and bank characteristics.

Table 1.2: Pass-through estimates by segment

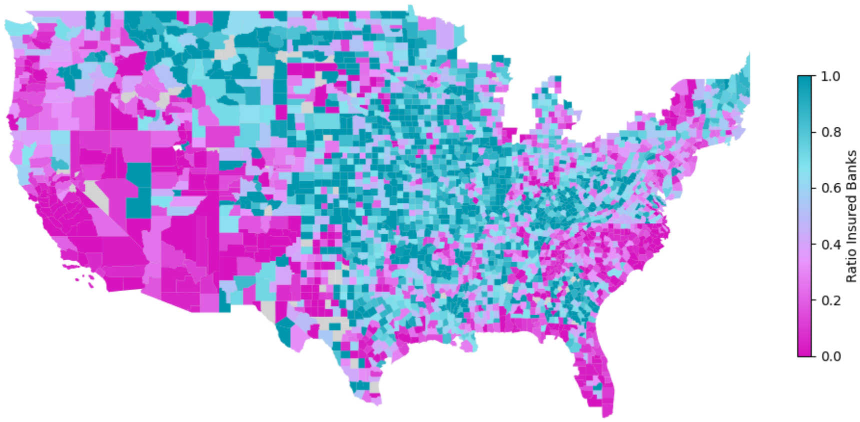
	Insured	Uninsured
Δf	0.081***	0.100***
	(0.003)	(0.004)
Observations	25756	25756
Adjusted R^2	0.148	0.145

Notes: The table shows the pass-through of the federal funds rate to insured and uninsured deposit rates. The regression is $\Delta r_{gjt} = \alpha_g \Delta \text{FF Rate}_t + \epsilon_{jt}$. The sample includes all banks in the RateWatch data from 2009 to 2019. Standard errors are clustered by bank.

Pass-through heterogeneity varies across banks. Table 1.20 and Figure 1.18 in the appendix show that medium and large banks compress the segmentation premium when policy rates rise, whereas small banks exhibit smaller effects, suggesting larger institutions face different competitive pressures or employ distinct pricing strategies during monetary tightening. Figure 1.14 displays the full distribution of pass-through coefficients, revealing that uninsured segment pass-throughs are more dispersed than insured, though the differences in tail behavior are not statistically significant.

While these reduced-form estimates are illustrative, they are not sufficient for a complete analysis. Deposit rates are equilibrium outcomes of banks' optimization decisions, reflecting both demand and supply forces. Contemporaneous shocks can affect both policy rates and deposit market conditions simultaneously. This creates an endogeneity problem that can bias the estimates.

Figure 1.2: Geographic distribution of insured deposit shares, 2019



Notes: This map shows the deposit-weighted share of banks in each county that hold predominantly insured deposits (>70% insured). Teal/cyan shading (value near 1) indicates counties where most deposit dollars are held by banks with insured-focused business models; pink/magenta shading (value near 0) indicates counties dominated by banks with uninsured-focused models. Both color and shading intensity encode the underlying value, so the map is interpretable without color distinction. Data source: Call Reports and SOD.

A structural model is therefore necessary to properly identify the underlying demand and supply parameters and to conduct policy counterfactuals. The model I develop explicitly accounts for segment-specific demand elasticities, supply-side strategic pricing, and spatial market structure to decompose these reduced-form pass-through differences into their fundamental economic drivers.

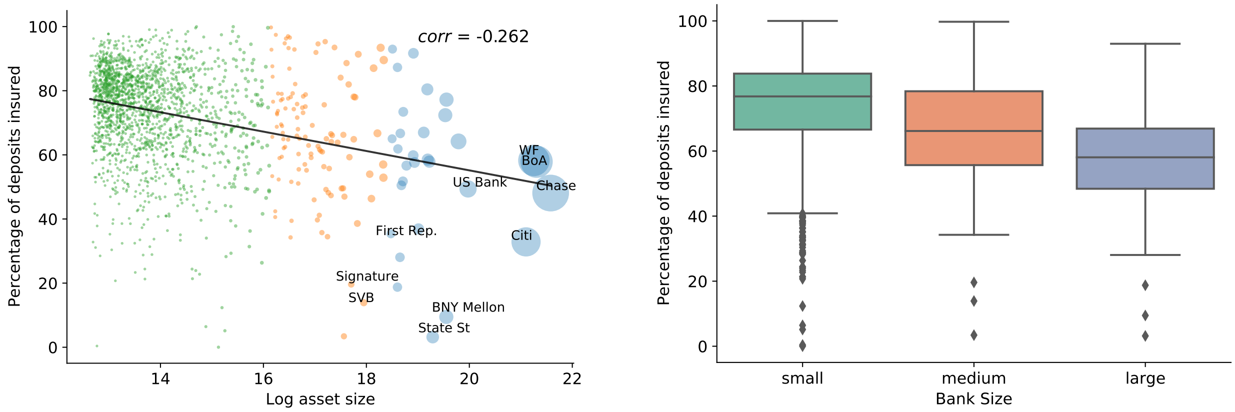
Spatial Heterogeneity in Banks with Uninsured Deposits

Figure 1.2 reveals striking spatial patterns in the distribution of banks' deposit composition. To construct this measure, I first classify each bank based on its deposit composition. I label a bank as "uninsured-focused" if less than 70 percent of its deposits are FDIC-insured—or equivalently, if more than 30 percent are uninsured. Then, for each county, I calculate what share of total deposits comes from these uninsured-focused banks. This gives me a deposit-weighted measure of how important uninsured-focused banks are in each local market. The resulting map takes values between 0 and 1, where counties dominated by uninsured-focused banks (pink, value near 0) contrast with counties dominated by insured-focused banks (blue, value near 1).[10]

The geographic clustering is stark: banks with high uninsured deposit shares concentrate

[10]As a robustness check, Appendix Figure 1.20 shows the simple unweighted average of banks' uninsured deposit shares by county in 2019, which exhibits very similar geographic patterns. Figure 1.19 shows the same map for years 2012, 2016 and 2020, demonstrating that these spatial patterns are stable over time, though smaller in magnitude in earlier years.

Figure 1.3: Distribution of insured deposit shares by bank size, 2019



(a) Scatter plot by total assets

(b) Box plot by size category

Notes: Panel (a) shows the distribution of banks by total insured deposits as a percentage of domestic deposits in 2019. The size of the dots represents total assets, with colors and shapes indicating bank size: small banks (<$10B, green circles), medium banks ($10B–$100B, orange triangles), and large banks (>$100B, blue squares). Panel (b) shows box plots of the same distribution by size category labeled “Small,” “Medium,” and “Large,” revealing that larger banks have higher and more dispersed uninsured deposit shares. Data source: Call Reports and SOD.

in major metropolitan areas and financial centers, particularly along the East and West coasts, while interior and rural counties are dominated by banks serving primarily insured depositors. This spatial pattern likely reflects the interaction of several forces: the geographic distribution of depositor types (wealthy households and large businesses concentrate in urban centers), banks’ strategic positioning and service specialization (some banks develop expertise in cash management for corporate clients), and local competitive dynamics. This geographic heterogeneity has important implications for understanding monetary policy transmission and motivates the spatial competition framework in my structural model, where banks compete across local markets with varying demographic compositions and competitive characteristics, allowing me to separately identify the contribution of depositor preferences versus banks’ strategic pricing decisions.

Uninsured Deposit Shares Increase with Bank Size

The geographic concentration of uninsured-focused banks documented above is closely related to bank size: larger banks systematically hold higher shares of uninsured deposits. This relationship between bank size and deposit composition has been recently documented by Begenau, Landvoigt, and Elenev (2024).

Figure 1.3 displays the distribution of insured deposit shares across banks in 2019, with marker sizes proportional to total assets and colors denoting size categories: small banks (<$10 billion, green), medium banks ($10–$100 billion, orange), and large banks (>$100 billion, blue). Panel (a) reveals a clear negative relationship between bank size and insured deposit share: larger banks hold substantially lower shares of insured deposits, equivalently higher shares of uninsured deposits. Panel (b) presents the same information as box plots by size category, showing that the median large bank has approximately 60% insured deposits compared to 75% for medium banks and over 80% for small banks. Substantial heterogeneity exists within each size category, indicating that bank size does not mechanically determine deposit composition. Strategic choices, market positioning, and local market characteristics also play important roles.

This systematic relationship between size and uninsured deposit share has several explanations. First, larger banks operate in more markets, including the competitive urban markets where uninsured depositors concentrate. Second, larger banks may have comparative advantages in serving business customers and high-net-worth individuals who hold uninsured balances, through specialized services, relationship banking, or superior technology. Third, uninsured depositors (those with large account balances exceeding FDIC coverage) may perceive larger banks as safer, making them willing to hold uninsured funds at these institutions despite potentially lower rates. The model accounts for this size heterogeneity by allowing banks to differ in their branch networks and market presence. These differences, in turn, shape each bank's equilibrium deposit composition, which determines how the bank responds to monetary policy shocks.

Table 1.3 documents the evolution of the U.S. deposit market structure from 2005 to 2020, broken down by bank size categories. Several patterns stand out. First, consolidation has concentrated deposits among fewer and larger institutions. The number of small banks fell sharply, from 8,764 in 2005 to 4,903 in 2020, a decline of nearly 44 percent. Meanwhile, the number of large banks tripled, growing from 11 to 33 over the same period. Second, large banks have dramatically restructured their branch networks, with the average large bank reducing branches from 2,858 to 1,020, while their total deposits increased, indicating a shift toward higher deposits per branch. Third, the insured deposit share (I.D. %) exhibits the size gradient documented in Figure 1.3: large banks consistently maintain lower insured shares (54–61%) compared to small banks (77–86%), confirming that the size-composition relationship is stable over time. Fourth, the standard deviation of insured deposit shares is highest for large and medium banks (19–23%), reflecting

Table 1.3: Descriptive statistics of the deposit market in the U.S.

Size	Banks	Dep. (bill)	Asset (bill)	MSAs	Branches	I.D. %	Std. I.D %
			year: 2005				
large	11	199.84	418.06	127.29	2857.57	58.89	12.49
medium	103	16.32	30.17	27.53	407.96	65.07	21.22
small	8764	0.23	0.32	1.97	8.99	77.29	15.64
			year: 2010				
large	19	199.2	409.27	89.25	1857.56	60.85	22.46
medium	85	18.56	29.37	16.89	193.27	72.96	20.96
small	7615	0.3	0.38	1.94	8.56	86.42	11.74
			year: 2015				
large	23	269.38	439.67	68.09	1369.77	51.39	23.24
medium	89	23.22	31.23	16.35	186.11	65.01	22.69
small	6218	0.38	0.47	1.9	8.15	82.15	12.36
			year: 2020				
large	33	312.31	445.39	53.39	1020.36	54.4	22.22
medium	117	22.63	28.42	12.61	123.57	64.21	19.02
small	4903	0.53	0.65	1.79	7.11	77.37	13.43

Notes: The table shows the number of banks, total deposits, total assets, the number of MSAs, the number of branches, the insured deposit share (I.D. %), and the standard deviation of insured deposit shares (Std. I.D %). Large banks are those with assets over 100 billion dollars, medium banks are those with assets between 10 and 100 billion dollars, and small banks are those with assets under 10 billion dollars. The data source is the Summary of Deposits and Call Reports from the FDIC for the years 2005, 2010, 2015, and 2020.

greater strategic heterogeneity among these institutions, while small banks are more homogeneous (12–16%).

These temporal patterns underscore that deposit market segmentation is not a recent phenomenon but a persistent structural feature. The 2008 financial crisis and the regulatory changes that followed (including the increase in FDIC insurance coverage from $100,000 to $250,000) affected banks of all sizes. However, the relative ordering of deposit compositions across bank size categories remained stable throughout this period. This stability suggests that the underlying demand and supply forces generating segmentation (differences in depositor preferences, banks' comparative advantages in serving different customer types, and spatial variation in market competition) are fundamental rather than transitory. The model developed in the next section is designed to capture these persistent structural forces. Appendix Tables 1.23 and 1.24 provide additional evidence on the determinants of uninsured deposit shares, regressing the share of uninsured deposits on bank risk measures (loan-loss provisions and equity-to-assets ratios) and bank characteristics; results confirm that riskier banks carry lower uninsured deposit shares, consistent with depositor flight toward insured accounts at distressed institutions.

Summary of Empirical Facts and Model Implications

The four empirical facts documented in this section jointly motivate the structural framework developed below. The segmentation premium (Fact 1) and differential pass-through (Fact 2) establish that insured and uninsured deposits have distinct pricing dynamics and respond differently to monetary policy, requiring separate treatment in both demand and supply. The spatial concentration of uninsured-focused banks (Fact 3) and the size gradient in deposit composition (Fact 4) demonstrate that market structure and competitive intensity vary systematically across geography and bank characteristics, requiring a model that incorporates spatial competition and allows for heterogeneous bank strategies. Together, these facts imply that aggregate monetary policy pass-through reflects a complex interaction of segment-specific demand elasticities, spatial market power, and banks' strategic choices over deposit composition.

1.4 Model of Bank Competition

The empirical facts documented in Section 1.3 establish that deposit markets are segmented, with distinct pricing and pass-through dynamics across insured and uninsured deposits, heterogeneous bank strategies across geography and size, and systematic relationships between deposit composition and monetary policy transmission. To analyze the economic mechanisms underlying these patterns, I develop a simple theoretical model of bank competition with segmented deposit markets. This model provides a conceptual framework for understanding how deposit market segmentation affects banks' funding choices and monetary policy transmission. The theoretical predictions guide the specification and interpretation of the structural model estimated in Section 1.5.

The modeling framework builds on Drechsler et al. (2017), who establish the "deposit channel" of monetary policy transmission. I extend their Cournot framework to incorporate deposit market segmentation, allowing for differential demand elasticities and cost structures between insured and uninsured deposits. This extension is critical for understanding the differential pass-through documented in Fact 2 and for predicting how monetary policy effects vary with banks' deposit composition, a first-order consideration given the systematic relationship between bank size and uninsured deposit shares documented in Fact 4.

Bank Profit Maximization and Funding Choices

Banks maximize profits by choosing their optimal funding mix across three sources: insured deposits (D^I), uninsured deposits (D^U), and wholesale funding (H). Let A denote the bank's total assets, consisting primarily of loans and securities. The balance sheet identity imposes a funding constraint linking these sources to total assets:

$$A = D^I + D^U + H \tag{1.2}$$

For simplicity, I subtract equity from assets so that A is assets net of equity, rather than modeling it as a separate funding source. This static formulation focuses on the bank's choice of funding composition conditional on its existing equity base, following standard practice in models of deposit competition.

Bank j's profit maximization problem at time t in market m is:

$$\max_{D^I, D^U, H} \quad \underbrace{\ell(A, f)}_{\substack{\text{asset}\\\text{revenue}}} - \underbrace{\omega(H, f) \cdot H}_{\substack{\text{wholesale}\\\text{cost}}} - \underbrace{\left(c^U + r^U(D^U, f)\right)D^U}_{\substack{\text{uninsured}\\\text{cost}}} - \underbrace{\left(c^I + r^I(D^I, f)\right)D^I}_{\substack{\text{insured}\\\text{cost}}} \tag{1.3}$$

subject to the funding constraint (1.2), where f denotes the federal funds rate.

The profit function reflects four economically distinct revenue and cost components. *Asset revenue* $\ell(A, f)$ represents returns from lending and securities holdings. I assume diminishing returns to scale in asset deployment: $\partial\ell/\partial A > 0$ but $\partial^2\ell/\partial A^2 \leq 0$, reflecting increasing costs of finding profitable lending opportunities or regulatory capital constraints. The function depends on the federal funds rate with $\partial\ell/\partial f > 0$, capturing that higher policy rates typically increase lending margins. *Wholesale funding cost* $\omega(H, f) \cdot H$ represents the total cost of non-deposit funding sources such as federal funds borrowing, Federal Home Loan Bank (FHLB) advances, or repurchase agreements. The marginal cost $\omega(H, f)$ increases in quantity ($\partial\omega/\partial H > 0$) and in the policy rate ($\partial\omega/\partial f > 0$), since wholesale rates are tightly linked to the federal funds rate.

The *deposit costs* for each segment $g \in \{I, U\}$ have two components: the interest rate $r^g(D^g, f)$ and the non-interest servicing cost c^g. The inverse demand functions $r^g(D^g, f)$ capture how banks must adjust rates to attract different deposit quantities, with $\partial r^g/\partial D^g > 0$ (larger quantities require higher rates) and $\partial r^g/\partial f > 0$ (depositors demand higher rates when policy rates rise). The servicing costs c^g differ across segments: c^I includes FDIC insurance premiums (3 to 45 basis points depending on bank risk category) and retail branch expenses, while c^U reflects relationship management and cash management services for larger depositors.

Taking first-order conditions with respect to D^I, D^U, and H, and using the funding constraint (1.2) to substitute for A, yields optimality conditions that equate marginal revenue from assets to marginal cost for each funding source:

$$\frac{\partial \ell}{\partial A} = \omega(H, f) + H\frac{\partial \omega}{\partial H} \qquad (\text{FOC}_H) \tag{1.4}$$

$$\frac{\partial \ell}{\partial A} = \left(c^g + r^g(D^g, f)\right) + D^g\frac{\partial r^g}{\partial D^g} \qquad (\text{FOC}_{D^g}),\ g \in \{I, U\} \tag{1.5}$$

Combining the deposit conditions eliminates the common marginal revenue term, yielding the cross-segment equilibrium condition:

$$c^I + r^I(1 + \eta^I) = c^U + r^U(1 + \eta^U) \tag{1.6}$$

where η^g is the inverse elasticity of deposit demand.[11] This condition says banks equate the marginal cost of obtaining deposits across segments. The full marginal cost includes the non-interest servicing cost c^g, the direct interest rate r^g, and the market power wedge $r^g\eta^g$, the additional cost from raising rates on the entire existing deposit base when expanding quantity. Rearranging yields $r^I\eta^I - r^U\eta^U = (c^U - c^I) + (r^U - r^I)$, revealing that the segmentation premium $r^U - r^I$ reflects both servicing cost differences and inverse elasticity differences across segments.

Comparative Statics: Monetary Policy Transmission

When the Federal Reserve raises the federal funds rate f, multiple channels activate simultaneously: depositors' outside options improve, wholesale funding costs increase directly, and loan demand and lending margins adjust. I focus on comparative statics with respect to an increase in the policy rate f, characterizing the sign and magnitude of responses in deposit quantities, deposit composition, wholesale funding, and total assets.

[11] The inverse elasticity η^g is defined as the diagonal element of the matrix $(\mathbf{J}^g)^{-1} \cdot D^g/r^g$, where $\mathbf{J}^g = \partial D^g/\partial r^g$ is the Jacobian of the demand system.

Proposition 1. *An increase in the policy rate f triggers substitution and scale effects on a bank's balance sheet. Under standard assumptions—asset revenue is increasing and strictly concave in quantity ($\ell_A > 0, \ell_{AA} < 0$), and total costs for each funding source are strictly convex in their respective quantities—the following predictions hold:*

1. *Total deposit outflows (scale effect)*: If the marginal cost of deposits rises at least as much as the marginal revenue from assets ($\partial c^g/\partial f + \partial r^g/\partial f \geq \partial \ell/\partial A \partial f$), then total deposits decline: $\frac{\partial (D^I + D^U)}{\partial f} < 0$.

2. *Asset contraction (scale effect)*: If the weighted average of net marginal cost increases (the rise in funding cost net of any rise in asset revenue) is positive, then total assets contract: $\frac{\partial A}{\partial f} < 0$.[12]

3. *Deposit segment shift (substitution effect)*: If uninsured deposits have sufficiently more semi-elasticic than insured deposits, the share of uninsured deposits declines: $\frac{\partial (D^U/D)}{\partial f} < 0$. Specifically, the condition is $(2r'_U + r''_U D_U) D_U < (2r'_I + r''_I D_I) D_I$.[13]

4. *Wholesale funding substitution*: Banks substitute toward wholesale funding if (i) its marginal cost is less sensitive to the policy rate than deposits ($\partial \omega/\partial f + \omega_{Hf} < \partial c^g/\partial f + \partial r^g/\partial f$ for $g \in \{I, U\}$), and (ii) its marginal cost does not rise more than marginal asset revenue ($\partial \omega/\partial f + \omega_{Hf} \leq \partial \ell/\partial A \partial f$): $\frac{\partial H}{\partial f} > 0$.[14]

For the functional forms chosen in Drechsler et al. (2017), conditions (1), (2), and (4) are automatically satisfied. I extend the analysis to segmented deposit markets where condition (3) depends on the stated sufficient conditions regarding relative demand elasticities.

The economic intuition works through two fundamental mechanisms. The *scale effect* reflects the overall profitability of financial intermediation: when policy rates rise, both funding costs and asset returns adjust, but if funding costs rise faster (as occurs when deposit demand is relatively

[12]The precise condition is: $\frac{(c^I_f + r^I_f) - \ell_{Af}}{2r^I_{D^I} + r^I_{D^I D^I} D^I} + \frac{(c^U_f + r^U_f) - \ell_{Af}}{2r^U_{D^U} + r^U_{D^U D^U} D^U} + \frac{(\omega_{Hf} + \omega_f) - \ell_{Af}}{\omega_{HH} + \omega_H} > 0$, where weights are the inverse of the slope of each funding source's marginal cost curve.

[13]This condition holds automatically if deposit supply curves are linear ($r'' = 0$), in which case it simplifies to $r'_U D^U < r'_I D^I$, or equivalently that uninsured deposits have lower inverse semi-elasticity. With non-linear supply, the condition requires that the inverse semi-elasticity gap is large enough to account for differences in the convexity of supply curves. See Appendix A for detailed discussion.

[14]This joint condition ensures that the positive substitution effect toward wholesale funding is not offset by a negative scale effect from balance sheet contraction.

inelastic and depositors require substantial rate increases to retain deposits), then the net interest margin declines and banks shrink their balance sheets. This contraction represents the core deposit channel of monetary policy transmission: tighter policy reduces bank lending capacity by making deposit funding more expensive. The *substitution effect* reflects relative cost changes across funding sources: banks reallocate their funding mix toward whichever sources experience the smallest cost increases. If uninsured depositors have better outside options (money market funds, Treasury bills) and are therefore more rate-sensitive, their deposits become relatively more expensive when policy tightens, inducing banks to shift toward insured deposits or wholesale funding.

Critically, the net effect on deposit composition is theoretically ambiguous and must be estimated empirically. It depends on three key structural features: (1) the segment-specific pass-through elasticities ($\partial r^g / \partial f$), which determine how much banks must raise rates in each segment to retain depositors when outside options improve; (2) the inverse demand slopes η^I and η^U, which govern how much additional rate increases are required to attract marginal deposits; and (3) the relative magnitudes of quantity versus price adjustments in equilibrium, which reflect the interaction of demand elasticities with competitive intensity. My counterfactual analysis quantifies these effects using the structurally estimated demand parameters and banks' revealed funding cost structures.

Proof sketch: The results follow from totally differentiating the first-order conditions (1.4)–(1.5) with respect to f and applying the implicit function theorem to solve the resulting linear system. The second-order condition for profit maximization requires that the Hessian determinant be negative. To determine the sign of each comparative static, I apply Cramer's rule. The sign depends on whether the numerator determinant is positive or negative, which gives the sufficient conditions stated above. Full derivations are provided in Appendix A.

Effect of segmentation on monetary transmission. While Proposition 1 characterizes direct effects of policy shocks, a key question remains: does segmentation itself amplify or dampen transmission relative to a unified deposit market? The answer depends on market structure. In monopoly, segmentation *dampens* transmission by enabling price discrimination—banks smooth deposit outflows by adjusting rates differentially across segments, reducing aggregate balance sheet volatility. In oligopoly, two opposing forces compete: price discrimination (dampening) versus intensified strategic competition across segments (amplifying). When banks compete over two segments rather than one unified market, they cannot simply match competitors' overall rates but must decide whether to compete aggressively in each segment, potentially intensifying rate competition. Following Corts (1998), this expanded strategy space can *amplify* transmission if competition effects dominate. **The net effect is empirically ambiguous** and depends on market concentration and elasticity gaps. This implies that **empirical analyses pooling deposits into a single aggregate will systematically mismeasure monetary transmission**, with bias in either direction depending on which mechanism dominates. See Appendix B for extended discussion.

1.5 Empirical Banking Model

This section translates the theoretical framework developed in Section 1.4 into an empirical model. The structural approach combines a demand system for deposits with a parametric specification of banks' asset-side revenue and funding cost technologies, together forming a complete equilibrium model of bank competition that I take to the data. The demand side specifies how depositors choose among banks and segments using a nested logit discrete choice framework, which delivers tractable closed-form expressions for market shares and demand elasticities while capturing realistic substitution patterns (depositors substitute more readily among similar banks than across different bank types). The supply side parametrizes the key technologies in banks' profit function: the asset revenue function $\ell(A, f)$ capturing returns on lending and securities, the wholesale funding cost function $\omega(H, f)$ capturing the marginal cost of non-deposit funding, and the deposit servicing costs c^g capturing branch operations and regulatory expenses. Together, these components allow me to recover the structural parameters governing deposit demand elasticities, market power, and policy pass-through.

Two central empirical challenges arise in estimating this model. First, to convert observed deposit quantities into market shares for demand estimation, I must estimate the total market size—the potential deposit balances available in each local market and segment, including both deposits held at banks and alternative savings vehicles. Section 1.5 describes how do this by combining household survey microdata with business-level proxies. Second, segment-level deposits by bank-market-time (D_{jmtg}) are not directly observed—banks report deposit quantities either by branch location (aggregating across segments) or by segment nationally (aggregating across markets), but not the intersection. I therefore develop an imputation procedure, described in Section 1.5, that leverages the marginal totals along with economic structure to estimate the unobserved segment-specific local market shares. With these imputed quantities in hand, I estimate demand parameters using instrumental variables methods to address the endogeneity of prices (deposit rates), then combine the estimated demand system with banks' first-order conditions to recover supply-side cost parameters.

Demand for Deposit Services

In every period $t = 1, \ldots, T$, a depositor i located in grographic market m chooses a bank $j \in J_{tm} = \{0, 1, \ldots, J\}$ and is assigned to an exogenous segment $g \in \{I, U\}$ based on deposit size, where I denotes insured deposits (balances $\leq$ \$250,000) and U denotes uninsured deposits (balances $>$ \$250,000). The outside option $(j = 0)$ represents money market mutual funds, which constitute the primary alternative savings vehicle for depositors in my main specification. Depositors do not choose their segment; the insured versus uninsured classification is determined mechanically by whether their deposit balance exceeds the FDIC insurance limit. I estimate separate demand systems for insured and uninsured depositors, treating segment as predetermined.

I model depositor choice using a nested multinomial logit framework following McFadden (1978). The nesting structure reflects hierarchical decision-making: depositors first choose a bank type based on size (small banks with average assets below \$10 billion, medium banks with \$10–\$100 billion, large banks above \$100 billion, or the outside option), then choose a specific bank within that type. This captures the empirically relevant pattern that depositors often first decide on bank category—community bank versus regional versus national bank—based on factors like brand trust, perceived stability, service offerings, and relationship preferences, before comparing specific institutions within that category. The nested logit imposes that a depositor's utility from choosing bank j has three components: mean utility from bank-market-segment observables (δ_{jmtg}), a random utility component shared by all banks in the same nest ($\zeta_{in(j)gmt}$, where $n(j)$ denotes bank j's nest), and an idiosyncratic bank-specific shock (ε_{ijmtg}).

Depositor i in segment $g \in \{I, U\}$ choosing bank j from nest n in market m at time t receives utility:

$$v_{ijmtg} = \underbrace{\delta_{jmtg}}_{\substack{\text{mean utility from}\\ \text{observables}}} + \underbrace{\zeta_{in(j)gmt}}_{\substack{\text{nest-specific}\\ \text{shock}}} + \underbrace{(1-\sigma_g)\varepsilon_{ijmtg}}_{\substack{\text{idiosyncratic}\\ \text{shock}}} \tag{1.7}$$

where δ_{jmtg} is the mean utility from bank-market-segment observables, $\zeta_{in(j)gmt}$ is a nest-specific shock common to all banks in nest n, and ε_{ijmtg} is an idiosyncratic preference shock. Both ζ and ε are assumed to be i.i.d. Type I Extreme Value distributed. The nesting parameter $\sigma_g \in [0,1]$ measures the correlation of preferences within a nest: $\sigma_g = 0$ corresponds to standard logit (no nesting), while $\sigma_g \to 1$ implies perfect correlation within the nest, meaning depositors view all banks in the nest as close substitutes.

The mean utility from bank j in market m and segment g captures the observable determinants of depositor preferences:

$$\delta_{jmtg} = \underbrace{\alpha_g r_{jmtg}}_{\substack{\text{rate}\\ \text{sensitivity}}} + \underbrace{\beta_g^{\rho}\rho_{jt}}_{\substack{\text{bank}\\ \text{risk}}} + \underbrace{\beta_g^{b} b_{jmt}}_{\substack{\text{branch}\\ \text{presence}}} + \underbrace{X_{jt}'\boldsymbol{\beta}_g}_{\substack{\text{bank}\\ \text{attributes}}} + \nu_{jg} + \iota_{mg} + \kappa_{tg} \tag{1.8}$$

The key observable determinants are as follows. *Deposit rate* r_{jmtg} is the annual percentage yield (APY) offered by bank j in market m for segment g, with $\alpha_g < 0$ reflecting that depositors have upward-sloping demand. Critically, α_g is allowed to differ across segments, capturing the differential rate sensitivity documented in Fact 2. *Bank risk* ρ_{jt} measures bank financial stability using a distance-to-default z-score.[15] The coefficient β_g^{ρ} captures how depositors in each segment respond to bank fragility: theory predicts $\beta_I^{\rho} \approx 0$ (insured depositors are protected by FDIC insurance and should be relatively insensitive to bank risk) and $\beta_U^{\rho} > 0$ (uninsured depositors bear default risk and should prefer safer banks), consistent with the market discipline literature (Park, 1995). *Branch presence* b_{jmt} is the number of branches bank j operates in market m, with $\beta_g^b > 0$ capturing the value of local banking access through physical proximity, relationship banking, and service convenience. Branch networks may be valued differently across segments if, for example, uninsured depositors (often businesses) require specialized cash management services available only at full-service branches.

[15] The z-score is calculated as $(\bar{ROA}_{jt} + E_{jt}/A_{jt})/\sigma(ROA_{jt})$, where $\bar{ROA}_{jt}$ is the rolling 4-quarter mean of return on assets ending at quarter t, E_{jt}/A_{jt} is the equity-to-assets ratio at quarter t, and $\sigma(ROA_{jt})$ is the rolling 4-quarter standard deviation of ROA ending at quarter t. Higher values indicate lower default risk.

Bank attributes X_{jt} include additional observable bank characteristics that control for heterogeneity in banks' service offerings and operational models. The *fixed effects* absorb unobserved heterogeneity at multiple levels: ν_{jg} are bank-segment fixed effects capturing time-invariant unobserved bank quality such as brand value, technology platforms, customer service reputation, and strategic positioning in each segment; ι_{mg} are market-segment fixed effects absorbing local characteristics that affect all banks symmetrically, including local wealth distribution, industry composition, financial sophistication, and regulatory environment; κ_{tg} are year-segment fixed effects absorbing aggregate time-varying shocks to deposit demand, including the aggregate effect of monetary policy on depositors' outside options, macroeconomic conditions, and financial market volatility. The mean utility of the outside option is normalized to zero: $\delta_{0mtg} = 0$, pinning down the level of utility.

Under the nested logit assumptions with Type I extreme value distributed idiosyncratic shocks, the market share of bank j in segment g, market m, and time t has the closed-form expression:

$$s_{jmtg} = \frac{\exp(\delta_{jmtg}/(1-\sigma_g))}{\sum_{k\in J_n}\exp(\delta_{kmtg}/(1-\sigma_g))} \cdot \frac{\left(\sum_{k\in J_n}\exp(\delta_{kmtg}/(1-\sigma_g))\right)^{1-\sigma_g}}{\sum_{n'}\left(\sum_{k\in J_{n'}}\exp(\delta_{kmtg}/(1-\sigma_g))\right)^{1-\sigma_g}} \tag{1.9}$$

where the first term is bank j's share within its nest n, and the second term is the nest's overall share. This nested logit structure has implications for substitution patterns: when a bank raises its deposit rate, it attracts depositors primarily from other banks in the same nest (e.g., other large banks) rather than uniformly from all banks, with the nesting parameter σ_g governing the strength of this within-nest substitution.

As noted earlier, estimating this demand system requires constructing market size measures (Section 1.5) and imputing unobserved segment-level local market shares (Section 1.5), both described in the following subsections.

Market Size Estimation

The market size M_{mtg} represents the total potential deposit balances in market m, segment $g \in \{I, U\}$, and time t, including both deposits held at banks and the outside option. Accurate market size estimates are essential because they determine the denominator when converting observed deposit quantities into market shares for demand estimation. I construct market sizes by combining four components: household-insured (HI), household-uninsured (HU), business-insured (BI), and business-uninsured (BU) deposits.

For household deposits, I estimate a parametric model using Survey of Consumer Finances (SCF) microdata that relates deposit holdings to income and demographics, then simulate local market distributions using Census demographic data. For business deposits, I use aggregate totals from the Federal Reserve's Flow of Funds Financial Accounts and distribute them to local markets using County Business Patterns payroll data as a proxy for deposit demand intensity. The insured/uninsured split for each depositor type is estimated by imputing national deposit distributions from SCF data: households are classified based on their simulated deposit balances relative to the \$250,000 FDIC threshold, while businesses are classified by employment size (establishments below 100 employees are predominantly insured-segment, larger establishments are uninsured-segment).

The total market size is then:

$$M_{mtg} = D^{hh}_{mtg} + D^{bus}_{mtg} + \mathrm{M}_{0mtg} \tag{1.10}$$

where D^{hh}_{mtg} and D^{bus}_{mtg} are the household and business deposit components for segment g, and M_{0mtg} captures the outside option (money market mutual funds), estimated from Federal Reserve Flow of Funds data and allocated to local markets proportionally to the depositor base. This approach ensures that for each local market, I obtain estimates of potential deposits across all four depositor-type and insurance-status combinations, which sum to give segment-specific market sizes.

Appendix G provides comprehensive details on the estimation methodology, including the household deposit regression specification, business deposit allocation procedure, outside option estimation and robustness checks, data sources, parameter estimates, and validation exercises comparing simulated to observed distributions.

Imputation of Segment-Level Market Quantities

To capture the spatial heterogeneity in deposit competition documented in Section 1.3, I extend the analysis to nearly 200 banks across 450 local markets. This geographic segmentation distinguishes my analysis from prior work such as Egan et al. (2017), whose market definition is national. However, extending to local markets creates a critical measurement challenge: segment-level local market shares (D_{jmtg} or equivalently s_{jmtg}) are not reported in the data. Banks report total deposits at the branch level through the Summary of Deposits, allowing me to compute local market totals D_{jmt}. They also report segment-level deposits (insured and uninsured) nationally through Call Reports, yielding D_{jtg} aggregated across all markets. However, the crucial intersection—deposits by bank j, in market m, for segment g—is unobserved. I address this challenge through a parametric imputation procedure.

The imputation procedure exploits the heterogeneous geographic scope of U.S. banks. A small number of large banks operate in hundreds or even thousands of local markets, while thousands of smaller banks focus their operations on just a few markets, and often operate in only one. For small banks, observed national segment totals D_{jtU} and D_{jtI} are almost entirely determined by activity in their limited set of markets, providing strong constraints on their segment-specific deposit quantities in those locations. For large multi-market banks, the imputation leverages how their deposit mix varies systematically across markets with different competitive structures, demographic compositions, and rival bank characteristics. This variation allows me to capture both bank-level segment specialization patterns and the influence of local market conditions on deposit composition.

I develop a parametric imputation model that decomposes bank-market-segment deposit quantities into three economically interpretable components: (1) a *bank-market baseline* μ_{jm} capturing bank j's overall deposit-taking capacity in market m, reflecting branch network density, historical presence, and local brand recognition; (2) a *bank-segment preference* w_j measuring bank j's comparative advantage in attracting uninsured deposits across all markets, reflecting national-level strategic choices about target customer segments; and (3) a *local spillover* parameter λ quantifying strategic complementarities—how bank j's success in attracting uninsured deposits depends on whether rival banks in that market also specialize in this segment. The log deposit quantity is modeled as:

$$\ln \hat{q}_{jmg}(\theta) = \begin{cases} \mu_{jm} + w_j + \lambda\, \bar{w}_{-j,m} & \text{if } g = U \text{ (uninsured)}, \\ \mu_{jm} & \text{if } g = I \text{ (insured)}, \end{cases} \tag{1.11}$$

where $\bar{w}_{-j,m} = \sum_{j' \neq j} (b_{j'm} / \sum_{k \neq j} b_{km}) w_{j'}$ is the branch-weighted average uninsured preference of other banks in market m.

I estimate the parameter vector $\theta = \{\mu_{jm}, w_j, \lambda\}$ using nonlinear least squares to match three observed aggregates: (1) total deposits of bank j in market m from SOD branch-level data, (2) total uninsured deposits of bank j nationally from Call Reports, and (3) total insured deposits of bank j nationally from Call Reports. The imputation successfully matches these observed aggregates: the median absolute percentage error is 0.75% across bank-market observations for local totals and bank-level observations for national segment totals (see Appendix Table 1.18 for complete fit statistics). While I cannot directly validate the imputed local segment-level shares (which are unobserved), the tight fit to both local and national aggregates suggests the imputation procedure successfully decomposes deposits along both geographic and segment dimensions. Appendix H provides complete details on the model specification, estimation algorithm, and validation results.

Demand Estimation and Identification

With imputed segment-level market shares $\hat{s}_{jmtg}$ constructed using the procedure detailed in Section 1.5, I estimate the parameters of the nested logit demand system using an instrumental variables (IV) approach to address the endogeneity of deposit rates and within-nest market shares.

The demand system is characterized by the standard nested logit estimating equation, which links market shares to the mean utility of choosing a particular bank:

$$\log(\hat{s}_{jmtg}) - \log(\hat{s}_{0mtg}) = \delta_{jmtg} + \sigma_g \log(\hat{s}_{j|n,mtg}) \tag{1.12}$$

where the mean utility, δ_{jmtg}, is a function of the deposit rate (r_{jmtg}), bank characteristics (X_{jt}), and a comprehensive set of fixed effects. The primary parameters of interest are the rate sensitivity, α_g, embedded within δ_{jmtg}, and the nesting parameter, σ_g, which governs substitution patterns across banks of similar size.

The fixed effects structure plays a crucial role in isolating the causal effect of deposit rates on demand while controlling for multiple sources of unobserved heterogeneity. I include three layers of fixed effects, each addressing a distinct identification threat. Bank-segment fixed effects (ν_{jg}) absorb all time-invariant unobserved bank quality differences that affect depositor utility within each segment. These fixed effects ensure that the estimated rate sensitivity α_g is identified from within-bank variation in rates over time, not from cross-sectional comparisons of high-quality banks (which charge low rates) versus low-quality banks (which must compensate with high rates). Market-segment fixed effects (ι_{mg}) control for all local market characteristics that affect deposit demand symmetrically across banks, including local wealth distribution, industry composition, financial sophistication, and regulatory environment. Without these fixed effects, the estimated rate coefficient could be confounded by spatial correlation between local deposit demand conditions and the rates banks choose to offer. Year-segment fixed effects (κ_{tg}) absorb aggregate time-varying shocks to deposit demand, most importantly the effect of monetary policy on depositors' outside options, macroeconomic conditions, and financial market volatility. By including year-segment fixed effects, I identify the rate sensitivity from differential rate changes across banks within a year and segment, purging the estimates of confounding from common shocks that move all deposit rates simultaneously. However, even with saturated fixed effects, OLS estimation would yield biased results due to endogeneity: the deposit rate, r_{jmtg}, is endogenous, as banks set rates in response to unobserved local demand shocks that are part of the error term. The within-nest share, $\hat{s}_{j|n,mtg}$, is also endogenous by construction, as it is mechanically correlated with the bank's own demand shock.

To address the endogeneity problem, I use a two-stage least squares (2SLS) approach with instruments that are correlated with the endogenous variables but plausibly unrelated to local demand shocks.

Instruments for Deposit Rates. To instrument for deposit rates, I use lagged cost shifters from banks' national balance sheets: credit losses and loan loss provisions (as ratios to total assets) and wholesale funding costs, all measured at time $t-1$. These cost-side instruments have been widely used in the banking literature to isolate supply-side variation in deposit pricing (Dick, 2008a; Ho and Ishii, 2011a). The key identification assumption is that lagged national balance sheet measures reflect banks' overall funding cost conditions and are orthogonal to contemporaneous demand shocks in any individual local market, as they are determined by banks' national operations rather than local deposit market conditions. The one-period lag ensures that the instruments are predetermined relative to current deposit rates.

Shift-Share Instrument for Within-Nest Market Share. To instrument for the within-nest market share $\hat{s}_{j|n,mtg}$, I construct a shift-share style instrument that exploits variation in local competitive intensity from rival banks in the same nest, weighted by both their national segment composition and local branch presence. The instrument is defined as:

$$Z_{jnmtg} = \sum_{k \in n, k \neq j} \underbrace{\left(\frac{s^{\text{nat}}_{kg,t-\tau}}{\sum_{k' \in n, k' \neq j} s^{\text{nat}}_{k'g,t-\tau}} \right)}_{\text{shift}} \times \underbrace{\left(\frac{b_{km,t-\tau}}{\sum_{k' \in n, k' \neq j} b_{k'm,t-\tau}} \right)}_{\text{share}} \tag{1.13}$$

where $s^{\text{nat}}_{kg,t-\tau}$ is the national share of segment g deposits for rival bank k at time $t-\tau$ (with lag $\tau = 1$ years), $b_{km,t-\tau}$ is the number of branches that bank k operates in market m at time $t-\tau$, and the sums are taken over all rival banks k in the same nest n as bank j, excluding bank j itself.

This instrument can be interpreted as a weighted count of effective rivals in nest n for segment g in market m, where each rival's weight reflects both how much they focus on that segment nationally and how present they are locally. This is conceptually similar to a count of competitors, but refined to capture the relevant competitive pressure: a rival bank that specializes in uninsured deposits nationally and has many local branches exerts more competitive pressure on bank j's uninsured deposits than a rival with few branches or low uninsured exposure. The instrument has a shift-share structure where each rival bank k in the nest is weighted by two predetermined factors: (1) its national propensity to serve segment g, captured by s^{nat}_{kg}, and (2) its local market presence, captured by branch share b_{km}. The economic intuition is that bank j's within-nest market share in segment g is mechanically affected by the number, segment specialization, and branch presence of rival banks in its size category operating in the same local market. However, both national segment shares and branch networks are highly persistent and determined by long-run strategic considerations—segment specialization reflects banks' business models and customer relationships built over decades, while branch networks involve substantial fixed costs, regulatory approvals, and multi-year planning horizons. By using lagged values, the instrument captures predetermined competitive intensity that affects current within-nest shares but is orthogonal to contemporaneous demand shocks. The instrument is valid under two key assumptions: relevance requires that lagged branch presence of competitors within the nest strongly predicts bank j's current within-nest share, which is mechanically satisfied because market shares are determined by relative presence across competitors and branch networks evolve slowly. The exclusion restriction requires that lagged competitor branch counts affect bank j's current deposits only through their impact on within-nest competitive intensity, not through direct effects on current deposit demand. This is plausible because the instrument uses lagged values (insulating it from contemporaneous demand shocks), branch networks respond to long-run market characteristics rather than short-run deposit demand fluctuations, and I control for market-segment-year fixed effects that absorb common shocks to deposit demand that might correlate with historical market structure.

First-stage regressions confirm the relevance of these instruments, with F-statistics well above conventional thresholds for weak instruments (typically exceeding 30 for deposit rates and 50 for within-nest shares), indicating a strong first stage. The final estimation is therefore conducted via 2SLS, separately for the insured and uninsured segments, with standard errors clustered at the bank level to account for unobserved correlation for the same bank across markets and time.

Empirical Supply of Banking Services

This subsection describes how I adapt the theoretical Cournot banking model from Section 1.4 to the empirical setting. The key challenge is that while the theoretical model characterizes a single bank's optimization problem, the data reveal banks operating across multiple local deposit markets while managing assets at the national level. I therefore make explicit assumptions about the geographic scope of competition and strategic behavior that bridge theory and estimation.

Geographic Structure and Strategic Assumptions. Bank j at time t chooses deposit quantities (D_{jt}^I, D_{jt}^U), wholesale funding H_{jt}, and assets A_{jt} to maximize:

$$\Pi_{jt} = \ell(A_{jt}, f_t) - \omega(H_{jt}, f_t) \cdot H_{jt} - \sum_{g \in \{I,U\}} \sum_{m \in \mathcal{M}_j} (c_{jmt}^g + r_{jmt}^g) D_{jmt}^g \tag{1.14}$$

subject to the funding constraint $A_{jt} = D^I_{jt} + D^U_{jt} + H_{jt}$, where $D^g_{jt} = \sum_{m \in \mathcal{M}_j} D^g_{jmt}$ aggregates deposits across the bank's local markets $\mathcal{M}_j$.

I make two critical assumptions that simplify estimation while preserving the essential economic forces. *First*, I assume banks manage assets at the national level but do not behave strategically in asset markets. That is, the asset revenue function $\ell(A_{jt}, f_t)$ depends only on the bank's own asset holdings and the policy rate, not on competitors' asset choices. This assumption is reasonable because banks primarily compete for deposits in local geographic markets, while their lending activities span broad national portfolios where individual banks are small relative to total credit markets. *Second*, I assume deposit competition occurs locally within segmented markets, as modeled in Section 1.5. Banks choose deposit quantities D^g_{jmt} taking into account how these choices affect equilibrium rates r^g_{jmt} in each local market m and segment g, but rates in one market do not directly affect demand in other markets (conditional on bank and market fixed effects).

These assumptions imply that the first-order conditions from the theoretical model (equations 1.4–1.5) carry over to the empirical setting with minor modifications. The wholesale funding condition equalizes the marginal revenue from assets to the marginal cost of wholesale funding at the national level. The deposit funding conditions equalize the marginal revenue from assets to the marginal cost of deposits in each segment, where the marginal cost now aggregates over local markets: $\sum_{m \in \mathcal{M}_j} \left(c^g_{jmt} + r^g_{jmt} + D^g_{jmt} \partial r^g_{jmt} / \partial D^g_{jmt} \right)$. The cross-segment equilibrium condition (equation 1.6) continues to hold, ensuring banks optimally balance funding costs across insured and uninsured deposits.

Functional Form Specifications. Given this empirical structure, I now parametrize the three key supply-side functions: asset revenue, deposit servicing costs, and wholesale funding costs. The parameter estimation strategy is presented in Section 1.6.

Asset Revenue Function. Following Egan et al. (2022), I specify the asset revenue function as Cobb-Douglas with policy-rate-dependent productivity:

$$\ell(A, f) = \phi(f) \cdot A^{\gamma}, \quad \text{where } \log \phi(f) = \phi_0 + \phi_1 f \tag{1.15}$$

The parameter $\gamma < 1$ reflects diminishing returns to scale in asset production—a standard assumption in banking models dating to Monti (1972) and Klein (1971), motivated by banks facing a limited pool of high-quality lending opportunities. The productivity term $\phi(f)$ allows asset profitability to vary with the policy rate, with ϕ_1 capturing how higher policy rates increase net interest margins by widening the spread between loan rates and funding costs. This is what I call the *asset revenue channel*: when the federal funds rate rises, banks can charge higher loan rates to borrowers, increasing the marginal revenue from assets and affecting banks' optimal funding mix.

Deposit Servicing Costs. The non-interest deposit servicing costs c^g_{jmt} for segment $g \in \{I, U\}$ in market m represent the marginal cost of maintaining deposits beyond the interest rate paid. These costs include branch operating expenses (staff salaries, rent, utilities), regulatory compliance costs, technology infrastructure (ATMs, online banking), FDIC insurance premiums (for insured deposits), and other administrative expenses. I allow costs to vary by segment because insured and uninsured depositors require different service levels: uninsured depositors (often businesses and high-net-worth individuals) may demand more personalized service, account monitoring, and liquidity management tools.

Wholesale Funding Cost. I specify the marginal cost of wholesale funding as convex in quantity and linearly increasing in the policy rate:

$$\omega(H, f) = f + h_1 H \tag{1.16}$$

This convex specification reflects banks facing upward-sloping supply curves in wholesale markets: as a bank increases wholesale borrowing, lenders demand higher spreads to compensate for concentration risk and information asymmetries (Diamond, 1984). The intercept f reflects that the baseline cost of wholesale funding tracks the policy rate (through federal funds, FHLB advances, or other short-term borrowing), while h_1 governs the slope of the supply curve.

1.6 Estimation and Results

This section presents the estimation and results. I first describe the demand estimation using the nested logit framework. I then explain how the supply-side parameters are recovered sequentially using the estimated demand system and the equilibrium first-order conditions. Finally, I report the

Table 1.4: Estimation sample: Descriptive statistics

Variable	**Insured**		**Uninsured**	
	Mean	Std. Dev.	Mean	Std. Dev.
Deposit interest rate (bps)	11.78	18.55	22.86	29.54
Market share	0.128	0.136	0.137	0.155
Large nest share	0.331	0.326	0.376	0.326
Medium nest share	0.148	0.275	0.099	0.201
Small nest share	0.079	0.227	0.042	0.153
Branches in market	11.78	18.55	22.86	29.54
Number of rivals	7.51	2.57	7.05	2.65
Total counties	26.65	27.15	27.69	27.29
Z-score (risk measure)	0.022	0.022	0.021	0.019

Notes: The unit of observation is bank-county cluster-year-segment. The sample includes 67,928 observations covering 198 banks, 450 county clusters, and 11 years (2009-2019). Each observation is weighted by segment market size (total depositors) in the county cluster-year. Large nest includes banks with assets >$100B, medium nest includes $10B-$100B, and small nest includes <$10B. Z-score is a distance-to-default measure; see Section 1.5 for calculation details.

estimation results and validate the model fit.

Table 1.4 reports descriptive statistics for the estimation sample. Deposit interest rates average 11.78 bps for insured deposits and 22.86 bps for uninsured deposits, consistent with the segmentation premium documented in Section 1.3. Market shares average 12-14% across segments, while nest shares vary by bank size category: large banks (>$100B assets) capture 33-38% of their size nest, medium banks ($10B-$100B) capture 10-15%, and small banks (<$10B) capture only 4-8%. Banks face approximately 7 rivals in each local market. The z-score risk measure averages 0.02, indicating moderate default risk in the sample period.

Demand Estimation Results

Table 1.5 reports the main demand estimation results from the nested logit IV regression. Columns (1) and (2) show results for insured deposits, while columns (3) and (4) show uninsured deposits. In columns (2) and (4), I include the within-nest share term $\log(s_{j|n,mtg})$ to allow for nesting by bank size.

The rate coefficients capture the sensitivity of deposit demand to interest rates in the nested logit utility specification. The estimates are $\alpha_I = 1.135$ for insured deposits and $\alpha_U = 0.812$ for uninsured deposits. These coefficients imply mean deposit rate elasticities of 0.14 for insured deposits and 0.21 for uninsured deposits. The finding that insured deposits have lower elasticity than uninsured deposits is consistent with Egan et al. (2017), though my estimates differ in magnitude due to several methodological differences: I estimate local demand elasticities rather than national; my

Table 1.5: Demand estimation: Insured vs. uninsured deposits

	Insured		**Uninsured**	
	(1)	(2)	(3)	(4)
Deposit rate (α_g)	1.146***	1.135***	0.875***	0.812***
	(0.281)	(0.260)	(0.198)	(0.180)
Log(branches in market) (β_g^b)	0.742***	0.671***	0.734***	0.652***
	(0.013)	(0.020)	(0.013)	(0.020)
Within-nest share (σ_g)	–	0.114***	–	0.131***
	–	(0.025)	–	(0.026)
Observations	33,764	33,764	34,168	34,168
Adjusted R^2	0.414	0.508	0.383	0.505
Bank size nests	–	✓	–	✓
Bank-segment FE	✓	✓	✓	✓
County-segment FE	✓	✓	✓	✓
Year-segment FE	✓	✓	✓	✓
Diagnostics				
K-P Wald F	62.3	41.6	47.1	30.7
Anderson-Rubin p-value	0.000	0.000	0.000	0.000
J-Hansen p-value	0.998	0.966	0.140	0.136
DWH p-value	0.000	0.000	0.000	0.000

Notes: Two-way clustered standard errors (by bank and by county-year) in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Sample: 198 banks, 450 county clusters, 2009-2019. Instruments for deposit rates: credit losses, provisions, wholesale funding costs. Instrument for within-nest share: weighted count of rivals in same nest. Controls not shown: z-score, total number of counties (10s), total number of branches (100s), employees per branch, and bank age. All specifications include bank-segment, county-segment, and year-segment fixed effects.

sample includes a larger and more diverse set of banks analyzed over a different sample period, and the depositors' outside option differs.

The branch coefficient β_g^b is large and precisely estimated. . A 10 percent increase in the number of branches in a market raises market share by about 6.7 percent. This result shows that physical presence remains important in deposit markets, even in the digital banking era. Branch networks provide not only convenience but also signal commitment to local markets, which depositors value. The similarity of branch coefficients across segments suggests that both insured and uninsured depositors value local access equally. This contrasts with rate sensitivity, where I observe clear differences between segments.

The within-nest share coefficients ($\sigma_I = 0.114$ and $\sigma_U = 0.131$) measure the degree of correlation in preferences within bank-size nests. Both are positive and significant, indicating that depositors view banks in the same size category as closer substitutes than banks in different categories. However, the nesting parameters are relatively small, suggesting that the bank-size dimension is not the dominant factor in depositor choice. Geographic proximity (captured by branch coefficients) appears more important than bank size. This finding supports the modeling choice to allow for rich spatial variation in deposit markets rather than treating bank size as the primary dimension of product differentiation. The diagnostic statistics confirm that the instruments are both relevant and valid.

Supply Estimation Results

The supply side of the model requires estimating three sets of parameters: (1) the asset revenue function $\ell(A, f) = \phi(f) \cdot A^{\gamma}$, (2) the wholesale funding cost parameter h_1, and (3) the non-interest deposit servicing costs c^I and c^U. I estimate these sequentially using a three-step procedure that exploits the equilibrium first-order conditions to identify parameters that would otherwise be unobservable.

The estimation strategy leverages the fact that the bank's first-order conditions link observables—deposit rates, deposit quantities, assets, and wholesale funding—to the unobservable cost parameters. First, I estimate the parameters of the asset revenue function (γ, ϕ_0, ϕ_1) by regressing log net income on log assets and controls. This step identifies the technology of asset production and how profitability varies with the policy rate. Second, given the estimated demand elasticities (from Section 1.6) and the estimated returns to scale parameter $\hat{\gamma}$, I recover the non-interest deposit servicing costs c^I_{jmt} and c^U_{jmt} using the cross-segment equilibrium condition (equation 1.6). This step exploits the fact that banks must equate the marginal cost of funds across segments: if one segment becomes relatively cheaper, banks would shift their entire funding mix toward that segment, violating the observed equilibrium. Third, I recover the wholesale funding cost parameter h_1 from the wholesale funding first-order condition (equation 1.4), which governs how the marginal cost of wholesale funding increases with quantity.

This sequential approach has several advantages. It does not require strong parametric assumptions beyond the Cobb-Douglas specification for asset revenue. It produces economically interpretable parameters that can be validated against external data sources (e.g., comparing recovered FDIC insurance costs to published FDIC premium schedules). Most importantly, it uses equilibrium restrictions to identify supply-side parameters that would be difficult to measure directly, such as the marginal cost of servicing different types of deposits.

Asset Revenue Function

Following Egan et al. (2022), I estimate the Cobb-Douglas asset revenue function $\phi_j(f) \cdot A_j^{\gamma}$ by regressing log net income on log assets and controls. The key parameter γ captures returns to scale in asset production. Assets are defined as total assets minus equity (book value), following the interpretation that equity-financed assets do not require deposit or wholesale funding.

The estimating equation is:

$$\ln Y_{jt} = \alpha + \gamma \ln A_{jt} + \gamma^b \ln b_{jt} + X_{jt}' \boldsymbol{\Gamma} + \vartheta_j + \tau_t + \varepsilon_{jt} \tag{1.17}$$

where Y_{jt} is income net of losses, A_{jt} is interest-bearing assets net of equity, b_{jt} is the total number of branches, X_{jt} contains additional bank-level controls, and ϑ_j and τ_t are bank and time fixed effects.[16] The coefficient γ on log assets identifies the returns to scale parameter in the production function.

Table 1.6 reports the estimation results. Column (1) shows OLS estimates, while columns (2) and (3) use instrumental variables to address the endogeneity of assets, which arises because banks expand asset holdings in response to unobserved profitability shocks (positive demand for loans, favorable lending opportunities). I instrument for $\log(A_{jt})$ using: (i) lagged (2 quarters) non-interest expenses on premises and fixed assets (rent), (ii) lagged (2 quarters) loan loss provisions, (iii) lagged (2 quarters) wage expenses, and (iv) BLP-style competitor instruments—the sum of rivals' average number of branches and counties, weighted by market presence. The cost-shifter instruments (rent, provisions, wage expenses) are valid because they shift banks' marginal cost of holding assets through their national operations, not through local demand shocks. The BLP instruments exploit variation in the competitive environment: a bank's optimal asset scale responds to rivals' branch networks, but conditional on bank and time fixed effects, competitors' characteristics enter only through market structure.

The IV estimate $\hat{\gamma} = 0.875$ indicates moderate decreasing returns to scale in asset production, consistent with Egan et al. (2022).

[16]The vector X_{jt} includes log employees, log non-interest expenses, leverage (assets-to-equity ratio), and standard deviation of ROA. These controls capture variation in operational scale, cost structure, financial risk, and earnings volatility that affect bank profitability independently of asset size. Including these controls ensures that γ is identified from variation in asset scale, not from correlated changes in bank size, cost efficiency, or risk-taking.

Table 1.6: Asset revenue function estimation

	Log(Net Income)		
	OLS	IV (Cost)	IV (Full)
Log(Assets) (γ)	0.573***	0.864***	0.875***
	(0.034)	(0.056)	(0.052)
Log(Branches) (γ^b)	0.234***	0.081*	0.075*
	(0.040)	(0.037)	(0.035)
Log(Leverage)	-0.182**	-0.174***	-0.174***
	(0.057)	(0.050)	(0.050)
Observations	6,098	6,098	6,098
Adjusted R^2	0.99	0.45	0.45
Clusters (Banks)	198	198	198
Bank FE	✓	✓	✓
Year FE	✓	✓	✓
First-stage diagnostics (IV specifications)			
K-P Wald F	–	87.3	92.1
Anderson-Rubin p	–	0.000	0.000

Notes: Standard errors clustered by bank in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Sample: quarterly data, 2009-2019. "IV (Cost)" instruments using lagged cost shifters only. "IV (Full)" adds BLP-style competitor instruments.

Cost Recovery

Given the demand parameters $(\hat{\alpha}_g, \hat{\sigma}_g)$ and the estimated returns to scale parameter $\hat{\gamma}$, I can recover the implied non-interest deposit servicing costs c^g_{jmt} from the first-order conditions. The deposit FOC (equation 1.5) implies:

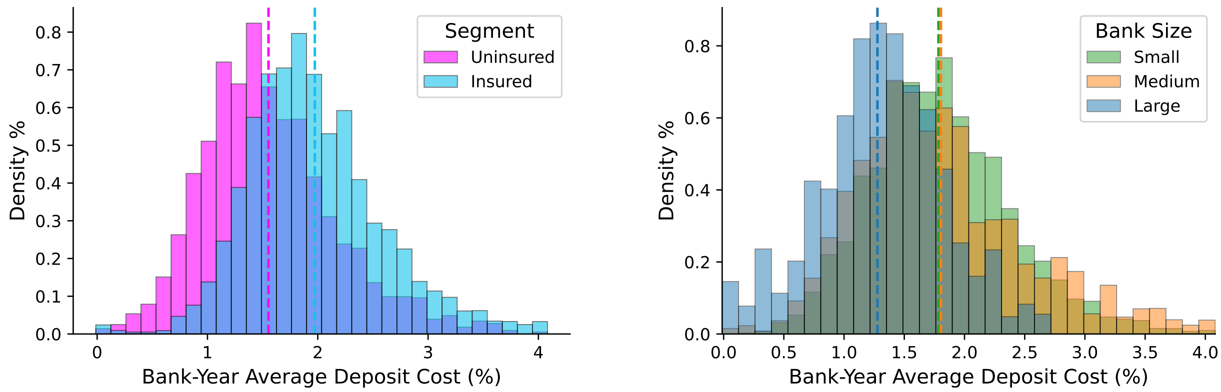
$$c^g_{jmt} = \hat{\gamma}\phi(f_t)A^{\hat{\gamma}-1}_{jt} - r^g_{jmt}(1 + \eta^g_{jmt}) \tag{1.18}$$

where $\hat{\gamma}\phi(f_t)A^{\hat{\gamma}-1}_{jt} = \frac{\partial \ell}{\partial A}$ is the marginal revenue from assets (using the Cobb-Douglas specification from equation 1.15) and $\eta^g_{jmt} = \frac{D^g_{jmt}}{r^g_{jmt}} \frac{\partial r^g}{\partial D^g}$ is the inverse elasticity of deposit demand for segment g, computed from the nested logit demand estimates.

The implied servicing costs are economically sensible: the median cost is 0.12% of deposits for insured deposits and 0.08% for uninsured deposits. The higher cost for insured deposits reflects FDIC insurance premiums (ranging from 3 to 45 basis points depending on the bank's risk category) plus additional regulatory compliance costs. These recovered costs are used in the counterfactual simulations.

Figure 1.4 shows the distribution of recovered costs across banks and years. Panel (b) decomposes costs by bank size category, revealing that smaller banks (assets <$10B) and medium banks ($10B-$100B) face systematically higher marginal costs, approximately 1.8% (1.8 cents per dollar of

Figure 1.4: Recovered deposit servicing costs



(a) Distribution by segment

(b) Distribution by bank size

Notes: Panel (a) shows histograms of bank-year average recovered costs for insured (cyan/teal bars, labeled "Insured") and uninsured (magenta/pink bars, labeled "Uninsured") deposits. Panel (b) shows the distribution of recovered marginal costs by bank size category (small: <$10B, medium: $10B-$100B, large: >$100B) and segment; each size-segment combination is distinguished by both color and bar position within the group. Costs are recovered from the supply-side first-order conditions and include operational costs plus FDIC premiums for insured deposits. Sample: 198 banks, 2009-2019. Data source: RateWatch, Call Reports; supply-side estimation sample.

deposits), reflecting economies of scale in deposit collection. Large banks (assets >$100B) have lower costs, around 1.2% (1.2 cents per dollar). Across segments, uninsured deposits have mean costs around 1.5%, while insured deposits have slightly higher costs due to FDIC premiums.

Wholesale Funding Costs

The wholesale funding cost parameter h_1 is recovered from the wholesale funding first-order condition (equation 1.4):

$$h_1 = \frac{\phi_j(f)\hat{\gamma}A_j^{\hat{\gamma}-1} - f}{H_j} \tag{1.19}$$

Using the estimated $\hat{\gamma}$ and observed (A_j, H_j, f), I estimate $\hat{h}_1 = 0.20 \times 10^9$ (median across banks). While most banks exhibit positive values indicating modestly convex wholesale funding costs—reflecting upward-sloping supply curves in wholesale markets due to credit risk premia—some banks show negative values, suggesting they face more favorable wholesale funding access, possibly due to stronger credit ratings or longstanding relationships with wholesale lenders.

Summary of Supply Parameters

Table 1.7 summarizes the key supply-side parameters. The fixed productivity term $\phi(f_t)$ averages 0.955, with substantial cross-sectional variation reflecting differences in banks' asset portfolios and lending opportunities. The recovered marginal costs c_{jmt} average 1.4 cents per dollar of deposits, consistent with FDIC insurance premiums and operational costs. The wholesale funding cost parameter h_1 (scaled by 10^9 in the table due to the billions unit of H_j) has a median of 0.20, with about 60% of banks exhibiting positive values indicating upward-sloping wholesale funding supply curves, while the remainder show negative values suggesting easier access to wholesale markets.

Table 1.7: Summary of recovered supply-side parameters

	Mean	Std. Dev.	1st Pct.	10th Pct.	Median	90th Pct.
Fixed productivity $\phi(f_t)$	0.955	0.223	0.614	0.688	0.934	1.243
Marginal cost c_{jmt} (%)	1.40	0.70	0.40	0.60	1.40	2.20
Wholesale cost h_1 ($\times 10^9$)	0.84	35.12	-0.61	-0.02	0.20	0.44

Notes: Statistics are bank-year level observations weighted by market size, pooled across both insured and uninsured segments for marginal costs. The h_1 parameter is scaled by 10^9 for readability. Sample includes 2,178 bank-year observations (198 banks, 2009-2019). Fixed productivity $\phi(f_t)$ varies by year with the federal funds rate. Marginal costs c_{jmt} include FDIC insurance premiums and operational costs, recovered from deposit first-order conditions. Wholesale cost parameter h_1 governs convexity of wholesale funding supply curve.

These parameters provide the foundation for the counterfactual analysis in Section 1.7, where I simulate the banking system's response to monetary policy shocks. The estimated returns to scale parameter $\hat{\gamma} = 0.875$ implies that a 1 percent increase in assets raises revenue by 0.875 percent, consistent with diminishing lending opportunities. The recovered costs show substantial economies of scale: large banks have marginal costs nearly 50 percent lower than small banks. Finally, the modest wholesale funding cost convexity ($h_1 \approx 0.0015$) suggests that banks can access wholesale markets without dramatically increasing marginal costs, facilitating substitution away from deposits when rates rise.

Monetary Policy Pass-Through

Having estimated both deposit demand and banks' asset revenue technology, I can now quantify the impact of monetary policy on deposit rates and loan rates.

Identification Strategy

Monetary policy affects deposit and lending markets through multiple channels, which are absorbed by the time fixed effects in the demand and supply estimations. Specifically, year fixed effects τ_t in the asset revenue equation (equation 1.17) capture all aggregate time-varying shocks to bank profitability, including the effect of policy rate changes on lending margins. Similarly, year-segment fixed effects κ_{tg} in the demand equation (equation 1.8) capture aggregate shocks to deposit demand, including how policy rate changes affect depositors' valuation of bank deposits relative to alternative investments. To quantify monetary transmission, I decompose the variation in these estimated fixed effects into the component attributable to federal funds rate changes versus other aggregate shocks.

The pass-through estimation exploits two key sources of variation. First, the asset revenue channel operates through the supply side: when the Federal Reserve raises rates, banks' net interest margins on assets typically increase because loan rates adjust faster than deposit rates. This effect is captured by the year fixed effects τ_t from the asset revenue regression. Second, the depositor demand channel operates through depositor preferences: when policy rates rise, alternative investments become more attractive, causing depositors to shift away from bank deposits. This is captured by the year-segment fixed effects κ_{tg} from the demand estimation.

To identify the causal effect of monetary policy on these channels, I estimate the following reduced-form regressions:

$$\Delta\hat{\tau}_t = \theta_0 + \theta^R \Delta f_t + u_t \quad \text{(Revenue Channel)} \tag{1.20}$$

$$\Delta\hat{\kappa}_{tg} = \theta_{0g} + \theta_g^D \Delta f_t + u_{tg} \quad \text{(Deposit Demand Channel)} \tag{1.21}$$

where Δf_t is the change in the federal funds rate from period $t-1$ to t, and $\Delta\hat{\tau}_t$, $\Delta\hat{\kappa}_{tg}$ are first-differenced fixed effects. The use of first differences removes any time-invariant bias in the fixed effect levels and isolates the response to policy changes. The coefficients θ^R and θ_g^D measure the elasticity of asset productivity and depositor utility (respectively) with respect to the policy rate.

This identification strategy is valid under the assumption that, conditional on bank characteristics and market conditions (absorbed by the first-stage fixed effects), variation in the federal funds rate is orthogonal to other unobserved shocks affecting profitability or deposit demand. This is plausible because the Federal Reserve sets rates based on macroeconomic aggregates, such as inflation and unemployment, rather than bank-specific or local market conditions. The first-difference specification further mitigates concerns about omitted trends by focusing on short-run policy responses.

Pass-Through Estimation Results

Table 1.8 reports the pass-through estimates for both channels. Panel A shows the supply channel: a 10 basis point increase in the federal funds rate raises asset productivity by 2.23 basis points, implying a 22.3% pass-through rate. This reflects the fact that banks' lending margins expand when policy rates rise, as loan rates reprice faster than deposit rates—a key friction that generates profits from monetary tightening on the asset side.

Panel B shows the demand channel, estimated separately for each segment. For uninsured deposits, a 1 percentage point policy rate increase reduces depositor utility by 0.157 utility units, indicating that uninsured depositors become less willing to hold deposits when rates rise, even controlling for the deposit rate itself. This likely reflects increased attractiveness of alternative safe assets. For insured deposits, the effect is nearly twice as large in magnitude: a 1 pp increase reduces utility by 0.293 utility units, though estimated less precisely. This larger response for insured depositors is consistent with their greater sophistication and willingness to chase yields across asset classes. To interpret these utility changes in monetary terms, I convert them to rate-equivalent willingness to pay using the estimated rate coefficients from demand estimation. For the same 1 pp policy rate increase, uninsured depositors would require a 19.3 bp increase in deposit rates to maintain their utility level, while insured depositors would require 25.8 bp. This means that despite the larger utility shock for insured depositors, their lower rate-sensitivity (higher α) moderates the rate adjustment needed to compensate them.

These pass-through estimates reveal how monetary policy operates through competing forces. On the supply side, higher rates make lending more profitable ($\theta^R > 0$), creating an incentive for banks to expand. On the demand side, higher rates reduce deposit demand ($\theta^D_g < 0$), forcing banks to either raise deposit rates or accept outflows. The net effect on bank balance sheets depends on the

Table 1.8: Monetary policy pass-through effects

	Panel A: Supply Channel	Panel B: Demand Channel	
	Δ Asset Productivity FE ($\Delta\hat{\tau}_t$)	Uninsured ($\Delta\hat{\kappa}_{tU}$)	Insured ($\Delta\hat{\kappa}_{tI}$)
$\Delta f\ (\theta^R, \theta^D_g)$	0.223***	-0.157***	-0.293*
	(0.089)	(0.037)	(0.150)
Constant	0.025	0.053	0.133
	(0.037)	(0.048)	(0.079)
Rate-equivalent for 1 pp policy increase ($\Delta\delta/\alpha$, in bps):		-19.3	-25.8
Observations	43	10	10
Adjusted R^2	0.12	0.82	0.38

Notes: Panel A reports results from regressing first-differenced year fixed effects from the asset revenue estimation (equation 1.17) on changes in the federal funds rate. Panel B reports results from regressing first-differenced year-segment fixed effects from the demand estimation (equation 1.8) on changes in the federal funds rate, estimated separately for insured and uninsured segments. The parameter θ^R measures the revenue channel pass-through, while θ^D_g measures the demand channel pass-through for segment g. All specifications use quarterly data from 2009Q1-2019Q4. Robust standard errors in parentheses. $^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

relative magnitudes of these forces and how they interact through the deposit market elasticities.

The stronger demand response for insured deposits creates a larger adverse shock when policy rates rise: insured depositors experience a nearly twice-as-large reduction in utility from the improved outside options. To retain these depositors, banks must raise insured deposit rates more aggressively, increasing marginal funding costs. However, because uninsured deposits are more elastic with respect to bank-specific rates, banks must also compete more aggressively on rates in the uninsured segment to prevent switching across banks. This creates offsetting forces: the larger initial shock for insured deposits pushes banks to raise insured rates more, while the higher cross-bank elasticity of uninsured deposits pushes banks to raise uninsured rates more. The counterfactual analysis in Section 1.7 quantifies which force dominates in equilibrium.

Figures 1.8 and 1.9 in Appendix I plot the relationship between fixed effects and the federal funds rate, showing the strong positive correlation for asset productivity and negative correlations for deposit demand. These patterns provide visual confirmation of the pass-through mechanisms and validate the linear specifications in equations 1.20–1.21.

1.7 Counterfactual: Monetary Tightening

I now use the estimated model to simulate the banking system's response to a 10 basis point increase in the federal funds rate. I choose this increment because it represents the typical scale of policy adjustments that banks and central bankers monitor in their operational decisions, making it directly relevant for understanding near-term transmission mechanisms. While the simulated effects may appear modest in magnitude, they reflect this relatively small policy change; a more typical tightening cycle of 100 basis points would generate proportionally larger effects, though not perfectly linearly due to the model's nonlinearities in demand elasticities and wholesale funding costs.

This counterfactual exercise addresses a central policy question: how does deposit market segmentation between insured and uninsured accounts affect the transmission of monetary policy through bank funding and lending? The estimated demand elasticities are crucial for understanding monetary policy transmission. When the Fed raises rates, banks increase deposit rates, but the response of deposit quantities depends on the rate sensitivity parameters α_g. With the estimated elasticities of 0.14 for insured deposits and 0.21 for uninsured deposits, a typical bank raising insured deposit rates by 10 basis points would see deposit quantities increase by approximately 1.4%, while a similar increase in uninsured rates would generate a 1.9% quantity response. These differential responses create asymmetric transmission across segments.

The counterfactual quantifies three competing forces that shape banks' equilibrium responses:

1. **Asset profitability channel (expansionary):** Higher policy rates increase the marginal product of bank assets via the productivity function $\phi_j(f)$, as loan rates typically reprice faster than deposit rates. This creates an incentive for banks to expand lending.

2. **Wholesale funding cost channel (contractionary):** Higher f directly raises the marginal cost of wholesale funding, making it more expensive for banks to substitute away from deposits. This forces banks to either raise deposit rates or shrink their balance sheets.

3. **Depositor demand channel (contractionary):** When policy rates rise, depositors find alternative investments more attractive and reduce their deposit holdings even if banks raise deposit rates. This outflow is segment-specific, with elasticity ε^g differing between insured and uninsured depositors.

The insight from the structural model is that deposit segmentation creates a strategic pricing incentive: banks cannot independently adjust rates across segments because the cross-segment equilibrium

Table 1.9: Counterfactual: Aggregate effects of 10 bp Fed funds increase

	Insured	Uninsured
Panel A: Deposit Rate Pass-Through		
Level change (basis points)	1.8 bp	2.5 bp
Pass-through coefficient	0.18	0.25
Percentage change	56%	40%
Panel B: Deposit Quantity Responses		
Percentage change in deposits	-0.25%	-0.08%
Implied elasticity	1.39	0.32
Panel C: Bank Balance Sheet Effects		
Total deposit outflow	-0.18%	
Wholesale funding increase	+0.12%	
Bank lending contraction	-0.06%	
Uninsured share increase	+0.02 pp	

Notes: Effects from a 10 bp increase in the federal funds rate. Pass-through coefficient is $\Delta r^g/\Delta f$ (change in deposit rates per basis point change in fed funds rate). Implied elasticity is $(\%\Delta D^g)/(\%\Delta r^g)$. Baseline fed funds rate: 15 bp (2015). Results are weighted average effects across all banks in the sample (198 banks, 450 county clusters, 2009-2019).

condition (equation 1.6) ties together the marginal cost of funds across insured and uninsured deposits. When the Fed raises rates, banks must balance two conflicting objectives: raising uninsured rates enough to retain cheaper uninsured funding, while not raising insured rates so much that they erode profitability on the larger (but stickier) insured deposit base. This strategic interaction generates differential pass-through and quantity responses across segments.

I solve for the new equilibrium $(D^{I*}, D^{U*}, H^*, A^*)$ for each bank by iterating the first-order conditions until convergence, holding demand parameters and bank characteristics fixed at their estimated values (algorithm details in Appendix J). The counterfactual compares the baseline equilibrium (2015, when the fed funds rate was 15 bp) to a new equilibrium with a 10 bp higher policy rate, allowing all endogenous variables—deposit rates, deposit quantities, wholesale funding, and bank lending—to adjust simultaneously.

Aggregate Counterfactual Results

Table 1.9 summarizes the aggregate effects of a 10 bp federal funds rate increase on deposit rates, quantities, and bank lending.

The counterfactual results reveal three findings that show how deposit segmentation alters monetary policy transmission.

Asymmetric pass-through reflects strategic pricing. Uninsured deposit rates rise by 2.5 basis points (25 percent pass-through) while insured rates rise by only 1.8 basis points (18 percent pass-through). This 40 percent larger pass-through to uninsured rates reflects banks' strategic incentive to retain cheaper uninsured funding by raising those rates more aggressively. The mechanism works as follows: when the Fed raises rates, banks face competing pressures to raise both insured and uninsured deposit rates to prevent outflows. However, because uninsured deposits have lower servicing costs (no FDIC premiums) and offer better net returns despite higher gross rates, banks prioritize retaining uninsured funding by passing through more to those rates. The cross-segment equilibrium condition ensures this differential pricing is sustainable: banks equate the marginal cost of funds across segments (inclusive of market power distortions), so the rate spread $r^U - r^I$ adjusts to reflect both cost differences and demand elasticity differences.

Compositional shift toward uninsured deposits. Despite higher pass-through to uninsured rates, insured deposit outflows are three times larger than uninsured outflows, declining by 0.25 percent compared to just 0.08 percent for uninsured deposits. This result reflects the interplay between demand elasticities and strategic pricing. Banks raise uninsured rates more aggressively (2.5 bp versus 1.8 bp) because lower servicing costs (0.08% versus 0.12% for insured deposits) make it optimal to retain cheaper uninsured funding. However, insured depositors are more responsive to outside investment opportunities and face more intense competition from alternatives with similar safety profiles (other insured accounts, money market funds), while uninsured depositors have fewer perfect substitutes that combine yield, liquidity, and relationship services. The net effect is that uninsured outflows are dampened by higher pricing, while insured outflows are larger despite smaller absolute rate increases.

Deposit outflows contract bank lending. The 0.18% deposit contraction forces banks to shrink their balance sheets. Banks attempt to substitute toward wholesale funding, which increases by 0.12%, but this substitution only partially offsets the deposit outflows. The incomplete substitution occurs because both funding sources become more expensive when policy rates rise: deposit rates must increase to retain depositors, while wholesale funding costs rise directly with the policy rate and become increasingly expensive as banks scale up (convex supply curve). The net effect is a 0.06% decline in total assets and lending, consistent with the deposit channel of monetary policy transmission first documented by Drechsler et al. (2017).

Critically, the lending contraction is accompanied by a compositional shift in funding: the uninsured deposit share increases by 2 basis points as banks substitute toward cheaper (but riskier) funding. This shift has potential financial stability implications. Uninsured deposits are more prone to runs because they lack deposit insurance protection, a mechanism that could help explain episodes like the 2008 financial crisis and 2023 regional bank failures (Silicon Valley Bank, First Republic), where rapid uninsured deposit outflows contributed to bank stress. Monetary tightening thus creates a double bind: it contracts bank lending while simultaneously increasing banks' reliance on flight-prone uninsured funding.

Heterogeneity Across Bank Types and Markets

Table 1.10 provides detailed heterogeneity analysis of how the counterfactual effects vary across bank sizes and market characteristics. The aggregate lending contraction of 0.06% masks substantial heterogeneity across bank types. Small banks cut lending by 0.09%, nearly three times the 0.03% reduction by large banks. This differential response reflects small banks' more limited access to wholesale funding markets due to higher credit risk premia and information frictions, and their greater exposure to local market competition, which limits their ability to extract rents from deposit relationships. The lending contraction occurs as higher deposit and wholesale funding costs reduce lending profitability, while deposit outflows force banks to shrink assets even when they substitute toward wholesale funding. These effects are amplified in competitive markets, where banks have less market power to pass through costs to depositors and must therefore absorb larger hits to their balance sheets.

The heterogeneity results reveal several important patterns:

Bank size differences. Small banks (assets <$10B) pass through more to uninsured rates (0.28 bp) but less to insured rates (0.16 bp), reflecting that small banks face more intense local competition for uninsured deposits, requiring higher pass-through to retain these marginal funding sources. Large banks (>$100B) show the opposite pattern. Small banks also experience larger lending contractions (-0.09% vs. -0.03%), reflecting their greater dependence on deposit funding and limited access to wholesale markets.

Market structure effects. In markets with above-median uninsured deposit shares ("Unins.-Heavy"), uninsured pass-through is particularly high (0.30 bp), and total deposit outflows are smaller (-0.12%), as banks strategically retain uninsured funding. In high-competition markets, pass-through is 22-32% higher across both segments, and deposit outflows are larger (-0.22%

Table 1.10: Counterfactual: Heterogeneity by bank size and market type

		Bank Size		Local Markets	
	Full Sample	Small	Large	Unins.-Heavy	High Comp.
Panel A: Deposit Rate Pass-Through					
Insured level change (bp)	1.8 bp	1.6 bp	2.0 bp	1.8 bp	2.2 bp
Uninsured level change (bp)	2.5 bp	2.8 bp	2.2 bp	3.0 bp	3.2 bp
Insured percentage change	56%	49%	62%	56%	68%
Uninsured percentage change	40%	45%	36%	48%	52%
Panel B: Deposit Quantity Responses					
Insured deposits	-0.25%	-0.30%	-0.20%	-0.28%	-0.35%
Uninsured deposits	-0.08%	-0.06%	-0.10%	-0.03%	-0.02%
Total deposit outflow	-0.18%	-0.19%	-0.17%	-0.12%	-0.22%
Panel C: Bank Balance Sheet Effects					
Wholesale funding increase	+0.12%	+0.10%	+0.14%	+0.12%	+0.16%
Bank lending contraction	-0.06%	-0.09%	-0.03%	-0.03%	-0.04%
Uninsured share increase (pp)	+0.02 pp	+0.02 pp	+0.01 pp	+0.03 pp	+0.03 pp

Notes: Effects from a 10 bp increase in the federal funds rate. Pass-through coefficient is $\Delta r^g / \Delta f$ (change in deposit rates per basis point change in fed funds rate). "Small Banks" have assets <$10B; "Large Banks" have assets >$100B. "Unins.-Heavy" markets have above-median uninsured deposit share. "High Comp." markets have above-median number of banks. Baseline fed funds rate: 15 bp (2015).

vs. -0.18% overall), yet lending contractions are smaller (-0.04% vs. -0.06% overall). This pattern suggests that banks in competitive markets have better access to wholesale funding markets (+0.16% vs. +0.12% overall), which more than offsets deposit losses and moderates the lending response.

Compositional shifts. Across all groups, banks substitute toward uninsured deposits (lower servicing costs), increasing uninsured shares by 0.01-0.03 percentage points. This shift is largest in uninsured-heavy and high-competition markets, amplifying financial stability concerns during monetary tightening.

Implication for monetary policy and financial stability. These results have two important policy implications. First, deposit segmentation is a key factor for understanding monetary policy transmission. As Proposition 2 establishes, models with homogeneous deposits can either overstate or understate the aggregate effects of monetary policy depending on the relative elasticities and cost structures across segments. Beyond the aggregate effects, segmentation creates different responses across banks and geographies: banks with different deposit compositions face different funding pressures, and the strength of monetary transmission varies systematically across local markets based on competitive conditions and depositor composition. This variation helps explain observed differences in deposit rate pass-through and lending responses across banks and regions, suggesting that policymakers should account for deposit composition when assessing how monetary policy affects different parts of the banking system.

Second, the counterfactual reveals a compositional shift toward uninsured deposits during monetary tightening, as banks substitute toward cheaper funding sources. While the model does not incorporate endogenous bank runs or systemic risk dynamics, this pattern suggests a potential stability concern: uninsured deposits lack deposit insurance protection and may be more prone to withdrawal during stress periods. Episodes like the 2023 regional bank failures (Silicon Valley Bank, First Republic), where rapid uninsured deposit outflows contributed to bank stress, illustrate how funding composition can interact with broader financial stability. These considerations suggest that macroprudential policy tools—such as capital requirements that account for funding composition, deposit insurance reform, or liquidity coverage ratios tailored to deposit mix—may be relevant complements to monetary policy, though a full analysis of these interventions would require extending the model to incorporate some dynamic stability mechanisms.

1.8 Conclusion

The deposit market is the main funding source for commercial banks, yet we know little about how segmentation between insured and uninsured deposits shapes monetary policy transmission. This paper provides an structural analysis of how banks strategically price and allocate funding across deposit segments in response to interest rate shocks, and quantifies the macroeconomic and financial stability consequences of this segmentation.

Using microdata on deposit rates, quantities, and bank characteristics for 198 banks across counties over 2009-2019, I estimate a model of segmented deposit competition that incorporates depositor heterogeneity, spatial variation in bank competition driven by branch networks, and banks' strategic pricing subject to a cross-segment equilibrium condition. The structural approach allows me to recover both demand parameters (deposit rate elasticities, branch sensitivity) and supply-side primitives (deposit servicing costs, asset revenue technology) that would be difficult to observe directly.

The counterfactual analysis reveals three key findings that help explain how deposit segmentation alters monetary policy transmission: asymmetric pass-through to deposit rates across segments, differential deposit outflows that generate compositional shifts in bank funding, and deposit contraction that forces banks to shrink lending. These effects vary substantially across banks and local markets depending on deposit composition and competitive conditions, helping explain observed heterogeneity in monetary transmission across the banking system.

These findings have broader implications for policy. Deposit segmentation is an important factor for understanding monetary policy transmission, as ignoring the distinction between insured and uninsured deposits can lead to misleading predictions about both aggregate effects and their distribution across banks and regions. The compositional shift toward uninsured deposits during monetary tightening also raises questions about the interaction between monetary policy and financial stability, suggesting potential roles for prudential regulation as a complement to interest rate policy. Finally, the spatial dimension of deposit competition highlights the importance of branch networks for market power, with implications for bank merger analysis: because competitive effects differ across deposit segments, traditional merger analysis based on aggregate deposit shares may mischaracterize how consolidation affects banks' pricing power and depositors' outside options in each segment.

The 2023 regional bank failures and ongoing debates about deposit insurance reform underscore that deposit segmentation and uninsurance exposure is not merely a microeconomic detail but an important consideration for macroeconomic policy.

Appendix

A Proof of Proposition 1

Setup

Totally differentiate FOCs with respect to policy rate f. Choice variables $D^g(f)$, $H(f)$, $A(f)$ for $g \in \{I, U\}$. Subscripts denote partial derivatives: $\ell_A = \partial\ell/\partial A$.

FOCs:

$$\ell_A - c^g - r^g - r^g_{D^g} D^g = 0, \quad g \in \{I, U\} \tag{1.22}$$

$$\ell_A - \omega_H - \omega = 0 \tag{1.23}$$

Differentiate with respect to f:

$$\ell_{AA}\frac{dA}{df} - K_g\frac{dD^g}{df} = R_g \tag{1.24}$$

$$\ell_{AA}\frac{dA}{df} - K_H\frac{dH}{df} = R_H \tag{1.25}$$

where $K_g \equiv 2r^g_{D^g} + r^g_{D^gD^g}D^g$, $K_H \equiv \omega_{HH} + \omega_H$, $R_g \equiv c^g_f - \ell_{Af}$, $R_H \equiv \omega_{Hf} + \omega_f - \ell_{Af}$. Funding constraint:

$$\frac{dA}{df} = \frac{dD^I}{df} + \frac{dD^U}{df} + \frac{dH}{df} \tag{1.26}$$

Matrix System

Assumptions: $\ell_{AA} < 0$, $K_I, K_U, K_H > 0$. Substitute (1.26) into (1.24) and (1.25) to obtain $\mathbf{Hx} = \mathbf{R}$:

$$\begin{pmatrix} \ell_{AA} - K_I & \ell_{AA} & \ell_{AA} \\ \ell_{AA} & \ell_{AA} - K_U & \ell_{AA} \\ \ell_{AA} & \ell_{AA} & \ell_{AA} - K_H \end{pmatrix} \begin{pmatrix} \frac{dD^I}{df} \\ \frac{dD^U}{df} \\ \frac{dH}{df} \end{pmatrix} = \begin{pmatrix} R_I \\ R_U \\ R_H \end{pmatrix} \tag{1.27}$$

Hessian determinant:

$$\det(\mathbf{H}) = K_I K_U K_H \left(\frac{\ell_{AA}}{K_I} + \frac{\ell_{AA}}{K_U} + \frac{\ell_{AA}}{K_H} - 1 \right) < 0 \tag{1.28}$$

Solve using Cramer's rule.

Results

Parts 1-2: Wholesale funding and deposits. Cramer's rule yields:

$$\frac{dH}{df} = \frac{K_I K_U R_H - \ell_{AA} \left[K_U (R_H - R_I) + K_I (R_H - R_U) \right]}{\det(\mathbf{H})} \tag{1.29}$$

$$\frac{dD^U}{df} = \frac{K_I K_H R_U - \ell_{AA} \left[K_H (R_U - R_I) + K_I (R_U - R_H) \right]}{\det(\mathbf{H})} \tag{1.30}$$

Sufficient conditions: $\frac{dH}{df} > 0$ if $R_g > R_H$ for $g \in \{I, U\}$ and $R_H \leq 0$. $\frac{dD^g}{df} < 0$ if $R_g > R_j$ for all $j \neq g$ and $R_g \geq 0$. Intuition: Banks substitute away from funding sources with relatively larger cost increases.

Part 3: Asset contraction. Sum funding sources:

$$\frac{dA}{df} = \frac{K_I K_U R_H + K_I K_H R_U + K_U K_H R_I}{\det(\mathbf{H})} \tag{1.31}$$

Necessary and sufficient condition for $\frac{dA}{df} < 0$:

$$\frac{R_I}{K_I} + \frac{R_U}{K_U} + \frac{R_H}{K_H} > 0 \tag{1.32}$$

Weights $1/K$ are inverse marginal cost slopes. Assets decline if weighted funding cost shock exceeds marginal return shock.

Part 4: Deposit composition. Insured share $S^I = D^I/(D^I + D^U)$ rises iff:

$$\frac{1}{D^I}\frac{dD^I}{df} > \frac{1}{D^U}\frac{dD^U}{df} \tag{1.33}$$

Subtract differentiated FOCs:

$$K_I\frac{dD^I}{df} - K_U\frac{dD^U}{df} = R_I - R_U \tag{1.34}$$

Let $\frac{dD^g}{df} = -Z_g$ where $Z_g > 0$. Then $K_U Z_U - K_I Z_I = R_U - R_I$ and S^I rises iff $\frac{Z_U}{Z_I} > \frac{D_U}{D_I}$, which gives $\frac{K_I}{K_U} + \frac{R_U - R_I}{K_U Z_I} > \frac{D_U}{D_I}$. Sufficient conditions: (1) $R_U > R_I$ and (2) $K_U D^U < K_I D^I$. Intuition: Two opposing forces determine the compositional shift. First, uninsured depositors face a larger outside option shock ($R_U > R_I$), creating stronger outflow pressure from this segment. Second, the condition $K_U D^U < K_I D^I$ captures how competitive dynamics attenuate quantity responses: when all banks simultaneously compete for deposits in equilibrium, segments with higher own-rate elasticity experience more intense strategic interaction, which dampens the aggregate quantity decline in that segment relative to the direct effect of the outside option shock. In the empirical model $R_U = R_I$, so only the second condition matters.

Case r″=0. A significant simplification occurs if I assume the deposit supply curves, $r_g(D_g)$, are linear. A linear supply curve of the form $r_g(D_g) = a_g + b_g D_g$ has the property that its second derivative is zero ($r''_g = 0$). This is a common assumption used to obtain sharp analytical results.

Under this assumption, the rigorous condition for the share of insured deposits to rise,

$$(2r'_U + r''_U D_U)D_U < (2r'_I + r''_I D_I)D_I$$

simplifies considerably, as the r'' terms vanish:

$$(2r'_U + 0)D_U < (2r'_I + 0)D_I$$

$$2r'_U D_U < 2r'_I D_I$$

The factor of 2 cancels, leaving a much simpler inequality:

$$r'_U D_U < r'_I D_I$$

This resulting expression is the inverse semi-elasticity of supply, which I denote $\tilde{\eta}_g \equiv r'_g D_g$ to distinguish it from the inverse elasticity η^g used in the main text.[17] Therefore, under the assumption of linear deposit supply curves, the complex condition from the general model becomes:

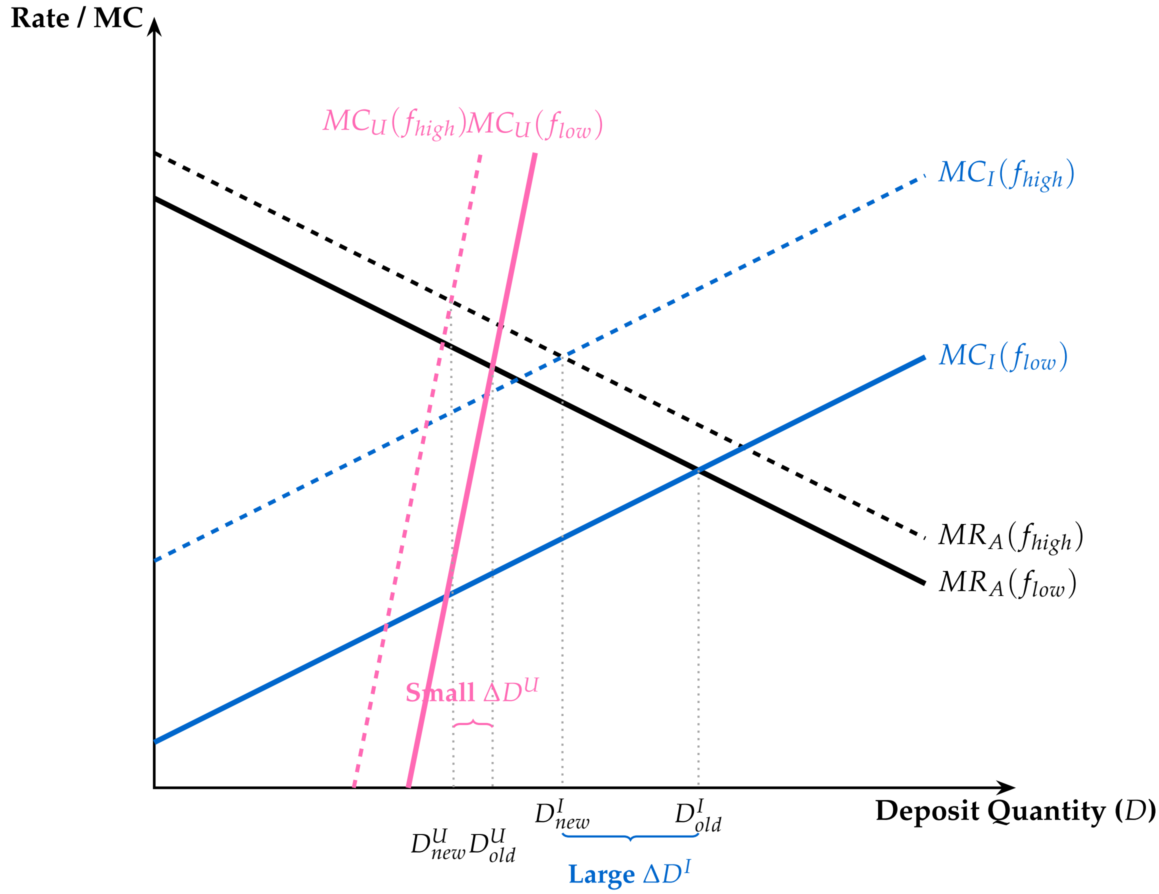
$$\tilde{\eta}_U < \tilde{\eta}_I$$

This condition states that uninsured deposits have lower inverse semi-elasticity than insured

[17] The inverse elasticity $\eta^g = \frac{D^g}{r^g}\frac{\partial r^g}{\partial D^g}$ measures the percentage change in rates needed for a percentage change in quantities. The inverse semi-elasticity $\tilde{\eta}_g = D^g \frac{\partial r^g}{\partial D^g}$ measures the absolute rate change needed for a percentage change in quantities. In the linear case with $r^g = a_g + b_g D^g$, we have $\tilde{\eta}_g = b_g D^g$ while $\eta^g = \frac{b_g D^g}{a_g + b_g D^g} = \frac{\tilde{\eta}_g}{r^g}$.

deposits. Economically, this means that in the linear case, the competitive dampening effect (captured by K_g) dominates when the segment requiring smaller absolute rate changes per unit quantity adjustment experiences smaller equilibrium outflows.

Intuition Graphics



B Extended Discussion: Segmentation and Monetary Transmission

This appendix provides a detailed discussion of how deposit market segmentation affects monetary policy transmission, complementing the condensed treatment in Section 1.4. While Proposition 1 characterizes the direct effects of monetary policy shocks on bank balance sheets, it treats segmentation as given. A fundamental question emerges: does deposit market segmentation itself amplify or dampen monetary policy transmission relative to a unified deposit market? This question is central to understanding whether regulatory or market forces that create segmentation (such as deposit insurance coverage limits) have unintended consequences for monetary policy effectiveness.

Main Result

The effect of deposit segmentation on monetary policy transmission depends on market structure:

1. **Monopoly**: Segmentation dampens policy transmission relative to a unified market: $\left|\frac{\partial A_{seg}}{\partial f}\right| < \left|\frac{\partial A_{unif}}{\partial f}\right|$.

2. **Oligopoly**: The net effect is ambiguous. Two opposing forces compete: segmentation enables price discrimination (dampening transmission) but also intensifies strategic competition across segments (amplifying transmission). The sign of $\left|\frac{\partial A_{seg}}{\partial f}\right| - \left|\frac{\partial A_{unif}}{\partial f}\right|$ depends on market concentration and the elasticity gap between segments.

3. **Empirical implication**: Models that pool all deposits into a single aggregate can generate biased estimates of monetary policy effectiveness, with bias in either direction depending on which effect dominates.

Proof Sketch

The result follows from comparing the first-order conditions under segmentation (two deposit types with distinct inverse demand slopes $\eta^I \neq \eta^U$) versus unification (single deposit type with demand-weighted average inverse slope). In monopoly, the price discrimination enabled by segmentation allows banks to smooth deposit outflows across segments when policy rates rise, reducing aggregate balance sheet volatility. In oligopoly, this smoothing effect competes with intensified strategic competition as banks can target specific segments.

Economic Intuition

The economic intuition works through the tension between market power and strategic interaction. With segmentation, a monopolist can set different rates r^I and r^U to extract surplus from each depositor type based on their elasticities. When policy rates rise, the monopolist attenuates the impact by adjusting rates differentially across segments—raising rates more in elastic segments to prevent large outflows while keeping rates lower in inelastic segments where depositors are captive. This flexibility reduces the aggregate quantity response relative to a unified market where the bank must set a single rate for all depositors.

Under oligopolistic competition, segmentation alters strategic interactions. When banks compete over two deposit segments rather than one, a bank cannot simply match a competitor's overall deposit rate; it must decide whether to compete aggressively in the insured segment, the uninsured segment, or both. This expanded strategy space can intensify competition: if one bank targets uninsured deposits with high rates to gain market share, competitors face a strategic dilemma that did not exist in a unified market. The result can be more aggressive rate competition and larger quantity responses to policy shocks. Following Corts (1998), segmentation can prevent the coordination on high markups that would occur in a unified market when firms compete in quantities across multiple segments with differential elasticities.

Policy Implications

First, this result demonstrates that empirical analyses of monetary policy transmission that ignore deposit market segmentation will systematically mismeasure the strength and distributional effects of the deposit channel. Because insured and uninsured deposits respond differently to policy rate changes, treating deposits as a homogeneous aggregate masks critical heterogeneity in transmission mechanisms. Reduced-form estimates of aggregate deposit pass-through or deposit elasticities will be biased, potentially leading to incorrect inferences about the effectiveness of monetary policy and misguided predictions about how policy changes propagate through the banking system. The structural estimation in the main text explicitly accounts for this segmentation to recover unbiased parameters.

Second, the result reveals that the institutional structure of deposit markets interacts with market structure to affect monetary transmission. In more concentrated markets where the market power effect dominates, segmentation may attenuate the deposit channel, requiring larger policy rate adjustments to achieve desired credit effects. In more competitive markets, segmentation may amplify transmission.

C Parametric Specifications for Supply-Side Model

This section documents the parametric functional forms used in the supply-side model. While the theoretical framework in Section 1.4 is general, empirical implementation requires specifying functional forms for the asset revenue function, wholesale funding cost function, deposit rate function, and non-interest servicing costs. These specifications follow standard formulations in the banking literature and enable tractable estimation and counterfactual analysis.

Asset Revenue Function

The asset revenue function $\ell(A, f)$ captures how banks transform deposits and other funding into profitable assets (primarily loans and securities). I adopt a Cobb-Douglas specification:

$$\ell(A, f) = \phi(f) \cdot A^{\gamma} \tag{1.35}$$

where A is total assets, $\phi(f)$ is an asset productivity parameter that varies with the federal funds rate f, and $\gamma \in (0, 1)$ is the returns-to-scale parameter. The restriction $\gamma < 1$ reflects diminishing returns to asset production, consistent with banks facing a limited pool of high-quality lending opportunities in any market.

The productivity term $\phi(f)$ allows asset profitability to vary with monetary policy. I specify:

$$\phi(f) = \phi_0 + \phi_1 \cdot f \tag{1.36}$$

This captures the asset revenue channel: higher policy rates typically increase net interest margins when banks can increase loan rates faster than deposit rates, expanding the marginal revenue earned on assets.

The Cobb-Douglas form is standard in production function estimation (Egan et al., 2022) and provides a tractable mapping from the bank's balance sheet to profitability. The parameters (ϕ_0, ϕ_1, γ) are estimated using IV regression of log net income on log assets and the federal funds rate, instrumenting for assets using lagged values to address simultaneity.

Wholesale Funding Cost Function

Banks access wholesale funding (Federal Home Loan Bank advances, brokered deposits, federal funds purchased) at costs that increase with quantity due to credit risk premia and regulatory constraints. I specify a convex cost function:

$$\omega(H, f) = f \cdot H + h_1 \cdot H^2 \tag{1.37}$$

where H is wholesale funding quantity, f is the base wholesale rate (proxied by the federal funds rate), and h_1 controls the convexity. The linear term $f \cdot H$ reflects the baseline cost of borrowing at the policy rate, while the quadratic term $h_1 \cdot H^2$ captures increasing marginal costs as banks borrow larger amounts. Note that while convexity is expected for most banks ($h_1 > 0$), some banks may have easier access to wholesale markets, reflected in negative or small values of h_1.

This convex specification matches the reality that banks face upward-sloping supply curves in wholesale markets. As a bank increases wholesale borrowing, lenders demand higher spreads to compensate for concentration risk and information problems. The parameter h_1 is recovered from the first-order condition for wholesale funding (equation 1.4) using observed quantities and deposit costs.

Deposit Rate Functions

Deposit rates are determined by the inverse demand system derived from the nested logit model. For segment $g \in \{I, U\}$, the relationship between deposit quantities and rates is:

$$r^g_{jmt} = r^g(D^g_{jmt}, D^g_{-j,mt}, f; \theta_g) \tag{1.38}$$

where $r^g(\cdot)$ is the inverse demand function implied by the nested logit utility specification (equation 1.12), D^g_{jmt} is bank j's deposit quantity in segment g, market m, time t, $D^g_{-j,mt}$ are rival deposits, and θ_g are the demand parameters (rate sensitivity α_g, nesting parameter σ_g, and other taste parameters).

The optimal deposit rate for segment g satisfies the first-order condition:

$$r^g_{jmt} = \frac{\mu_j - c^g}{1 + \eta^g_{jmt}(r^g_{jmt}, \boldsymbol{r_{-jmt}}, f)} \tag{1.39}$$

where μ_j is the bank's shadow value of funds, c^g is the marginal servicing cost for segment g, and η^g_{jmt} is the inverse elasticity of demand for segment g, which depends on the bank's own rate and competitors' rates.

Summary of Structurally Estimated and Recovered Parameters

Table 1.11 summarizes the parametric specifications and estimation/recovery approach for each component:

These parametric specifications balance parsimony with economic realism. The Cobb-Douglas asset revenue function and quadratic wholesale cost function are standard in the banking literature and provide tractable marginal conditions for the bank's optimization problem. The nested logit demand system delivers closed-form inverse demand curves that can be inverted to solve for

Table 1.11: Parametric specifications and estimation strategy

Component	Functional Form	Estimation/Recovery Method
Asset revenue	$\ell(A, f) = \phi(f) \cdot A^{\gamma}$ where $\phi(f) = \phi_0 + \phi_1 f$	IV regression: log net income on log assets and f, instrumenting assets with lagged values
Wholesale costs	$\omega(H, f) = f \cdot H + h_1 \cdot H^2$	Recover h_1 from wholesale FOC (eq. 1.4) using observed H, rates, and deposit costs
Deposit rates	$r^g(D^g, D^g_{-j}, f; \theta_g)$ from nested logit inverse demand and supply FOC	Estimate $\theta_g = (\alpha_g, \sigma_g, \beta_g)$ via 2SLS (Section 1.5)

Notes: This table summarizes the parametric functional forms and structural estimation/recovery procedures for the supply-side model components. IV = instrumental variables, 2SLS = two-stage least squares, FOC = first-order condition. All parameters are structurally estimated or recovered from equilibrium conditions. See Sections 1.5 and 1.6 for details on the sequential estimation strategy.

equilibrium rates. Together, these specifications enable computation of counterfactual equilibria under alternative monetary policy scenarios while maintaining economic interpretability of the recovered parameters.

D Demand Estimation: First-Stage and Instrument Diagnostics

This section presents first-stage regressions and instrument diagnostics for the nested logit IV estimation (Section 1.5). The specification instruments for deposit rates r_{jmtg} and within-nest market shares $\log(\hat{s}_{j|n,mtg})$.

First-Stage Results

Deposit Rate

Table 1.12 shows first-stage regressions for deposit rates. Lagged (t-1) balance sheet cost shifters strongly predict rates with expected signs. Loans secured by real estate enter positively and significantly: 11.5 bps for insured, 17.5 bps for uninsured deposits. The larger coefficient for uninsured deposits confirms greater risk sensitivity. The shift-share instrument (weighted rivals branch nest) enters negatively, reflecting competitive intensity effects.

Within-Nest Market Share

Table 1.13 shows first-stage regressions for the within-nest market share term $\log(\hat{s}_{j|n,mtg})$. The shift-share instrument (weighted rivals branch nest) enters strongly with coefficient approximately -0.20 (highly significant), confirming that greater rival presence mechanically reduces bank j's within-nest share. This validates the instrument's relevance for identifying the nesting parameter.

Instrument Diagnostics Summary

The main IV results (Section 1.6) include comprehensive diagnostics. Key findings: (1) Kleibergen-Paap Wald F-statistics range from 46-70 (insured) and 55-84 (uninsured), well above the weak

Table 1.12: First stage results: Deposit rate

	(1) Insured FE1	(2) Insured FE2	(3) Uninsured FE1	(4) Uninsured FE2
exp. premises/asset (lagged)	3.3152	3.2675	-28.1315***	-28.8371***
	(2.3778)	(2.3735)	(3.5277)	(3.5108)
loans secured by real estate (lagged)	11.5097***	11.4421***	17.5873***	17.3260***
	(0.9817)	(0.9812)	(1.6966)	(1.6870)
z-score	0.4145***	0.4166***	0.9031***	0.9104***
	(0.0859)	(0.0858)	(0.1267)	(0.1267)
log (branches mkt.)	-0.0021**	-0.0030**	-0.0007	-0.0046***
	(0.0011)	(0.0012)	(0.0014)	(0.0016)
ln_totbr	-0.0544***	-0.0554***	-0.0287	-0.0334
	(0.0131)	(0.0131)	(0.0227)	(0.0225)
log (counties)	0.0733***	0.0748***	0.0456**	0.0522***
	(0.0100)	(0.0099)	(0.0179)	(0.0178)
weighted rivals branch nest	–	-0.0014**	–	-0.0065***
	–	(0.0007)	–	(0.0011)
Observations	37019	37019	37523	37523

Standard errors in parentheses, two-way clustered by bank and market. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. *Notes:* First-stage regressions of deposit rates on excluded instruments and controls. FE1 includes county, bank, and year fixed effects. FE2 additionally includes all controls. Cost shifter instruments are lagged one period (t-1). Weighted rivals branch nest is the shift-share instrument defined in equation 1.13.

Table 1.13: First stage results: Within-nest market share

	(1) Insured	(2) Uninsured
exp. premises/asset (lagged)	-12.4749*	5.3537
	(6.5661)	(7.8007)
loans secured by real estate (lagged)	-5.8301**	-0.8847
	(2.7230)	(3.2266)
weighted rivals branch nest	-0.2061***	-0.1995***
	(0.0061)	(0.0060)
z-score	-1.2516***	0.1045
	(0.2158)	(0.3204)
log (branches mkt.)	0.5032***	0.5117***
	(0.0139)	(0.0138)
ln_totbr	-0.0553	-0.0929**
	(0.0354)	(0.0400)
log (counties)	-0.0000	0.1001***
	(0.0327)	(0.0350)
Observations	37019	37523

Standard errors in parentheses, two-way clustered by bank and market. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. *Notes:* First-stage regressions of log within-nest market share on excluded instruments and controls. Both specifications include county, bank, and year fixed effects. The shift-share instrument (weighted rivals branch nest) is defined in equation 1.13.

IV threshold of 10. (2) K-P LM test strongly rejects underidentification ($\chi^2 \approx$ 55-100, p<0.01). (3) Hansen J-test fails to reject instrument validity (p-values 0.10-0.40), supporting the exclusion restriction. (4) Durbin-Wu-Hausman test strongly rejects exogeneity (p<0.01), confirming IV is necessary. Overall, the instruments satisfy both relevance and validity requirements.

E Households Depositor Heterogeneity and Types of Accounts Preferences

This section describes the deposit market participants on the demand side. In particular, I will focus on the predictors of household deposit amounts and the number of accounts they hold.

Consumer households make up a large share of deposits through their savings accounts, checking accounts, certificates of deposit (CDs), and other personal banking products. These deposits are a primary way for individuals to store their money, manage their finances, and earn interest. Households hold around half of the total deposits in the US. To understand the composition of the deposit market, I use the Survey of Consumer Finances (SCF) to describe the characteristics of the households that hold deposits.

To build the total deposits variable, I aggregated the three categories represented in the survey: CDs, savings, and checkings.[18] The category with higher average deposits is savings, followed by checking and CDs. Checking accounts are the most common type of account, followed by savings and CDs. Less than 10% of the households have CD accounts, and slightly more than half have savings accounts. However, conditional on being a larger depositor, the probability of having a CD account is higher (around 30%).

Table 1.14: Summary statistics of household deposit variables

	Mean	Min	10%	Median	90%	Max
# financial institutions	2.58	0.0	1.00	2.00	5.0	15.0
# financial institutions with deposits	1.54	0.0	1.00	1.00	3.0	6.0
# financial institutions with CDs	0.09	0.0	0.00	0.00	0.0	6.0
Number of accounts	2.71	0.0	1.00	2.00	5.0	27.0
Total deposits ($1000)	37.09	0.0	0.05	4.60	78.5	2565.0
Amount Savings ($1000)	18.23	0.0	0.00	0.13	36.0	2540.0
Amount CDs ($1000)	6.49	0.0	0.00	0.00	0.0	1500.0
Amount Checking ($1000)	12.37	0.0	0.01	2.00	22.5	1708.0

Notes: This table presents summary statistics of the variables related to deposits. The quantities are in thousands of dollars. The statistics are weighted using the survey weights. The table includes all households in the SCF from 2010, 2013, 2016, and 2019.

Wealthy households hold the majority of personal deposits in the US. The analysis shown in table 1.15 emphasizes these points. Deposits are more skewed than income, meaning that the distribution of deposits is more concentrated in the right tail. Deposits also have higher kurtosis than income, meaning that the distribution of deposits has fatter tails than the distribution of income. The Gini coefficient for income is 0.56 and for deposits is 0.86, which shows that the distribution of deposits is more unequal than the distribution of income. All of this suggests a higher concentration in deposits and a nonlinear relationship between income and deposits.

[18]The saving category includes money markets. I did not include IRA/Keogh or 401K in this analysis.

Table 1.15: Distributional measures of income and deposits for households

	Mean	Median	Std	Skewness	Kurtosis	Gini
Income	95.58	54.94	235.78	22.42	791.26	0.56
Deposits	38.55	4.00	219.15	29.73	1228.57	0.86

Notes: This table presents summary statistics and distributional measures of income and deposits. The quantities are in thousands of dollars. This data is from the SCF from 2010, 2013, 2016, and 2019.

Table 1.16: Number of accounts per household conditional on having at least k account

	Account 1	Account 2	Account 3	Account 4	Account 5
count	34980.00	34236.00	24464.00	13296.00	7340.00
mean	27.42	13.68	7.50	5.30	4.26
std	181.19	129.20	29.18	18.28	15.40
25%	1.10	0.90	0.68	0.50	0.42
50%	4.00	2.20	2.00	1.50	1.00
90%	50.00	24.00	15.00	10.00	7.50
99%	327.00	170.00	100.00	60.00	55.00
max	10004.00	10000.00	1250.00	500.00	287.00

Notes: This table shows the number of accounts per household conditional on having at least k account. The means and other statistics are in thousands of dollars. The unit of observation is household/year. The data is from the SCF from 2010, 2013, 2016, and 2019.

Table 1.16 shows the total amount of deposits in the first five accounts, where the account k is the k-th largest account in terms of deposits. This is conditional on having an account and that it is not empty. The table shows that the average dollar amount in the first account is 27,420 thousand dollars, and the median is 4,000. Almost the same amount of households have a second account, but the average amount of dollars in this is almost half. For the subsequent number of accounts, the number of people with accounts and the average amount in the account decreases, but it is still considerable. Nonetheless, around 65% of household deposit money in the economy is held in the first account.

F Households' Deposit Distributions and Simulation

To model the consumer's deposit quantity demanded I use the following model:

$$\log d_i = \gamma_1 \log y_i^I + \gamma_2 (\log y_i^I)^2 + \mathbb{1}(y^I = 0) + \gamma_3 y_i + \varepsilon_i \tag{1.40}$$

where d_i is the deposits by household i, y_i^I is their income, y_i is a vector of demographic variables and wealth proxies, and ϵ_i is an error term. I include the quadratic term to capture the nonlinear relationship between income and deposits. I include the zero-income dummy to account for an unusual group of households that have zero income but positive and dispersed deposits. The covariate variables include age, ethnicity, marital status, and year-fixed effects. Additionally, home value, renter status, rent, and some quadratic terms are included.

The regression coefficients are shown in Table 1.26. The results confirm the concave shave of log income and log deposits. Almost all demographics are predictors of deposits in the expected sign and magnitude. Home value and rent positive increase in a convex way with respect to log deposits. Households with fewer people have fewer deposits. Similar results are obtained when using the number of accounts and uninsured deposits as the dependent variable.

Simulation Details and Fit

To simulate the deposit distribution I use the following procedure. First, I estimate the parameters of a similar equation to 1.40 using the SCF data. The covariates used in this estimation are age, ethnic group categories, their interactions, income, income squared a dummy for zero income, as well as the interactions between age and demographic and the income squared. I chose this and no other demographics because these are strong predictors and they are available in the Census data. To capture the dispersion of deposits, I use a log-normal distribution, that is, $\epsilon_i \sim \mathcal{N}(0, \sigma^2)$. I experimented with versions in which the variance of the error term can vary with year and income category. This is because there is less dispersion of log deposits for lower-income households. To deal with heteroscedasticity robust standard errors are used and income bins fixed effects are included in one of the specifications.

Table 1.17: Comparison of income and deposits simulated data using Census and SCF data by year

	Census		SCF	
Mean	Income	Deposits	Income	Deposits
2010	89,453	35,588	86,788	35,417
2013	96,252	42,116	96,422	37,575
2016	109,320	47,815	106,753	45,420
2019	122,294	57,446	104,817	50,865
Median	Income	Deposits	Income	Deposits
2010	53,016	2,372	50,794	3,100
2013	51,774	2,721	48,822	3,500
2016	54,445	3,158	53,219	4,500
2019	57,486	4,279	55,420	5,400

Notes: The table shows income and deposits mean and median for the SCF and the simulated data using Census by year. The quantities are in dollars. Variables are winsorized at the 1% and 99% levels.

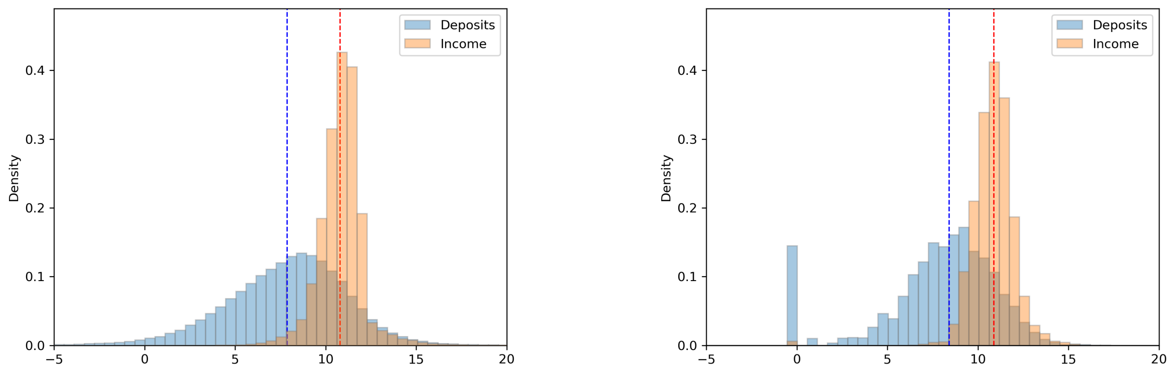
Figure 1.5: Comparison of simulated data using Census and SCF data, year 2016

	Census		SCF	
	Income	Deposits	Income	Deposits
Mean	116,158	47,815	106,753	45,420
Std	341,659	126,604	414,360	266,326
Median	54,445	3,158	53,219	4,500

Notes: The table shows income and deposit statistics for the SCF and the simulated data using the Census. The quantities are in dollars. Variables are winsorized at the 1% and 99% levels. Sources: SCF; U.S. Census (ACS).

Next, I use the Census data to simulate the demographic distribution of households in each market. I sample demographics using Census tract-level distribution of income, age, and ethnicity per household; and when a variable is not in the joint distribution, I sample it independently using block group-level distribution. Then, I recover the mean and variance of the log deposit distribution for each demographic group. I use the estimated parameters with the Census sample to simulate the deposit distribution. Then I use the estimated parameters and the sample from the Census to obtain the simulated deposits in each market *tm* (year-MSA or year-county).

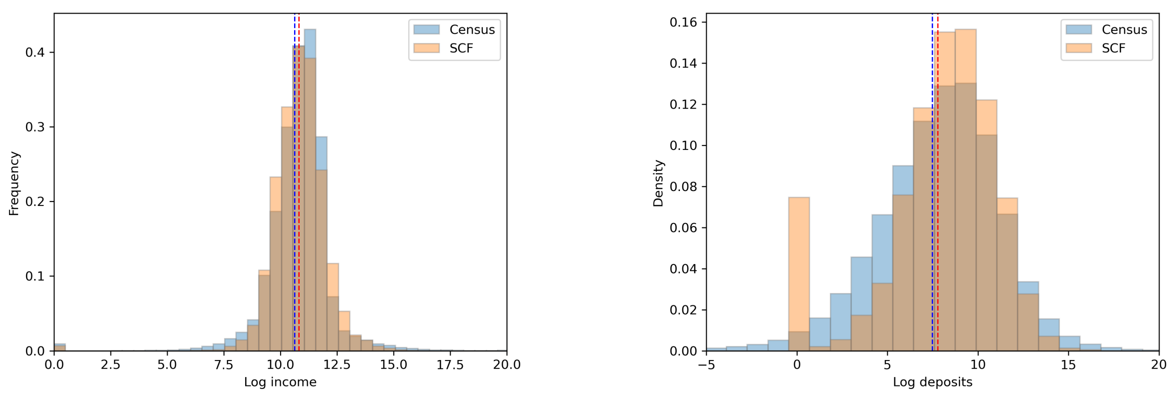
Figure 1.6: Fit of simulated data using Census and SCF data, year 2016



(a) Simulated data **(b)** SCF data

Notes: Side-by-side histograms of log income and log deposits for simulated Census-based data and SCF data, 2016. Both panels overlap closely, validating the simulation. Sources: SCF, U.S. Census.

Figure 1.7: Fit of simulated data using Census and SCF data, year 2016



(a) Income **(b)** Deposit

Notes: Histograms compare simulated Census distribution and SCF distribution for log income and log deposits, 2016. Distributions align well across both variables. Sources: SCF, U.S. Census.

Table 1.5 displays the mean, median, and standard deviation of income and deposits for the SCF and the simulated data using the Census for the year 2016, and table 1.17 shows the same statistics by year. . The simulated data using Census shows a higher mean and median for income and deposits this year. The standard deviation is also higher for the simulated data using Census. This suggests that the simulated data is more dispersed than the SCF data. The first two columns of table 1.5 and table 1.17 show income and deposit mean, standard deviation, and median for the simulated data, using the Census. Columns 3 and 4 show SCF data. The simulated data using Census shows a higher mean and median for income and deposits this year. The standard deviation is also higher for the simulated data using the Census. This suggests that the simulated data is more dispersed than the SCF data.

A closer inspection reveals that the tails are not well-fitted. The tails are longer in the simulated data using Census which might explain why the mean is larger. This might have to do with a larger estimated standard deviation, as well as inexact sampling when getting the demographic distribution from the Census.[19]

G Market Size Estimation

This section describes how I construct market size estimates M_{mtg} for each market m, segment $g \in \{I, U\}$, and year t. Market size represents the total potential deposit balances available in a local market and segment, including both deposits held at banks and alternative savings vehicles (the outside option). Accurate market size estimation is necessary for converting observed deposit quantities into market shares for demand estimation.

Overview: Four-Component Structure

The total market size is constructed by summing four distinct components corresponding to the cross-classification of depositor type (household vs. business) and insurance status (insured vs. uninsured):

$$M_{mtg} = \underbrace{D_{mt}^{HH,I} + D_{mt}^{HH,U}}_{\text{Household deposits in segment } g} + \underbrace{D_{mt}^{BUS,I} + D_{mt}^{BUS,U}}_{\text{Business deposits in segment } g} + M_{0mtg} \tag{1.41}$$

where $D_{mt}^{HH,I}$ and $D_{mt}^{HH,U}$ are household deposits classified as insured and uninsured respectively, $D_{mt}^{BUS,I}$ and $D_{mt}^{BUS,U}$ are business deposits classified as insured and uninsured, and M_{0mtg} is the outside option (money market funds and other non-bank savings vehicles). For each segment g, the market size aggregates the relevant household and business components:

$$\begin{aligned} M_{mtI} &= D_{mt}^{HH,I} + D_{mt}^{BUS,I} + M_{0mtI} \quad \text{(Insured segment)} \\ M_{mtU} &= D_{mt}^{HH,U} + D_{mt}^{BUS,U} + M_{0mtU} \quad \text{(Uninsured segment)} \end{aligned}$$

The key methodological challenge is that deposit data are not available at the intersection of depositor type, insurance status, and local market. I therefore combine multiple data sources and estimation procedures to construct each component separately, then aggregate to obtain segment-specific market sizes. The following subsections describe the estimation of each component in detail.

[19] The demographic distribution is obtained from the Census using the American Community Survey (ACS) 5-year estimates. The distribution uses income bins and assumptions were made about the shape of the distribution within each bin.

Household Deposits

Household deposit estimation combines microdata from the Survey of Consumer Finances (SCF) with Census demographic data to simulate local market deposit distributions. The detailed methodology, including the parametric deposit model, simulation procedure, and validation exercises, is provided in Appendices E (depositor heterogeneity) and F (simulation details and fit). Here I summarize the key steps and how households are allocated across insurance segments.

I estimate a log-normal model of household deposit holdings using SCF microdata. Following equation 1.40 in Appendix F, I specify:

$$\log d_i = \gamma_1 \log y_i^I + \gamma_2 (\log y_i^I)^2 + \mathbb{1}(y^I = 0) + \gamma_3 X_i + \varepsilon_i, \quad \varepsilon_i \sim \mathcal{N}(0, \sigma^2)$$

where d_i is household deposit balance, y_i^I is income, X_i includes demographics (age, ethnicity, homeownership, family size), and the error is normally distributed. The estimated parameters $\hat{\gamma}$ and $\hat{\sigma}$ characterize the conditional distribution of log deposits given observable characteristics.

To construct market-level deposit estimates, I combine the estimated model with American Community Survey (ACS) tract-level demographic data. For each market m and year t, the ACS provides the distribution of households across income bins, age categories, and demographic cells. For each demographic cell c with frequency N_{mtc} households, I compute the expected deposit holdings:

$$\mathbb{E}[d_i | X_i \in c] = \exp\left(\hat{\gamma}_1 \log y_c + \hat{\gamma}_2 (\log y_c)^2 + \hat{\gamma}_3 X_c + \frac{\hat{\sigma}^2}{2}\right)$$

where the exponential transformation accounts for the log-normal specification, and the term $\hat{\sigma}^2/2$ is the standard adjustment for converting the mean of log deposits to the mean of deposits in levels. The total household deposits in market m and year t are obtained by summing expected deposits across all demographic cells, weighted by their frequencies:

$$D_{mt}^{HH} = \sum_c N_{mtc} \cdot \mathbb{E}[d_i | X_i \in c]$$

To classify households into insured versus uninsured segments, I use a threshold-based classification using the estimated expected deposits for each demographic cell.[20] For each demographic cell c, I compute the expected deposits $\hat{\mu}_c = \mathbb{E}[d_i | X_i \in c]$ using the estimated lognormal deposit distribution. I then classify the entire cell based on whether the expected deposits exceed the FDIC threshold:

$$\begin{aligned} &\text{If } \hat{\mu}_c > \$250{,}000: && \text{Cell } c \text{ is classified as uninsured} \\ &\text{If } \hat{\mu}_c \leq \$250{,}000: && \text{Cell } c \text{ is classified as insured} \end{aligned}$$

[20]An alternative approach would be to compute the probability that a household's deposits exceed \$250,000 within each cell using the full lognormal distribution: $\pi_c^U = P(d_i > \$250{,}000 | X_i \in c) = 1 - \Phi\left(\frac{\log(250{,}000) - \mu_c}{\sigma}\right)$, and then allocate deposits proportionally. While this probability-based method would account for within-cell heterogeneity more explicitly, it requires computing truncated expectations of the lognormal distribution and is more sensitive to distributional assumptions. Given the granularity of the demographic cells (income bins × race × age × education), the threshold-based approach provides a simpler and more transparent approximation with minimal loss of accuracy.

The insured and uninsured household deposits in market m are then:[21]

$$D_{mt}^{HH,I} = \sum_{c:\hat{\mu}_c \leq 250K} N_{mtc} \cdot \hat{\mu}_c + \sum_{c:\hat{\mu}_c > 250K} N_{mtc} \cdot 250{,}000$$

$$D_{mt}^{HH,U} = \sum_{c:\hat{\mu}_c > 250K} N_{mtc} \cdot \max(\hat{\mu}_c - 250{,}000, 0)$$

This approach aggregates expected deposits conditional on household characteristics rather than simulating individual draws, which provides more stable estimates and ensures consistency with the parametric model. Validation exercises (Appendix F) confirm that the estimated distributions closely match SCF aggregates, with a correlation of 0.87 between simulated and observed market-level means, and the distributions reproduce key features of deposit concentration among high-income households.

Business Deposits

Business deposit holdings cannot be estimated directly from microdata because comprehensive surveys of business deposits do not exist. I therefore construct estimates using aggregate data from the Federal Reserve's Flow of Funds Financial Accounts combined with geographic proxies from County Business Patterns (CBP).

Data Sources

I combine three primary data sources to estimate business deposit market size:

County Business Patterns (CBP). The Census Bureau's County Business Patterns reports annual data on establishments, employment, and payroll by industry (NAICS code) and county. I use the universe of county-industry-year observations covering 2008-2021. Key variables include: (i) number of establishments, (ii) employment size categories (1-4, 5-9, 10-19, ..., 1000-2499, 2500+), (iii) total annual payroll in thousands of dollars, and (iv) total employment. The CBP data are particularly valuable because they provide fine geographic granularity (county level) and establishment size distributions, which allow me to proxy for business deposit demand and allocate deposits across insurance segments.

BEA KLEMS Database. The Bureau of Economic Analysis KLEMS database reports industry-level measures of gross output, capital, labor, energy, materials, and services at the national level. I use the KLEMS data to construct industry-specific ratios of gross output to payroll, which capture differences in deposit intensity across industries. For example, financial services firms and real estate businesses typically hold larger deposit balances per dollar of payroll compared to manufacturing or retail firms. The KLEMS data cover 65 industries defined at varying levels of NAICS aggregation and span 1998-2021.

Flow of Funds Financial Accounts. To calibrate the overall scale of business deposits and the distribution across industries, I use aggregate data from the Federal Reserve's Flow of Funds

[21] For households classified as uninsured (i.e., with $\hat{\mu}_c > \$250{,}000$), the uninsured deposit amount is calculated as $\max(\hat{\mu}_c - 250{,}000, 0)$ to account for the fact that the first \$250,000 of deposits in any account is insured. This calculation ensures that total deposits equal insured deposits (capped at \$250,000) plus uninsured deposits (the excess above \$250,000).

Financial Accounts (Table L.109 for nonfinancial corporate business and noncorporate business). These data report total business deposits in the U.S. banking system at quarterly frequency. I use annual averages to match the frequency of CBP and KLEMS data.

Estimation Methodology

The core idea is to use establishment payroll as a proxy for business deposit demand, with industry-specific adjustment factors to account for heterogeneity in deposit intensity across sectors. The estimation proceeds in four steps:

Step 1: Industry Crosswalk and Aggregation. I create a crosswalk between NAICS codes (used in CBP) and the production account codes used in KLEMS. For CBP establishments reported at detailed NAICS levels (e.g., 6-digit), I aggregate to match the KLEMS industry definitions. For each county-industry-year observation in CBP, I assign the corresponding KLEMS industry code. This crosswalk allows me to merge CBP county-level establishment data with KLEMS national industry-level output and revenue measures.

Step 2: Payroll-Based Deposit Proxy. Following the assumption that businesses hold deposits proportional to their operational scale, I estimate total business deposits in market m (county or county cluster), industry k, and year t as:

$$D^{bus}_{mkt} = \phi_k \cdot \text{Payroll}_{mkt} \tag{1.42}$$

where Payroll_{mkt} is total annual payroll (in thousands of dollars) from CBP, and ϕ_k is an industry-specific coefficient. I use the payroll proxy because businesses need transaction balances for payroll processing, accounts payable/receivable, and working capital management. Larger payrolls mean larger cash flow needs and therefore greater demand for deposit accounts.

To estimate ϕ_k, I use the KLEMS gross output data and aggregate Flow of Funds business deposits. Specifically, I compute:

$$\phi_k = \frac{\text{Total Business Deposits}}{\sum_k \omega_k \cdot \text{Total Payroll}_k} \tag{1.43}$$

where ω_k is an industry weight capturing relative deposit intensity, computed as the ratio of gross output to payroll in industry k from KLEMS:

$$\omega_k = \frac{\text{Gross Output}_k/\text{Payroll}_k}{\text{Average(Gross Output/Payroll)}} \tag{1.44}$$

This adjustment ensures that industries with high output relative to payroll (e.g., capital-intensive industries or those with high deposit turnover) receive higher weights in the deposit allocation. In practice, I estimate ϕ_k by matching aggregate CBP payroll to Flow of Funds business deposits, adjusting for the industry composition implied by the KLEMS weights.

Step 3: Allocation Across Insurance Segments. To split business deposits into insured and uninsured components, I use the relationship between establishment size and the likelihood of exceeding the $250,000 FDIC insurance limit. CBP reports the number of establishments in each employment size category (1-4 employees, 5-9, ..., 2500+). I make the following assumptions based on establishment size:

- *Small establishments* (fewer than 100 employees): These businesses have modest payroll and working capital needs. I assume 90% of their deposits fall below the $250,000 threshold and are therefore insured. This assumption reflects typical cash balances for small businesses documented in surveys of small business finances.
- *Medium establishments* (100-500 employees): These businesses have larger payroll cycles and operational cash needs. I assume 50% of their deposits exceed $250,000 and are uninsured, reflecting a mix of operating accounts (often swept below insurance limits) and larger cash holdings.
- *Large establishments* (500+ employees): These businesses maintain substantial working capital, payroll accounts, and concentration accounts that frequently exceed insurance limits. I assume 80% of their deposits are uninsured.

Using the establishment size distributions from CBP, I compute weighted averages of insured and uninsured shares for each county-industry-year cell. Specifically, let $N_{mkt}^{(e)}$ denote the number of establishments in employment size category e, and let $\pi_I^{(e)}$ denote the assumed insured share for that size category. Then:

$$D_{mkt}^{bus,I} = \phi_k \cdot \text{Payroll}_{mkt} \cdot \left(\sum_e \frac{N_{mkt}^{(e)}}{\sum_{e'} N_{mkt}^{(e')}} \cdot \pi_I^{(e)} \right) \tag{1.45}$$

$$D_{mkt}^{bus,U} = \phi_k \cdot \text{Payroll}_{mkt} \cdot \left(1 - \sum_e \frac{N_{mkt}^{(e)}}{\sum_{e'} N_{mkt}^{(e')}} \cdot \pi_I^{(e)} \right) \tag{1.46}$$

These size-based assumptions are calibrated to match aggregate evidence from Park (1995), who document that approximately 75% of business deposits are uninsured and 25% are insured. My weighted allocation procedure reproduces this aggregate split while allowing for geographic variation driven by differences in local establishment size distributions.

Step 4: Aggregation to County Clusters. To match the geographic market definition used in the main estimation (county clusters based on commuting patterns and deposit market integration), I aggregate county-level business deposits to 400 county clusters. For each cluster c, year t, and segment g:

$$D_{ctg}^{bus} = \sum_{m \in c} D_{mtg}^{bus} \tag{1.47}$$

where the sum is over all counties m within cluster c. This aggregation ensures consistency with the household deposit estimates and the market definition used for demand estimation.

Validation and Robustness

I conduct several validation exercises to assess the plausibility of the business deposit estimates:

Aggregate Calibration. Summing the estimated business deposits across all markets and segments, I obtain total business deposits of $1.8 trillion in 2019, compared to $1.7 trillion reported in the Flow of Funds for nonfinancial business deposits. The close match (within 6%) provides confidence that the payroll-based proxy and industry adjustments are reasonable.

Geographic Distribution. I compare the geographic distribution of estimated business deposits to alternative proxies based on GDP, employment, or corporate tax revenues. The correlation between my payroll-based estimates and these alternatives ranges from 0.82 to 0.91, suggesting that the payroll proxy captures meaningful variation in business deposit demand across markets. Urban markets with large business sectors (e.g., New York, San Francisco, Chicago) have the highest estimated business deposits, consistent with intuition.

Segment Split Validation. The estimated 75% uninsured share for business deposits aligns with evidence from Park (1995) and more recent analyses by Pancost and Robatto (2023) and Narayanan and Ratnadiwakara (2024), who document high uninsured deposit concentrations among business customers during the 2023 banking stress. This pattern is also consistent with bank Call Report data showing that large banks (which serve more business customers) have higher uninsured deposit shares. I also verify that the segment split is stable over time: the uninsured share ranges from 73% to 77% across 2008-2021, with modest increases during periods of low interest rates when businesses may consolidate accounts.

Sensitivity to Industry Weights. To assess robustness to the KLEMS-based industry weights ω_k, I re-estimate market sizes using equal weights across industries (i.e., setting $\omega_k = 1$ for all k). This alternative specification yields total business deposits 8% lower than the baseline, and the correlation between baseline and equal-weighted estimates across markets is 0.96. The high correlation indicates that most variation in business deposits is driven by payroll levels rather than industry composition, though industry adjustments do improve the aggregate calibration.

Outside Option: Money Market Funds and Non-Bank Savings

The outside option M_{0mtg} represents deposits held in alternative savings vehicles outside the traditional banking system, primarily money market mutual funds (MMMFs). Depositors can substitute between bank deposits and these alternatives in response to relative returns, safety considerations, and liquidity needs. Including the outside option in market size is essential for two reasons: (1) it affects the interpretation of market shares and the magnitude of estimated demand elasticities, and (2) it captures an important margin of adjustment when monetary policy changes the attractiveness of non-bank alternatives relative to bank deposits.

Data and Methodology

I estimate the outside option using aggregate data from the Federal Reserve's Flow of Funds Financial Accounts. Specifically, I use Table L.121 (Money Market Mutual Funds) which reports total assets held in retail and institutional money market funds quarterly. I convert these to annual averages to match the frequency of deposit data. The Flow of Funds provides national totals but does not disaggregate by geography or by the insurance status equivalent for non-bank alternatives.

To distribute the national outside option total to local markets, I assume that money market fund holdings are proportional to the potential depositor base in each market. Specifically, for each market m and year t:

$$M_{0mt} = \text{Total MMMF}_t \cdot \frac{N_m^{HH} + N_m^{BUS}}{\sum_{m'}(N_{m'}^{HH} + N_{m'}^{BUS})} \tag{1.48}$$

where N_m^{HH} is the number of households in market m (from Census), N_m^{BUS} is the number of business establishments in market m (from CBP), and the denominator normalizes to ensure the sum across markets equals the national total. This assumption reflects that money market funds are widely accessible and that holdings per household or business are roughly similar across geographic markets (conditional on the depositor mix).

To allocate the market-level outside option across insurance segments, I assume proportionality to the deposit base in each segment:

$$M_{0mtI} = M_{0mt} \cdot \frac{D_{mt}^{HH,I} + D_{mt}^{BUS,I}}{D_{mt}^{HH,I} + D_{mt}^{BUS,I} + D_{mt}^{HH,U} + D_{mt}^{BUS,U}} \tag{1.49}$$

$$M_{0mtU} = M_{0mt} \cdot \frac{D_{mt}^{HH,U} + D_{mt}^{BUS,U}}{D_{mt}^{HH,I} + D_{mt}^{BUS,I} + D_{mt}^{HH,U} + D_{mt}^{BUS,U}} \tag{1.50}$$

This allocation assumes that households and businesses with insured-level deposits have similar propensities to hold money market funds as those with uninsured-level deposits, scaled by the relative size of each segment in the market. While this assumption ignores potential differences in outside option usage across depositor types (e.g., sophisticated uninsured depositors likely have better access to money market funds), it provides a reasonable baseline that ensures the outside option is present in both segments and varies with local deposit market characteristics.

Magnitude and Time Variation

The outside option shows substantial time variation, driven primarily by changes in money market fund yields relative to deposit rates. During the zero lower bound period (2009-2015), money market fund yields were near zero, reducing the attractiveness of the outside option and likely increasing deposit market shares. In contrast, during periods of rising policy rates (2016-2019), money market fund yields increased sharply, making the outside option more competitive and potentially triggering deposit outflows to non-bank alternatives. This time variation is captured in the year fixed effects in the demand estimation, but including the outside option explicitly in market size ensures that estimated demand elasticities reflect the full choice set available to depositors.

Robustness to Alternative Market Share Specifications

To assess the robustness of the demand estimates to alternative specifications of market shares and the outside option, I consider two variations:

Expanded outside option with Treasury securities. In the baseline specification, the outside option consists primarily of money market mutual funds. As a robustness check, I expand the outside option to include short-term Treasury securities (T-bills), which are also close substitutes for bank deposits, particularly for sophisticated depositors. I obtain Treasury holdings from the Federal Reserve's Flow of Funds Financial Accounts and allocate them to local markets using the same proportional allocation as money market funds. Including Treasury securities increases the outside option by approximately 30-40% depending on the year, reflecting that Treasury bills represent a substantial alternative savings vehicle especially during periods of rising interest rates.

Residual-based outside option from national shares. As an alternative approach, instead of directly estimating the outside option from Flow of Funds data, I calculate it as the residual between the estimated total market size $\hat{M}_{mtg}$ (from household and business deposit components) and the sum of observed bank deposits in the market: $M_{0mtg} = \hat{M}_{mtg} - \sum_{j \in m} Q_{jmtg}$. This residual-based approach implicitly assumes that any gap between the estimated potential market size and actual bank deposits in the market represents holdings in non-bank alternatives. This specification treats the outside option as locally determined rather than being allocated from national aggregates, allowing for greater geographic heterogeneity in depositors' propensity to use non-bank alternatives.

Under both alternative specifications, the estimated demand elasticities remain qualitatively similar to the baseline. The rate sensitivity parameters α_g change by approximately 10-15%, and the relative ranking (uninsured deposits more elastic than insured) is preserved. The nesting parameters σ_g are similarly robust. These results indicate that while the precise magnitude of estimated elasticities depends on market size specification, the key comparative statics across segments and the identification of differential pass-through patterns are robust to reasonable alternative assumptions about the outside option.

H Segment Quantity Imputation: Model Specification and Algorithm

This appendix describes the imputation procedure used to recover segment-level local market deposit quantities, which are not directly observed in the data. Section 1.5 in the main text summarizes the key identification intuition and validation results; here I provide the complete model specification, estimation algorithm, and computational implementation.

Economic Motivation and Model Components

Banks report total deposits at the branch level through the Summary of Deposits (SOD), allowing computation of local market totals D_{jmt}. They also report segment-level deposits (insured and uninsured) nationally through Call Reports, yielding D_{jtg} aggregated across all markets. However, the crucial intersection—deposits by bank j, in market m, for segment g—is unobserved. This creates a fundamental measurement challenge for estimating local deposit demand.

The parametric model decomposes bank-market-segment deposit quantities into three components that exploit both cross-sectional and spatial variation in the data:

Bank-Market Baseline (μ_{jm}). This parameter captures bank j's overall deposit-taking capacity in market m, reflecting branch network density, historical presence, customer relationships, and local brand recognition. The baseline μ_{jm} represents the quantity of deposits—primarily insured deposits—that bank j attracts in market m regardless of its strategy toward large-balance depositors. This baseline varies across markets because banks face different levels of local competition, demographic characteristics, and geographic proximity to population centers. For banks operating in only one or two markets, μ_{jm} is tightly identified by observed local market totals D_{jmt} from SOD data.

Bank-Segment Preference (w_j). This bank-specific parameter measures bank j's comparative advantage in attracting uninsured deposits across all markets. A high w_j indicates that the bank's business model, reputation, service offerings, or relationship management capabilities make it particularly attractive to large depositors such as businesses and high-net-worth individuals. w_j is constant across markets for a given bank, reflecting national-level strategic choices about target customer segments, but it interacts with local conditions through the spillover term. For small banks with limited geographic scope, w_j is identified by the observed national segment split from Call Reports. For large multi-market banks, w_j is identified by how the bank's deposit mix varies systematically across markets with different competitive and demographic characteristics.

Local Spillover (λ). This parameter captures strategic complementarities in banks' uninsured deposit strategies within local markets. It measures how bank j's success in attracting uninsured deposits depends on the average uninsured preference ($w_{j'}$) of rival banks in that market. A positive λ means banks attract more uninsured deposits in markets where competitors also specialize in this segment, consistent with agglomeration effects: markets with concentrated commercial activity, wealth management infrastructure, or sophisticated financial services attract multiple banks pursuing similar uninsured deposit strategies. This spillover effect differs from direct competition (which depresses quantities) because it reflects positive externalities from shared market characteristics. The parameter λ is identified by comparing how banks with similar national uninsured preferences (w_j) perform differently across markets with varying competitive structures.

These three components allow the model to match both the extensive margin (which markets does bank j serve?) and the intensive margin (within a market, how much does bank j's deposit mix differ from its rivals?), while keeping the number of parameters manageable.

Functional Form and Parameter Specification

I model the log of deposit quantities $q_{jmg} \equiv D_{jmtg}$ (suppressing the time subscript for clarity) as:

$$\ln \hat{q}_{jmg}(\theta) = \begin{cases} \mu_{jm} + w_j + \lambda\, \bar{w}_{-j,m} & \text{if } g = U \text{ (uninsured)}, \\ \mu_{jm} & \text{if } g = I \text{ (insured)}, \end{cases} \tag{1.51}$$

where μ_{jm} is a bank-market fixed effect capturing bank j's average presence in market m, w_j is a bank fixed effect for uninsured deposits reflecting bank j's national propensity to attract uninsured deposits (e.g., due to reputation, clientele, or business model), and $\bar{w}_{-j,m} = \sum_{j' \neq j} \frac{b_{j'm}}{\sum_{k \neq j} b_{km}} w_{j'}$ is the average uninsured preference of other banks in market m weighted by their market presence (branches), where b_{jm} is the number of branches of bank j in market m. The parameter λ captures strategic spillovers: if $\lambda > 0$, bank j's uninsured deposits are higher in markets where competitors also have high uninsured preferences, potentially due to local market characteristics that favor uninsured deposits.

The parameter vector is $\theta = \{\mu_{jm}, w_j, \lambda\}$. The model implies $\hat{q}_{jmU}(\theta) = \exp(\mu_{jm} + w_j + \lambda \bar{w}_{-j,m})$ and $\hat{q}_{jmI}(\theta) = \exp(\mu_{jm})$.

Estimation via Nonlinear Least Squares

I estimate $\theta = \{\mu_{jm}, w_j, \lambda\}$ using nonlinear least squares (NLLS) to minimize the distance between predicted and observed aggregates. The observed aggregates impose three types of moment conditions: (1) total deposits of bank j in market m, denoted $q_{jm} = \sum_g q_{jmg}$ and observed from SOD branch-level data; (2) total uninsured deposits of bank j nationally, $Q_j^U = \sum_m q_{jmU}$, from Call Reports; and (3) total insured deposits of bank j nationally, $Q_j^I = \sum_m q_{jmI}$, also from Call Reports. The objective function in logs is:

$$\mathcal{L}(\theta) = \sum_{j,m} \left[\ln q_{jm} - \ln\left(\hat{q}_{jmU}(\theta) + \hat{q}_{jmI}(\theta)\right)\right]^2 + \sum_j \left[\ln Q_j^U - \ln \sum_m \hat{q}_{jmU}(\theta)\right]^2 + \sum_j \left[\ln Q_j^I - \ln \sum_m \hat{q}_{jmI}(\theta)\right]^2. \tag{1.52}$$

The problem involves thousands of parameters (one μ_{jm} for each observed bank-market combination, one w_j per bank, plus the common λ), but the Jacobian matrix has sparse structure that I exploit computationally. I solve the system using the Gauss-Newton algorithm with iterative updates $\theta^{(k+1)} = \theta^{(k)} - \left[J(\theta^{(k)})^\top J(\theta^{(k)})\right]^{-1} J(\theta^{(k)})^\top \mathbf{f}(\theta^{(k)})$, where $J(\theta)$ is the Jacobian and $\mathbf{f}(\theta)$ is the residual vector.

Computational Implementation

Estimation minimizes the nonlinear least squares objective by solving residual equations from three moment conditions. The residual vector $\mathbf{f}(\theta)$ is composed of:

$$\begin{aligned} f_{jm}^{(1)}(\theta) &= \ln q_{jm} - \ln\left(\exp(\mu_{jm} + w_j + \lambda \bar{w}_{-j,m}) + \exp(\mu_{jm})\right), \\ f_j^{(2)}(\theta) &= \ln Q_j^U - \ln \sum_m \exp(\mu_{jm} + w_j + \lambda \bar{w}_{-j,m}), \\ f_j^{(3)}(\theta) &= \ln Q_j^I - \ln \sum_m \exp(\mu_{jm}). \end{aligned}$$

The Gauss-Newton update step is $\theta^{(k+1)} = \theta^{(k)} - \left[J(\theta^{(k)})^\top J(\theta^{(k)})\right]^{-1} J(\theta^{(k)})^\top \mathbf{f}(\theta^{(k)})$, where $J(\theta)$ is the Jacobian matrix of the residual vector.

Jacobian derivatives. Let $D_{jm} = \exp(\mu_{jm} + w_j + \lambda \bar{w}_{-j,m}) + \exp(\mu_{jm})$. For the first residual type $f_{jm}^{(1)}$:

$$\frac{\partial f_{jm}^{(1)}}{\partial \mu_{jm}} = -1, \quad \frac{\partial f_{jm}^{(1)}}{\partial \lambda} = -\frac{\exp(\mu_{jm} + w_j + \lambda \bar{w}_{-j,m})}{D_{jm}} \cdot \bar{w}_{-j,m},$$

$$\frac{\partial f_{jm}^{(1)}}{\partial w_k} = \begin{cases} -\frac{\exp(\mu_{jm} + w_j + \lambda \bar{w}_{-j,m})}{D_{jm}} & \text{if } k = j, \\ -\frac{\exp(\mu_{jm} + w_j + \lambda \bar{w}_{-j,m})}{D_{jm}} \cdot \lambda \cdot e_{km} & \text{if } k \neq j \text{ and } k \in \mathcal{J}_m. \end{cases}$$

For the second residual type $f_j^{(2)}$, let $A_j = \sum_{m \in \mathcal{M}_j^U} \exp(\mu_{jm} + w_j + \lambda \bar{w}_{-j,m})$. Then:

$$\frac{\partial f_j^{(2)}}{\partial \mu_{jm}} = -\frac{\exp(\mu_{jm} + w_j + \lambda \bar{w}_{-j,m})}{A_j}, \quad \frac{\partial f_j^{(2)}}{\partial \lambda} = -\frac{1}{A_j} \sum_{m \in \mathcal{M}_j^U} \bar{w}_{-j,m} \cdot \exp(\mu_{jm} + w_j + \lambda \bar{w}_{-j,m}),$$

$$\frac{\partial f_j^{(2)}}{\partial w_k} = \begin{cases} -1 & \text{if } k = j, \\ -\frac{1}{A_j} \sum_{m \in \mathcal{M}_j^U} \lambda \cdot e_{km} \cdot \exp(\mu_{jm} + w_j + \lambda \bar{w}_{-j,m}) & \text{if } k \neq j \text{ and } k \in \mathcal{J}_m. \end{cases}$$

For the third residual type $f_j^{(3)}$, let $B_j = \sum_{m \in \mathcal{M}_j^I} \exp(\mu_{jm})$. Then $\frac{\partial f_j^{(3)}}{\partial \mu_{jm}} = -\frac{\exp(\mu_{jm})}{B_j}$, with no dependence on w_k or λ.

Initial values are set using a 50/50 segment split assumption for μ_{jm} and observed national ratios for w_j; Levenberg-Marquardt damping ($\delta = 10^{-4}$) ensures robust convergence, typically achieved in 10-15 iterations with tolerance $\epsilon = 10^{-6}$. Post-estimation validation confirms marginal matching errors below 1% and a 0.87 correlation between imputed and SCF-based bank-level uninsured shares (see Section 4.3). Algorithm 1 provides the complete implementation.

Imputation Fit

The imputation model is estimated separately for each of the $T = 12$ periods. The number of parameters and moments is substantial. Given the non-linear nature of the model, evaluating the goodness-of-fit requires a nuanced approach beyond a single metric like Mean Squared Error (MSE), which can be sensitive to outliers.

To provide a comprehensive picture, I analyze the full distribution of prediction errors pooled across all periods. The residual for the primary local quantity moments is defined as $f_{jm,t} = \ln(q_{jm,t}^{\text{obs}}) - \ln(\hat{q}_{jm,t}^{\text{pred}})$. I translate this log-difference into an intuitive absolute percentage error (APE) for each observation, where $\text{APE} = \left| \exp(f_{jm,t}) - 1 \right|$.

The results, summarized in Table 1.18, demonstrate a high degree of accuracy. The median APE is only 0.75%, indicating that for at least half of all bank-market-year observations, the imputed quantity is within approximately 1% of the true value. Furthermore, the 95th percentile of the error is only 10.23%, confirming that the model provides a very close fit for the vast majority of the sample. The long tail of the error distribution is evident in the 99th percentile, which reaches 29.15%. These outliers are highly concentrated in a few specific bank-market pairs, likely representing unique market structures that are not captured by my parsimonious model specification.

Algorithm 1 Estimate parameters for segment-level imputation

EstimateImputationParameters(q, Q^U, Q^I, K)

$\triangleright$ q, Q^U, Q^I are observed deposits; K is branch data for weights.

$\triangleright$ *Step 1: Initialization*
Initialize parameter vector $\theta^{(0)} = \{\mu_{jm}^{(0)}, w_j^{(0)}, \lambda^{(0)}\}$ (e.g., with zeros).
Set tolerance ϵ and iteration counter $k \leftarrow 0$.

$\triangleright$ *Step 2: Iterative Minimization via Gauss-Newton*
while not converged:
    $\triangleright$ *2a: Compute predicted quantities based on current* $\theta^{(k)}$
    for each bank j and market m:
        $\bar{w}_{-j,m}^{(k)} \leftarrow \sum_{j' \neq j} \frac{K_{j'm}}{\sum_{i \neq j} K_{im}} \cdot w_{j'}^{(k)}$
        $\hat{q}_{jm}^{U,(k)} \leftarrow \exp(\mu_{jm}^{(k)} + w_j^{(k)} + \lambda^{(k)} \bar{w}_{-j,m}^{(k)})$
        $\hat{q}_{jm}^{I,(k)} \leftarrow \exp(\mu_{jm}^{(k)})$

    $\triangleright$ *2b: Construct the full residual vector* $F(\theta^{(k)})$
    $F_1 \leftarrow$ vector of $\{\ln q_{jm} - \ln(\hat{q}_{jm}^{U,(k)} + \hat{q}_{jm}^{I,(k)})\}$ for all (j, m).
    $F_2 \leftarrow$ vector of $\{\ln Q_j^U - \ln(\sum_m \hat{q}_{jm}^{U,(k)})\}$ for all j.
    $F_3 \leftarrow$ vector of $\{\ln Q_j^I - \ln(\sum_m \hat{q}_{jm}^{I,(k)})\}$ for all j.
    $F(\theta^{(k)}) \leftarrow \text{stack}(F_1, F_2, F_3)$

    $\triangleright$ *2c: Compute the Gauss-Newton update step*
    $J(\theta^{(k)}) \leftarrow$ Compute Jacobian matrix of F w.r.t. θ using the derivatives.
    $\Delta\theta \leftarrow -\left[J(\theta^{(k)})^\top J(\theta^{(k)})\right]^{-1} J(\theta^{(k)})^\top F(\theta^{(k)})$

    $\triangleright$ *2d: Update parameters and check for convergence*
    $\theta^{(k+1)} \leftarrow \theta^{(k)} + \Delta\theta$
    if $||\Delta\theta|| < \epsilon$:
        converged $\leftarrow$ True

    $k \leftarrow k + 1$

$\triangleright$ *Step 3: Return Final Parameters*
$\hat{\theta} \leftarrow \theta^{(k)}$
return $\hat{\theta} = \{\hat{\mu}_{jm}, \hat{w}_j, \hat{\lambda}\}$

Table 1.18: Summary of Imputation Fit Across All Periods

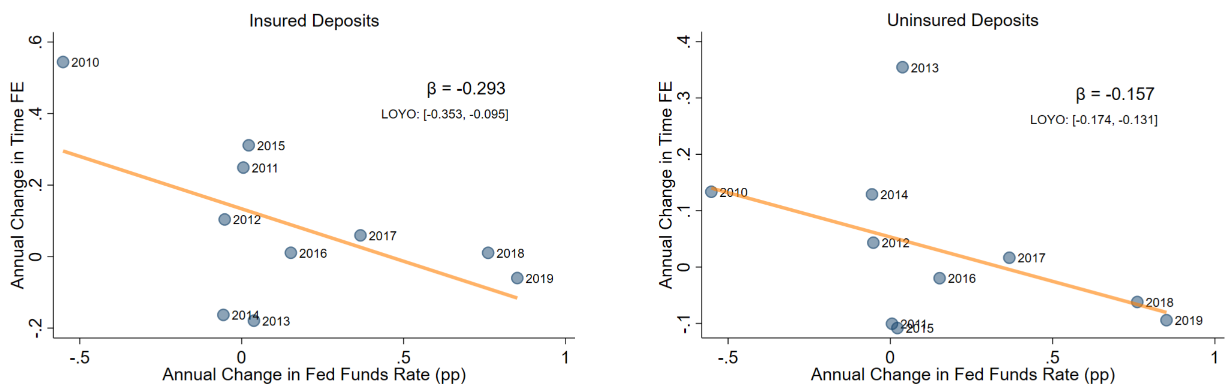
Statistic	Value
Mean	2.42%
Median	**0.75%**
90th pct	5.57%
95th pct	10.23%
99th pct	29.15%

Note: Statistics are calculated on the pooled set of all local quantity ($q_{jm,t}$) residuals from $T = 12$ separate estimations. APE is the absolute percentage error, calculated as $|\exp(f_{jm,t}) - 1|$.

I Pass-Through Estimation Figures

This appendix presents visual evidence of the monetary policy pass-through effects estimated in Section 1.6. Figures 1.8 and 1.9 plot the relationship between the federal funds rate and the estimated fixed effects from the structural model, illustrating how monetary policy transmits through both demand and supply channels.

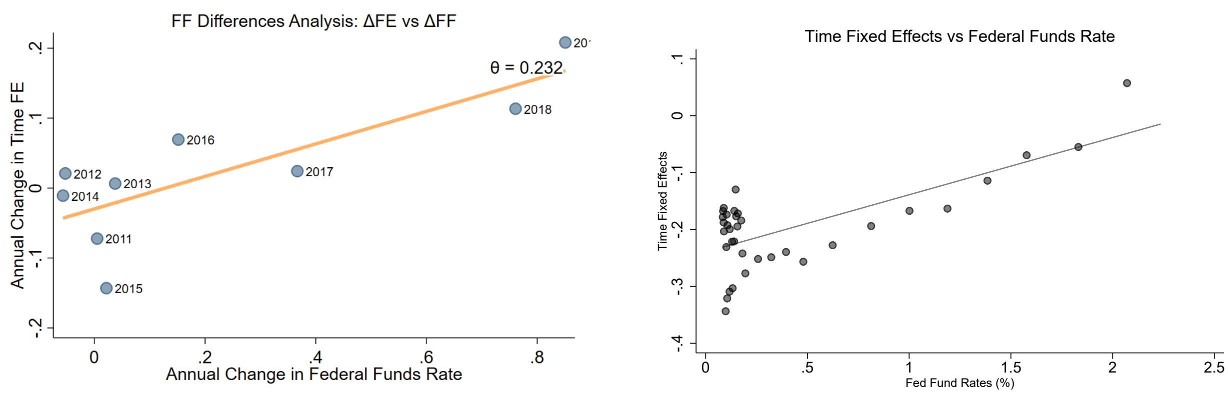
Figure 1.8: Demand channel pass-through: Year-segment fixed effects vs. federal funds rate



(a) Insured deposits **(b)** Uninsured deposits

Notes: This figure shows the relationship between year-segment fixed effects from the demand estimation ($\Delta\hat{\kappa}_{tg}$) and changes in the federal funds rate (Δf_t), along with fitted lines from regression 1.21. In both panels, each data point is a teal/blue circle labeled by year, and the fitted regression line is shown in orange. Panel (a) shows results for insured deposits, panel (b) for uninsured. The negative slopes indicate that depositor utility declines when policy rates increase (demand channel), controlling for deposit rates and bank characteristics. The steeper slope for uninsured deposits ($\beta_{1U} = -0.293$) compared to insured deposits ($\beta_{1I} = -0.157$) reflects that uninsured depositors are more sensitive to monetary policy changes, consistent with their greater sophistication and ability to substitute toward alternative investments. Sample: 2009–2019, yearly frequency. Data sources: RateWatch, FDIC SOD, FRED.

Figure 1.9: Supply channel pass-through: Year fixed effects vs. federal funds rate



(a) Yearly frequency **(b)** Quarterly frequency

Notes: This figure shows the relationship between year fixed effects from the asset revenue estimation ($\Delta\hat{\tau}_t$) and changes in the federal funds rate (Δf_t), along with the fitted line from regression 1.20. In panel (a), data points are teal/blue circles labeled by year; in panel (b), each data point is a circle corresponding to one quarter (not labeled). A fitted regression line is shown in each panel. Panel (a) aggregates the quarterly fixed effects to yearly averages for visual clarity, while panel (b) shows the full quarterly frequency data; the relationship is similar at both frequencies. Sample: 2009Q1–2019Q4. Data sources: Call Reports, FDIC SOD, FRED.

J Counterfactual Algorithm

This appendix details the step-by-step algorithm used to compute the full Nash Equilibrium response of the banking system to a monetary policy shock. The algorithm solves for a mutually consistent set of strategies for all banks j in a given time period t.

Overview and Counterfactual Environment

Having estimated the structural parameters of bank behavior, I conduct a counterfactual policy experiment to quantify the general equilibrium response of the banking system to a persistent monetary tightening. Specifically, I simulate a sustained 10 basis point increase in the federal funds rate ($\Delta f = 10$ bps) for every bank in every year of my sample. By re-solving each bank's optimization problem under this new policy environment—while holding all estimated structural parameters and non-policy fundamentals fixed—I measure how deposit rates, funding composition, and total assets adjust.

The policy rate f_t enters the bank's optimization problem in four ways:

1. **Asset revenue productivity.** $\log \phi_j(f_t) = \phi_{0j} + \phi_1 f_t$. Under the counterfactual, $\phi_j^{CF} = \phi_j(f_t^{CF})$, raising the marginal return to assets.
2. **Wholesale funding cost.** The marginal cost is $\text{MC}_{jt}^H(H, f_t) = f_t + h_1 H_{jt}$. Under the counterfactual, the intercept shifts to f_t^{CF}.
3. **Deposit demand preferences.** The segment-year fixed effects in the demand system shift with the policy rate: $\kappa_{gt}^{CF} = \kappa_{gt}(f_t^{CF})$. Under the counterfactual, for each market m, time t, and segment g, the mean utility components δ_{jtg}^{CF} and δ_{jmt}^{CF} incorporate the new policy environment.
4. **Deposit demand elasticities.** The demand system parameters remain fixed, but equilibrium elasticities adjust endogenously through changes in market shares.

All other primitives—the curvature of the asset technology (γ), the deposit servicing costs (c^I, c^U), the slope of the wholesale cost curve (h_1), and the demand system parameters—remain unchanged.

Equilibrium Conditions

Banks maximize profits by equating the marginal revenue of assets to the marginal cost of each funding source. In the counterfactual environment, the first-order conditions are:

$$\text{MR}_{jt}^A(A_{jt}, f_t^{CF}) = c^U + r_{jmt}^U\left(1 + \eta_{jmt}^U\right) \quad \forall m, \tag{1.53}$$

$$\text{MR}_{jt}^A(A_{jt}, f_t^{CF}) = c^I + r_{jmt}^I\left(1 + \eta_{jmt}^I\right) \quad \forall m, \tag{1.54}$$

$$\text{MR}_{jt}^A(A_{jt}, f_t^{CF}) = f_t^{CF} + h_1 H_{jt}. \tag{1.55}$$

These conditions hold subject to the balance sheet constraint:

$$A_{jt} = \sum_m (D_{jmt}^I + D_{jmt}^U) + H_{jt}.$$

Let $\mathbf{J}^{g}_{jmt} = \frac{\partial D^{g}_{jmt}}{\partial r^{g}_{jmt}}$ denote the Jacobian (derivative of deposit quantity with respect to rate) for bank j in market m and segment g. The vector of deposit demand elasticities is $\boldsymbol{\varepsilon}^{g}_{jmt} = \mathbf{J}^{g}_{jmt} \cdot \frac{r^{g}_{jmt}}{D^{g}_{jmt}}$. The inverse elasticity of deposit demand, denoted η^{g}_{jmt}, is the diagonal element of $(\mathbf{J}^{g}_{jmt})^{-1} \cdot \frac{D^{g}_{jmt}}{r^{g}_{jmt}}$, representing the slope of the inverse demand curve for segment g. Note that $\eta^{g}_{jmt} = \frac{1}{\varepsilon^{g}_{jmt}}$ only in the monopoly case when the bank faces no competition; more generally, η^{g}_{jmt} captures how the bank's own rate responds to changes in its own deposit quantity, holding competitor rates fixed.

Let μ_{jt} denote the **shadow value of funds** for bank j at time t, which represents the marginal value of an additional dollar of funding to the bank. This shadow value equates the marginal revenue from deploying funds in assets to the marginal cost of obtaining those funds from any source (insured deposits, uninsured deposits, or wholesale funding). Formally, $\mu_{jt} = \text{MR}^{A}_{jt}(A_{jt}, f_t)$ is the common value that satisfies all first-order conditions. The shadow value is central to the bank's optimization: it determines the bank's optimal deposit rates in each market and its wholesale funding decisions, ensuring that the marginal benefit of the last dollar raised equals the marginal cost across all funding sources.

Solving for the Full Nash Equilibrium

Following the monetary policy shock, the new equilibrium is a set of strategies—one for each bank—where each bank is maximizing its own profit given the strategies of all other banks. This is a Nash Equilibrium. The core of each bank's strategy is its shadow value of funds, μ_{jt}, which represents the marginal value of a dollar of funding to the bank. Therefore, the goal is to find the equilibrium vector of shadow values, $\boldsymbol{\mu}^{\boldsymbol{CF}}_{\boldsymbol{t}} = (\mu^{CF}_{1t}, \dots, \mu^{CF}_{Jt})$, where every element is a best response to all others.

This high-dimensional problem is solved using a Gauss-Seidel iteration, a numerical method that finds the fixed point of the system by updating each bank's strategy one at a time. The algorithm works in two main stages: initialization and iteration.

Initialization

The iteration begins with an initial guess for the equilibrium vector, $\boldsymbol{\mu}^{(\mathbf{0})}_{\boldsymbol{t}}$. The vector of pre-shock, baseline shadow values serves as a natural and effective starting point.

Gauss-Seidel Iteration for the Equilibrium Vector

I solve for the equilibrium vector $\boldsymbol{\mu}^{\boldsymbol{CF}}_{\boldsymbol{t}}$ using a Gauss-Seidel best-response iteration. Unlike Gauss-Jacobi iteration (which updates all banks simultaneously based on the previous iteration's values), Gauss-Seidel immediately incorporates each bank's updated shadow value when computing subsequent banks' best responses within the same iteration. This typically leads to faster convergence.

1. **Initialization:** I initialize the iteration with the vector of baseline shadow values, $\boldsymbol{\mu}^{(\mathbf{0})}_{\boldsymbol{t}}$.

2. **Iteration:** For $k = 0, 1, 2, \dots$, I sequentially update each bank's shadow value:

   - For each bank $j = 1, \dots, J$:

a) Use the current state of the vector (which includes already-updated values for banks $1, \ldots, j-1$ and previous values for banks $j+1, \ldots, J$) to compute competitor rates.

b) Find bank j's best-response $\mu_{jt}^{(k+1)}$ by solving the scalar root-finding problem $F_{jt}(\mu \mid \boldsymbol{r}_{-jt}) = 0$ using Brent's method.

3. **Convergence:** The iteration continues until the maximum absolute difference between consecutive iterations is below a tolerance threshold:

$$\max_j |\mu_{jt}^{(k+1)} - \mu_{jt}^{(k)}| < \text{tolerance}$$

The converged vector is the Nash Equilibrium $\boldsymbol{\mu}_t^*$.

Finding Each Bank's Best Response: Brent's Method

For any single bank j, given a vector of its competitors' deposit rates $\boldsymbol{r}_{-jt}$, its optimal shadow value μ_{jt} is found by solving a scalar root-finding problem that enforces its balance sheet constraint. I use Brent's method, a robust hybrid algorithm that combines bisection, secant, and inverse quadratic interpolation to efficiently find the root without requiring derivatives.

The function to be solved is the balance sheet gap function:

$$F_{jt}(\mu \mid \boldsymbol{r}_{-jt}) = A_{jt}^{\text{funding}}(\mu) - A_{jt}^{\text{production}}(\mu) = 0 \tag{1.56}$$

where:

- $A_{jt}^{\text{funding}}(\mu) = \sum_m (D_{jmt}^I(\mu) + D_{jmt}^U(\mu)) + H_{jt}(\mu)$ is total assets from the funding (liability) side
- $A_{jt}^{\text{production}}(\mu) = \left(\frac{\mu}{\phi_j(f_t^{CF})\gamma}\right)^{\frac{1}{\gamma-1}}$ is total assets from the production (asset) side FOC

For any candidate value of μ:

1. **Deposit Rates and Quantities.** Given the candidate μ and the fixed competitor rates $\boldsymbol{r}_{-jt}$, the bank's optimal deposit rates $r_{jmt}^g(\mu)$ are determined by solving the inner fixed-point between its first-order condition and the demand system using Newton-Raphson iteration (described below). This yields the deposit quantities $D_{jmt}^g(\mu)$.

2. **Wholesale Funding.** Wholesale funding is solved directly from its FOC:

$$H_{jt}(\mu) = \frac{\mu - f_t^{CF}}{h_1}$$

3. **Balance Sheet Consistency.** The bank's best-response μ_{jt} is the unique root of $F_{jt}(\mu \mid \boldsymbol{r}_{-jt}) = 0$, found using Brent's method bracketed between $[\mu_{min}, \mu_{max}]$.

The Inner Loop: Solving for Optimal Deposit Rates via Newton-Raphson

Similar to a mean utility iteration in classic demand estimation, the deposit optimization is a highly non-linear problem: for a given bank j with a candidate shadow value μ_j, and given a set of rates for all its competitors $\boldsymbol{r_{-jmt}}$ in market m, we must find its optimal rate r^g_{jmt} for segment g. This rate must simultaneously satisfy the bank's first-order condition and the nested logit demand system.

The rate r^g_{jmt} is the solution to the fixed-point problem:

$$r^g_{jmt} = \frac{\mu_j - c^g}{1 + \eta^g_{jmt}(r^g_{jmt}, \boldsymbol{r_{-jmt}})}$$

where the inverse elasticity η^g_{jmt} itself depends on r^g_{jmt} through the market share function $s^g_{jmt}(r^g_{jmt}, \boldsymbol{r_{-jmt}})$ from the nested logit model.

I solve this scalar fixed-point problem using Newton-Raphson iteration with Levenberg-Marquardt damping for numerical stability. Define the function:

$$G(r) = r - \frac{\mu_j - c^g}{1 + \eta(r)}$$

The Newton-Raphson update is:

$$r^{(n+1)} = r^{(n)} - \frac{G(r^{(n)})}{G'(r^{(n)})}$$

where the derivative $G'(r)$ is computed using the chain rule through the inverse elasticity function. To ensure convergence in difficult cases, I employ Levenberg-Marquardt trust-region damping and adaptive step-size control: if a proposed step increases the residual, the damping parameter λ is increased and the step is retried; if the step succeeds, λ is reduced for faster convergence. Additionally, I use adaptive over-relaxation (with parameter $\omega \in [0.7, 1.8]$) to accelerate convergence when progress is smooth. This procedure converges rapidly (typically in 10-35 iterations) to the optimal rate r^{g*}_{jmt}.

Complete Algorithm

Algorithm 2 provides the complete pseudocode for solving the counterfactual equilibrium, incorporating the three-level nested structure:

1. **Outer loop:** Gauss-Seidel iteration over all banks to find equilibrium $\boldsymbol{\mu}$ vector
2. **Middle loop:** Brent's method to find each bank's best-response μ_j
3. **Inner loop:** Newton-Raphson to solve for optimal rates in each local market

Convergence and Uniqueness

Uniqueness of the Cournot equilibrium is guaranteed under standard regularity conditions: concavity of the profit function (ensured by $\gamma < 1$ and convex wholesale funding costs $\partial^2\omega/\partial H^2 >$

0) and upward-sloping deposit demand (ensured by positive rate elasticities from the nested logit model). I verify uniqueness empirically by solving from multiple initial conditions and confirming convergence to the same equilibrium.

The algorithm typically converges in 25-40 outer Gauss-Seidel iterations with tolerance $\epsilon = 10^{-6}$ for the $\boldsymbol{\mu}$ vector. For each bank, Brent's method converges in 15-25 function evaluations of the gap function. Each gap function evaluation requires solving approximately 50-100 local market-segment rate problems (depending on the bank's geographic footprint), with Newton-Raphson converging in 5-15 iterations per rate.

Outcomes and Transmission Metrics

For each bank-year-market, I compute changes:

$$\Delta X = X^{CF} - X, \quad \%\Delta X = 100 \cdot \frac{X^{CF} - X}{X}$$

Key outcomes include:

- Deposit rates r^I, r^U and pass-through elasticities $\beta_j^g = \Delta \bar{r}_j^g / \Delta f$
- Deposit volumes D^I, D^U, wholesale funding H, and total assets A
- Funding shares $s^g = D^g / A$, $s^H = H / A$
- Uninsured deposit share $s^U_{deposits} = D^U / (D^I + D^U)$

These aggregated results are reported in Tables 1.9 and 1.10 in Section 1.7.

Algorithm 2 Solve for full counterfactual Nash equilibrium

SOLVEFULLNASHEQUILIBRIUM($\Delta f, \Theta$)

▷ Θ contains all estimated parameters and baseline data for time period t.
▷ **Step 1: Define Counterfactual Environment**
$f_t^{CF} \leftarrow f_t + \Delta f$
for each bank j:
    $\phi_{jt}^{CF} \leftarrow \exp(\phi_{0j} + \phi_1 f_t^{CF})$ ▷ New asset productivity

for each market m, time t, segment g:
    Shift δ_{jmtg}^{CF} ▷ Demand preferences respond to policy

▷ **Step 2: LOOP 1 (Outer) - Gauss-Seidel Iteration over $\boldsymbol{\mu}$**
$\boldsymbol{\mu} \leftarrow \boldsymbol{\mu}_{baseline}$ ▷ Initialize with pre-shock shadow values
repeat
    max_change $\leftarrow 0$
    for each bank $j = 1, \ldots, J$:
        ▷ **LOOP 2 (Middle) - Brent's Method for Bank j's Best Response**
        Define gap function: $\text{Gap}_j(\mu) = A_j^{prod}(\mu) - A_j^{fund}(\mu)$
        ▷ where $A_j^{prod}(\mu) = (\mu/(\phi_j^{CF}\gamma))^{1/(\gamma-1)}$
        ▷ and $A_j^{fund}(\mu) = D_j^{total}(\mu) + H_j(\mu)$

        ▷ To evaluate $D_j^{total}(\mu)$ at candidate μ:
        $\boldsymbol{r}_{-j} \leftarrow$ COMPUTECOMPETITORRATES($\boldsymbol{\mu}_{-j}, \Theta$)
        $D_{j,total} \leftarrow 0$
        for each market m where bank j operates:
                for each segment $g \in \{I, U\}$:
                        ▷ **LOOP 3 (Inner) - Newton-Raphson for Optimal Rate**
                        $r_{jmt}^g \leftarrow$ SOLVEOPTIMALRATE_NR($\mu, \boldsymbol{r}_{-jmt}^g, c^g, \Theta$)
                        $D_{jmt}^g \leftarrow$ COMPUTEDEPOSITQUANTITY($r_{jmt}^g, \boldsymbol{r}_{-jmt}^g, \Theta$)
                        $D_{j,total} \leftarrow D_{j,total} + D_{jmt}^g$

        $H_j(\mu) \leftarrow \max\{(\mu - f_t^{CF})/h_{1,j}, 0\}$
        $A_j^{fund}(\mu) \leftarrow D_{j,total} + H_j(\mu)$

        ▷ Find root μ_j^* where $\text{Gap}_j(\mu) = 0$ using Brent
        $\mu_{j,new} \leftarrow$ BRENTROOT($\text{Gap}_j, [\mu_{min}, \mu_{max}]$)

        change $\leftarrow |\mu_{j,new} - \boldsymbol{\mu}[j]|$
        max_change $\leftarrow$ max(max_change, change)
        $\boldsymbol{\mu}[j] \leftarrow \mu_{j,new}$ ▷ Gauss-Seidel update

until max_change $< \epsilon$

▷ **Step 3: Recover All Counterfactual Outcomes**
$\boldsymbol{\mu}^* \leftarrow \boldsymbol{\mu}$
for each bank j:
    for each market m and segment g:
        Compute final rates r_{jmt}^{g*} and quantities D_{jmt}^{g*} using μ_j^*

    Compute final H_j^* and A_j^*
    Store outcomes $\{r_j^*, D_j^*, H_j^*, A_j^*\}$

return All counterfactual outcomes

Algorithm 3 Solve for optimal rate via Newton-Raphson

SolveOptimalRate_NR($\mu, \boldsymbol{r}_{-jmt}, c^g, \Theta$)

$\triangleright$ Solve fixed-point: $r = (\mu - c^g)/(1 + \eta(r))$ with Levenberg-Marquardt damping
$r \leftarrow r_{initial}$ $\triangleright$ Initialize with previous rate or heuristic
$\lambda \leftarrow 10^{-4}$, $\omega \leftarrow 1.2$ $\triangleright$ LM damping and over-relaxation parameters
repeat
  $s \leftarrow$ ComputeMarketShare($r, \boldsymbol{r}_{-jmt}, \Theta$) $\triangleright$ From nested logit
  $\eta \leftarrow$ ComputeInverseElasticity(s, r, Θ) $\triangleright$ Inverse elasticity from shares
  $G(r) \leftarrow r - (\mu - c^g)/(1 + \eta)$ $\triangleright$ Fixed-point residual
  $G'(r) \leftarrow 1 - \frac{\partial}{\partial r}\left[\frac{\mu - c^g}{1+\eta(r)}\right]$ $\triangleright$ Derivative via chain rule
  $r_{new} \leftarrow r - (G'(r) + \lambda I)^{-1} G(r)$ $\triangleright$ LM-damped Newton step
else : $\lambda \leftarrow 4\lambda$, retry
  $r \leftarrow (1 - \omega) r + \omega \cdot r_{new}$ $\triangleright$ Adaptive over-relaxation
until $|G(r)| <$ tolerance
return r

K Clustering Counties

I start with all counties nationally to capture heterogeneity across both urban and rural areas. However, estimating the demand model at the county level is computationally infeasible given the large number of distinct geographic units. Additionally, market share data for smaller or more rural counties can be subject to considerable measurement error. To balance geographic granularity with computational feasibility and data reliability, I aggregate contiguous counties into larger, economically meaningful market definitions, following d'Avernas et al. (2023).

The aggregation uses an agglomerative (bottom-up) hierarchical clustering approach that iteratively merges adjacent counties based on two criteria: (1) all final clusters must exceed a minimum threshold of 20,000 households, and (2) the total number of clusters should not exceed a target maximum (to keep estimation tractable). The algorithm works as follows. Starting with each county as its own cluster, I identify the smallest cluster that falls below the household threshold. I then merge this cluster with its smallest adjacent neighbor, where adjacency means counties share a border. This process repeats, progressively combining small counties with nearby small counties, until all clusters meet the size threshold and the total number of clusters is below the target. The result is a set of geographically contiguous market definitions that respect natural economic boundaries (I only merge neighbors) while ensuring sufficient sample size for reliable estimation in each market. Urban counties with large populations typically remain standalone markets, while I group rural counties with nearby counties to form larger, more stable market units.

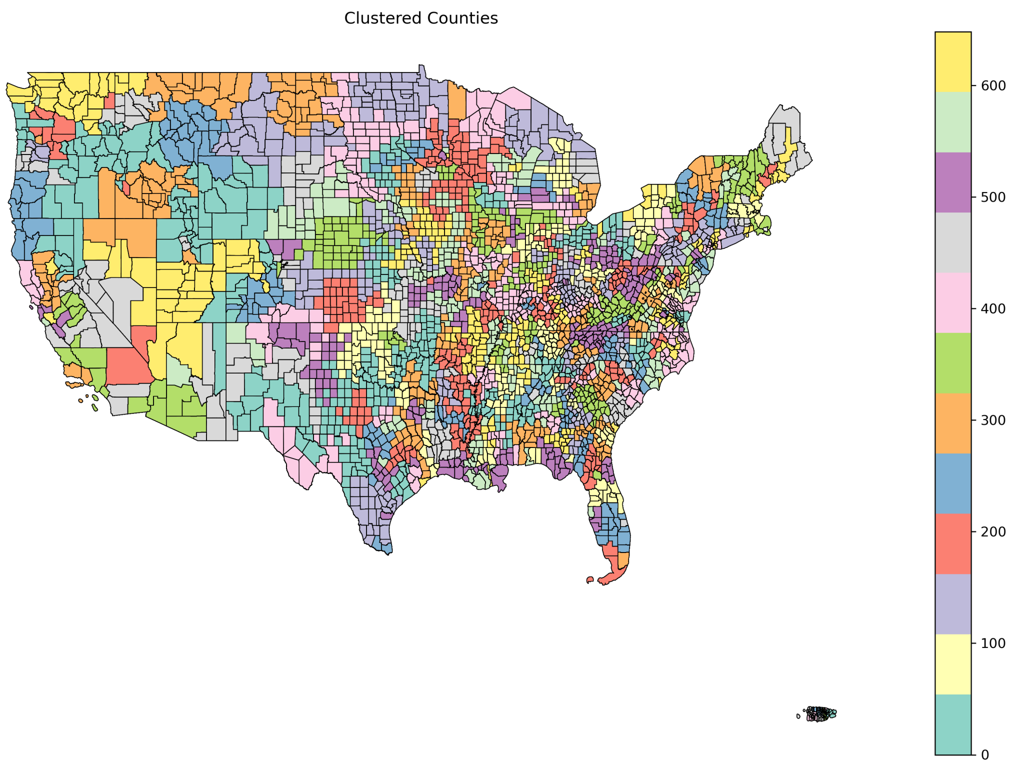
Algorithm 4 provides the formal specification of this procedure, where adjacent county clusters are progressively merged based on a chosen weight metric (such as population) until minimum size thresholds and a target number of final clusters are achieved.

Algorithm 4 County clustering by iterative merging

CLUSTERCOUNTIES(G, county_data, w_{min}, N_{target})

$\triangleright$ G: County adjacency graph.
$\triangleright$ county_data: Contains county weights (e.g., population).
$\triangleright$ w_{min}: Minimum weight threshold for a cluster.
$\triangleright$ N_{target}: Target maximum number of clusters.
Initialize clusters $\mathcal{C}$: each county j is a cluster $\{j\}$ with members $M_{\{j\}} = [j]$ and weight $W_{\{j\}}$.
Initialize set of isolated clusters $\mathcal{I} = \emptyset$.
while $(|\mathcal{C}| > N_{target}$ OR $\exists c \in \mathcal{C}$ s.t. $W_c < w_{min})$
    Identify potential clusters to merge: $\mathcal{S} = \{c \in \mathcal{C} \setminus \mathcal{I} \mid W_c < w_{min}$ or $|\mathcal{C}| > N_{target}\}$.
    if $\mathcal{S} = \emptyset$
        Break $\triangleright$ Exit loop.
    Select smallest cluster to initiate merge: $c^* = \arg\min_{c \in \mathcal{S}} \{W_c\}$.
    Find adjacent clusters to c^*: $N(c^*) = \{c' \in \mathcal{C} \mid \exists u \in M_{c^*}, v \in M_{c'}, (u, v) \in E(G), c' \neq c^*\}$.
    if $N(c^*) = \emptyset$
        $\mathcal{I} \leftarrow \mathcal{I} \cup \{c^*\}$ $\triangleright$ Mark as isolated.
        Continue $\triangleright$ Proceed to next iteration.
    Select smallest neighboring cluster to merge into: $c'^* = \arg\min_{c' \in N(c^*)} \{W_{c'}\}$.
    $\triangleright$ Perform Merge:
    $M_{c'^*} \leftarrow M_{c'^*} \cup M_{c^*}$ $\triangleright$ Update members.
    $W_{c'^*} \leftarrow W_{c'^*} + W_{c^*}$ $\triangleright$ Update weight.
    $\mathcal{C} \leftarrow \mathcal{C} \setminus \{c^*\}$ $\triangleright$ Remove merged cluster. $\triangleright$ End While
return Final cluster mapping $\{\text{anchor}_c : M_c \text{ for } c \in \mathcal{C}\}$.

Figure 1.10: Clustering counties



Notes: County map showing the clustering of U.S. counties into 650 groups by the iterative-merging algorithm described in this section. Each color marks a distinct cluster; color is used purely to distinguish adjacent clusters and is categorical (not ordinal), so the map cannot be read by color intensity. Clusters span groups of contiguous counties. Data source: U.S. Census.

L Model Extensions

Extended Demand Specification with Household and Business Depositors

This section presents a more general specification of the deposit demand model that explicitly incorporates both household and business depositors, their heterogeneous characteristics, and spatial choice patterns. While the main text uses a simplified nested logit specification for tractability, this extended model captures richer patterns of depositor heterogeneity and provides a foundation for future extensions.

Depositor Types and Characteristics

Depositors can be of two types: households and businesses, $\tau \in \{H, B\}$. Both types of depositors have a deposit endowment dep and characteristics y. The vector of characteristics y includes demographics, but also type τ and location variables (county), m, of the depositor.

Depositors' decision-making follows a discrete choice model in which depositors in every market $t = 1, \ldots, T$ choose a segment $g \in \{I, U\}$ and depository institution $j \in J_t = \{0, 1, \ldots, J\}$ where I stands for insured deposits and U for uninsured deposits. A depositor chooses only one account in one bank. Market t is defined as a time period (year or quarter).

Utility Specification

A depositor i's indirect utility of choosing segment g in bank j in market t is:

$$v_{ijtg} = \underbrace{\delta_{jtg}}_{\substack{\text{bank-segment} \\ \text{mean utility}}} + \underbrace{\mu_{ijtg}}_{\substack{\text{customer-bank} \\ \text{interaction}}} + \underbrace{\delta_{jmt}}_{\substack{\text{local} \\ \text{market term}}} + \epsilon_{ijtg}, \tag{1.57}$$

where $\epsilon_{ijtg} \sim$ T1EV and $m = m(i)$ is the depositor's county.

The bank-segment mean utility is

$$\delta_{jtg} = \beta_g^\rho \rho_{jt} + X_{jt}' \boldsymbol{\beta} + \nu_j + \kappa_{gt} + \xi_{jtg}, \tag{1.58}$$

where ρ_{jt} is the risk measure for bank j in period t, and β_g^ρ captures the risk aversion of depositors in segment g. X_{jt} represents bank-level characteristics such as employees per branch and total number of counties, ν_j are bank fixed effects, κ_{gt} are segment-year fixed effects, and ξ_{jtg} captures unobservable bank-segment characteristics.

The local market term reflects county-level factors:

$$\delta_{jmt} = L_{mt}' \beta^m + d_{jmt} \beta^d + \xi_{jmt}, \tag{1.59}$$

where L_{mt} denotes county m's demographics and economic conditions (e.g., population, income, local competition), d_{jmt} is the number of branches of bank j in county m, and ξ_{jmt} is a local unobservable.

The customer-bank interaction term is

$$\mu_{ijtg} = r_{jtg} \alpha_i + d_{jmt} \beta_i^d + \beta_i^m L_{mt} + \xi_{ijtg}^c, \tag{1.60}$$

where r_{jtg} is the deposit rate offered by bank j in segment g, and $\alpha_i = \alpha_H \tau_H + \alpha_U g_U + \alpha_D dep_i$ scales rate sensitivity by depositor type and deposit size. β_i^m includes interactions with τ_H, g_U, and dep_i. Finally, ξ_{ijtg}^c is an idiosyncratic interaction shock.

The outside option is to choose credit unions and local banks that compete only in one market, as well as other investment options. For simplicity, I normalize the outside option to zero in all their characteristics:

$$v_{i0tg} = \xi_{0t} + \epsilon_{i0tg}. \tag{1.61}$$

Choice Probabilities and Market Shares

Given this utility and the set of parameters $\theta = \{\alpha_i, \beta, \gamma_H, \gamma_B, \nu_j, \eta_t, \kappa_{gt}, \xi_{jtg}, \xi_{jmt}, \xi_{ijgt}\}$, the probability that depositor i chooses (j, g) is

$$P_{ijgt}(\theta) = \frac{\exp\left(\delta_{jtg} + \mu_{ijtg} + \delta_{jmt}\right)}{\sum_{k \in J_{t,g(i)}: d_{kmt} > 0} \exp\left(\delta_{ktg} + \mu_{ikgt} + \delta_{kmt}\right)}, \tag{1.62}$$

where I only consider banks with at least one branch in m. Note that this conditional probability is a function of the depositors' consideration set J_i.

Let $F_{tg}(dep, y)$ be the distribution of deposit endowments and characteristics in market t for segment g. The share of deposits in market t that bank j collects in segment g is given by:

$$s_{jtg}(\theta) = \frac{\int dep\, P_{ijgt}(dep, z)\, dF_{tg}(dep, z)}{\sum_{k \in J_t} \int dep\, P_{ikgt}(dep, z)\, dF_{tg}(dep, z)}, \tag{1.63}$$

where dep is the deposit endowment, $F(dep, y)$ is the distribution of deposit endowments and characteristics which includes type of depositors and location, and $P_{ijgt}(dep, y)$ is the probability of depositor i in market t choosing bank j in segment g given the deposit endowment and characteristics.

Local Market Shares

Additionally, define local market shares s_{jtm} as the share of deposits in market t that bank j collects in county m, from the closest branch to the depositor's location. This is a simplification, but it is consistent with the data collection process in which banks report deposits as belonging to the consumers' closest retail branch. In the simplest case, depositors can only choose banks that are in the same county as them. The model can be extended to allow depositors to choose banks that are not in the same county, but have a branch in the county (see Appendix F).

The local market share s_{jtm}[22] is given by:

$$s_{jtm}(\theta) = \frac{\displaystyle\int \sum_{g \in \{I,U\}} dep\, P_{ijgt}(dep, z)\, dF_m(dep, z)}{\displaystyle\sum_{k \in J_t} \int \sum_{g} dep\, P_{ikgt}(dep, z)\, dF_m(dep, z)}. \tag{1.64}$$

Equations (1.57)–(1.64) together define the extended structural deposit-demand model. This specification nests the simplified nested logit model used in the main text and provides a framework for incorporating richer heterogeneity in depositor characteristics, spatial choices, and type-specific preferences. The key advantage of this formulation is that it explicitly models the deposit-weighted market shares, accounting for the fact that larger depositors (both households and businesses) may have different choice patterns than smaller depositors. Future extensions could use this structure to analyze differential responses to monetary policy across depositor types and geographic markets.

Depositors' Choice Sets in Demand Model

The consideration sets of consumer choice in the banking industry were introduced by Abrams (2019). I extend this idea by allowing the mapping of depositors' characteristics to banks' segments and banks in the choice set. Let the choice probability be defined as $P_{ijtg} = \varphi(\tilde{P}_{ijtg}; \phi_{ijtg})$, where ϕ_{ijtg} is the consideration probability, and $\tilde{P}_{ijtg}$ is the conditional probability of choosing bank j in market t given the bank's and depositor's characteristics and it's as follows: Hence, ϕ_{itjg} is the probability that depositor i in market t considers bank j's segment g given the bank's and depositors' characteristics. This probability is a function of the depositor's characteristics y_{it}, the bank's characteristics X_{jt}, and the market's characteristics T_t. I assume that this probability can be disentangled into two independent probabilities: the likelihood that the depositor considers the bank and the likelihood that the depositor considers the segment. Thus $\phi_{itjg} = \phi_{itj}\phi_{itg}$.

Choice Set of Banks: Depositors can choose any bank in the country, but they care about the distance to the branches, and other bank characteristics like the number of branches in the county, online banking, advertising, etc. Then the probability that depositor i in market t considers bank j is $\phi_{itj} = \Phi^J_{itj}(X_{jt}, d_{ijt}, y_{it}; \lambda^J)$, where Φ^J_{itj} is the probability distribution that depends on X_{jt}, d_{ijt}, y_{it}. The parameters that determine this probability are denoted λ^J. Let $C(j)$ be the set of all consideration sets where bank j is included. If only the closes bank is considered then $C(j) = \{\{j\}\}$, but if all banks are considered then $C(j) = \{J_t\}$. A simpler version is to assume that a depositor considers all banks in the country, or that this is simulated instead of calculated to ease the computational burden.

[22] Local market share can also be written as follows: Let D_{jtm} be the total deposits in market t that bank j collects in county m. Let $\lambda_m(y, j)$ be a function that maps the depositors' location to banks' j branches in m. If for depositor i the closest branch of bank j is in county m, then $\lambda_m(y, j) = 1$, otherwise $\lambda_m(y, j) = 0$. Then, the total reported deposits are:

$$D_{jtm} = \int_{dep,y} \sum_{g \in \{I,U\}} dep \cdot P_{ijgt}(dep, y)\lambda_m(y, j)\, dF(dep, y)$$

Thus $s_{jtm} = \frac{D_{jtm}}{\sum_{k \in J_t} D_{ktm}}$.

Choice Set of Segment: Depositors are restricted by their deposit size and influenced by information and risk aversion. Parameters that determined ϕ_{itg} are denoted λ^S, i.e. $\phi_{itg} = \Phi^S(\lambda^S, X_{jt}, d_{ijt}, y_{it})$. Some possible assumptions that are not necessarily exclusive are below:

1. Total separation: Households can only choose insured products, and firms can only choose uninsured products. Thus $\phi_{itg} = 1(\tau(i) = H)1(g = I) + 1(\tau(i) = B)1(g = U)$.

2. Wealthy depositors choose in the uninsured segment, while less wealthy depositors can only choose insured accounts. Thus $\phi_{itg} = 1(dep_{it} > d\bar{e}p)1(g = U) + 1(dep_{it} \leq d\bar{e}p)1(g = I)$.

3. Wealthy depositors can choose both segments, but less wealthy depositors can only choose insured accounts. Thus $\phi_{itg} = 1(dep_{it} > d\bar{e}p)1(g = U) + 1(g = I)$.

4. Exogenous segment choice and no substitution: Depositors' choice of the segment is exogenous and can be inferred from observed data, that is $\phi_{itg} = 1(g \in g(i))$. This idea is similar to a latent type analysis, where the segment choice is exogenous and unobservable. I can assume this is determined exogenously and can be inferred from observed data using observations of depositors' choices and a classification algorithm.

5. Substitution: Both types of depositors can choose between insured and uninsured deposits. Thus $\phi_{itg} > 0$ for all g for some depositors.

Example of a parametric choice set: If it assumed that all depositors choose insured and uninsured deposits as a bijection of their endowment, then $\phi_{itg} = 1(dep_{it} > d\bar{e}p)1(g = U) + 1(dep_{it} \leq d\bar{e}p)1(g = I)$ (Case 2). If for the bank choice set, a logistic function is used to calculate the probability that a depositor considers a bank, then $\phi(itj) = \Lambda(\lambda, X_{jt}, d_{ijt}, y_{it})$, where Λ is a logistic function, and λ^J is a vector of parameters. Then the probability of consideration of depositor i in market t of choosing bank j in segment g is:

$$\phi_{itjg} = \phi_{itj}\phi_{itg} = \Lambda(\lambda^J, X_{jt}, d_{ijt}, y_{it}) \cdot (1(dep_{it} > d\bar{e}p)1(g = I) + 1(dep_{it} \leq d\bar{e}p)1(g = U)), \quad (1.65)$$

and the (unconditional) probability choice is:

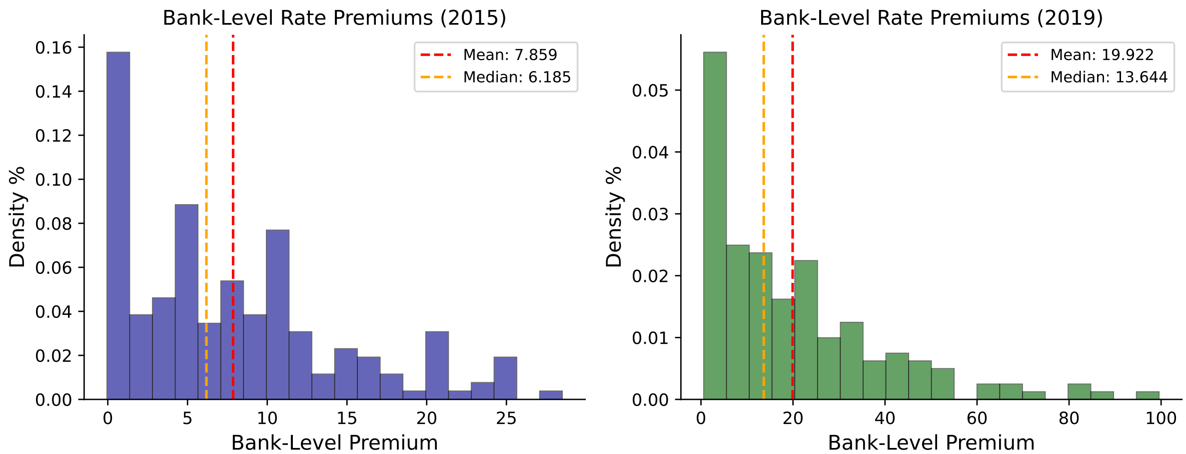
$$P_{ijtg} = \sum_{J \in C(j)} \prod_{k \in J} \phi_{itkg}(1 - \phi_{itkg})\tilde{P}_{ijtg}(J) \quad (1.66)$$

where $C(j)$ is the consideration sets were bank j is included.

M Distribution of Segment Premiums

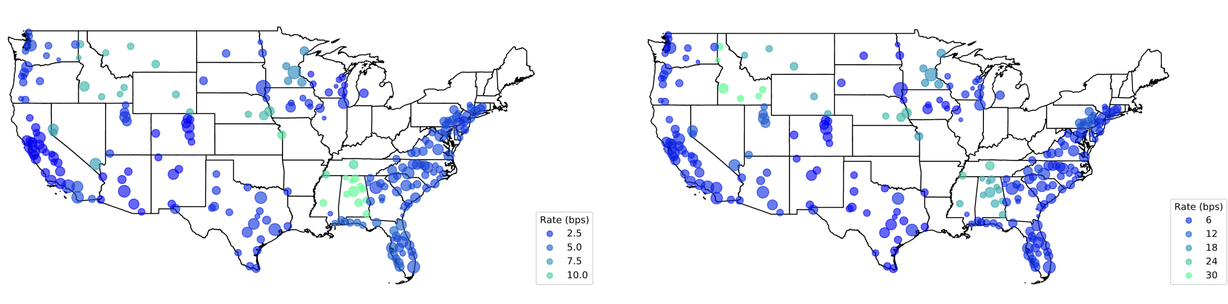
Figure 1.11 shows the distribution of segment premiums (difference between MM250K and MM2.5K rates) across banks in 2015 and 2019. The distributions are right-skewed with considerable variation: while the median premium is around 10 basis points, some banks offer premiums exceeding 40 basis points. The distributions shift to the right from 2015 to 2019, showing that the gap between insured and uninsured deposit products increased as monetary policy returned to normal after the financial crisis.

Figure 1.11: Segment premium distributions by year



Notes: This figure shows histograms of bank-level segment premiums (MM250K rate minus MM2.5K rate) for 2015 (blue/darker bars, labeled "2015") and 2019 (red/lighter bars, labeled "2019"). The 2019 distribution shifts rightward relative to 2015, indicating the premium grew over the sample period. Distributions are unweighted across banks. Sample includes multi-market banks with rate data for both segments. Source: RateWatch.

Figure 1.12: Wells Fargo deposit rates by geography, 2019



(a) MM2.5K (insured proxy) **(b)** MM250K (uninsured proxy)

Notes: Geographic distribution of Wells Fargo's deposit rates in 2019: MM2.5K accounts (left panel, insured proxy) and MM250K accounts (right panel, uninsured proxy). Darker shading indicates higher rates. The Southeast and California show the highest rates in both panels, while the Midwest shows systematically lower rates. This spatial pattern illustrates that even within a single large bank, local competitive conditions generate substantial rate variation. Uninsured rates are higher than insured rates across virtually all markets. Source: RateWatch.

Geographic Heterogeneity in Deposit Rates: Wells Fargo Example

Figure 1.12 illustrates the geographic variation in deposit rates for Wells Fargo, one of the largest U.S. banks, in 2019. The maps show that Wells Fargo offers higher rates on MM250K accounts (uninsured proxy) compared to MM25K accounts (insured proxy) across most markets, with substantial spatial heterogeneity in both rate levels and segment premiums. This geographic variation reflects local market conditions, competitive pressures, and the bank's strategic pricing decisions across different regions.

Segment Premiums Over Time

Table 1.19 presents the evolution of segment premiums from 2009 to 2019. The mean segment premium declined from 48 basis points in 2009 to a low of 8 basis points in 2014-2015, before rising again to 19 basis points in 2019. This pattern closely tracks the federal funds rate and reflects the zero lower bound period (2009-2015) when deposit rates were compressed near zero, followed by monetary policy normalization (2016-2019) when rate differentiation across segments re-emerged. The persistent positive premium indicates that banks consistently compensate uninsured depositors for bearing default risk, with the premium magnitude varying with the overall level of interest rates.

Table 1.19: Segment Premium by Year

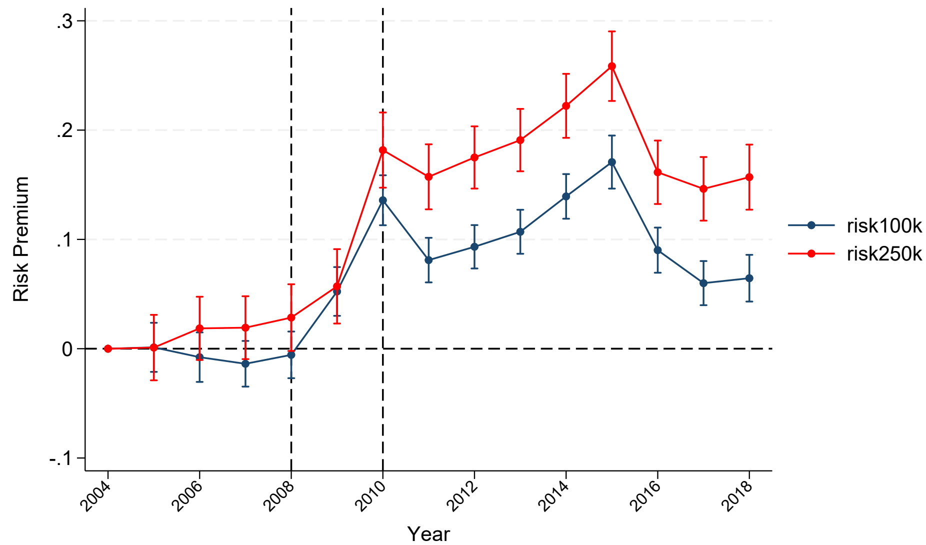
Year	Mean (bp)	Median (bp)
2009	48.07	35.55
2010	29.19	24.65
2011	20.85	18.68
2012	14.97	12.48
2013	10.52	9.42
2014	8.21	6.96
2015	7.66	5.99
2016	8.37	6.53
2017	8.44	6.06
2018	11.17	9.18
2019	19.12	12.84

Notes: Mean and median segment premiums (in basis points) by year. Segment premium is calculated as the difference between MM250K and MM2.5K deposit rates at the bank level. The premium follows the federal funds rate cycle, declining during the zero lower bound period and rising during monetary policy normalization. Source: RateWatch.

Dynamic Evolution Around the 2008 Crisis

Figure 1.13 shows the year fixed effects from the estimation of the log segmentation premium differences between MM250K and MM2.5K in red, and between MM100K and MM2.5K in blue. After 2008, both premiums rise, but the MM250K premium increases substantially more and diverges from the MM100K premium. This pattern reflects banks' repricing response to the change in the deposit insurance threshold to $250,000 in 2008 (later made permanent), combined with heightened run risk during the crisis period. Banks adjusted their segmentation premia to reflect the altered insurance boundary and associated funding costs.

Figure 1.13: Risk premium dynamic analysis around the 2008 Crisis



Notes: The figure shows year fixed effects from log segmentation premium regressions: the MM250K–MM2.5K premium (red solid line, labeled "250K–2.5K") and the MM100K–MM2.5K premium (blue dashed line, labeled "100K–2.5K"). Both premiums rise sharply after the 2008 crisis, when the FDIC insurance threshold increased to $250,000; the MM250K premium increases substantially more, reflecting the changed insurance boundary. Regressions include market and bank fixed effects; omitted year is 2004. Unit of observation is bank/year/MSA. Source: RateWatch and SOD.

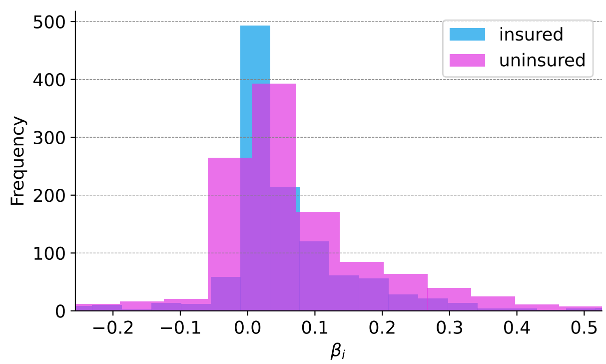
N Pass-Through Estimation by Bank

The following regression model is used to estimate the passthrough β_i for each segment:

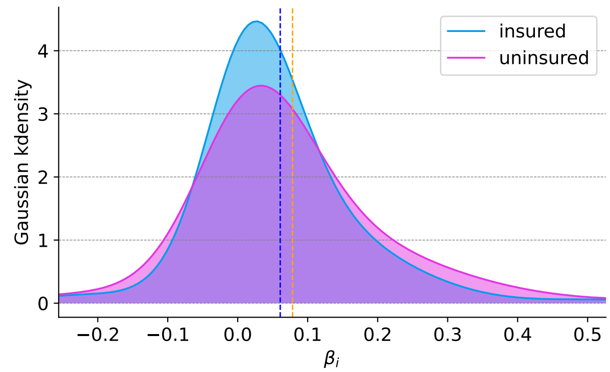
$$\Delta r_{igt} = \alpha_i + \beta_i \cdot \Delta f_t + \epsilon_{it} \tag{1.67}$$

where Δr_{igt} is the change in the deposit interest rate of bank i in segment g at time t, Δf_t is the change in the federal funds rate at time t, and α_i is the bank fixed effect. The passthrough β_i is estimated for each segment g and bank i. Only banks with rates in both segments and at least 8 quarter observations are included in the estimation.

Figure 1.14: Pass-Through Distribution for All Banks



(a) Histogram of Pass-Through Estimates



(b) Gaussian Kernel Density Estimate

Notes: Distribution of bank-level pass-through estimates (β_i) from Equation 1.67. Left panel shows histogram of pass-through estimates. Right panel shows Gaussian kernel density estimate. Products included: MM25K (insured) and MM250K (uninsured). Sample includes banks with rates in both segments and at least 8 quarter observations. The distribution is approximately bell-shaped and centered slightly below 0.5, consistent with substantial but incomplete pass-through across banks. Data source: RateWatch.

Table 1.20: Monetary Policy Pass-Through to Segmentation Premium by Bank Size

	Small Banks		Medium Banks		Large Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
ΔFF (mean)	-0.061***	-0.037***	-0.084***	-0.071***	-0.026*	-0.028**
	(0.006)	(0.004)	(0.014)	(0.012)	(0.015)	(0.012)
Constant	0.061***	0.061***	0.059***	0.059***	0.046***	0.046***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)
Observations	20024	19863	4493	4487	1407	1406
Adjusted R^2	0.019	0.442	0.032	0.278	0.006	0.240
Bank Fixed Effects	–	✓	–	✓	–	✓

Notes: The product here refers to Money Market accounts with minimum deposits of $25,000 (MM25K) and $250,000 (MM250K). The analysis covers the period from 2012 to 2019. The panels are divided by bank size: small, medium, and large banks. The equation used is: $\Delta\text{Risk Premium}_{jt} = \Delta\text{FF Rate}_t + \epsilon_{jt}$ where the difference in segmentation premium is calculated as the difference in deposit rates between MM250K and MM25K, and the difference in FF Rate refers to changes in the federal funds rate.

O Additional Figures and Tables

Table 1.21: Rate dispersion measures within the bank, 2019

	MM25K	MM250K
Mean (bp)	25.99	40.28
	(29.39)	(38.44)
Coeff. of var.	0.18	0.18
	(0.29)	(0.39)
90-10 percentile	1.67	1.72
	(2.14)	(2.41)
count	223	223

Notes: This table compares statistical measures for MM25K and MM250K accounts, including mean interest rates (expressed in basis points), coefficient of variation, and the spread between the 90th and 10th percentiles. The rates are in basis points. A unit of observation is bank/year/MSA. The table are constructed using data from RW and SOD.

Table 1.22: Log segmentation premium pricing determinants for large banks

	(1)	(2)	(3)	(4)	(5)	(6)
Large (δ)	-0.158***	-0.159***	-0.157***	-0.161***	-0.162***	-0.161***
	(0.009)	(0.009)	(0.010)	(0.009)	(0.009)	(0.010)
Employees (thousands)	0.000	0.000**	0.000**	0.000*	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number MSA (tens)	-0.028***	-0.032***	-0.032***	-0.031***	-0.035***	-0.035***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
Branches (hundreds)	0.011***	0.011***	0.011***	0.012***	0.012***	0.012***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Year FE	✓	✓	✓	✓	✓	✓
Market FE	–	✓	✓	–	✓	✓
Year-Market FE	–	–	✓	–	–	✓
Observations	33838	33838	33797	33838	33838	33797
Adjusted R^2	0.067	0.101	0.062	0.067	0.102	0.062

Notes: This table present results of the model $\ln(r^U_{jym}) - \ln(r^I_{jym}) = \alpha_0 + \delta L_{jy} + X_{jym}\beta + \tau_y + \eta_m + \epsilon_{jym}$. The dependent variable is the log difference between the segmentation premium on uninsured deposits and the segmentation premium on insured deposits. Large bank (L) is a dummy variable that takes the value of one for banks with assets above 100 billion. The regression shows that large banks offer lower premiums for uninsured deposits. The sample includes all multimarket banks in the SOD from 2010 to 2020. Large bank (L) is a dummy variable that takes the value of one for banks with assets above 100 billion. The standard errors are robusst, *** p<0.01, ** p<0.05, * p<0.1.

Table 1.23: Share uninsured correlation determinants

	(1)	(2)	(3)	(4)
Loan Losses (γ)	-0.004***	-0.004***	–	–
	(0.000)	(0.000)	–	–
Equity to Assets Ratio (γ)	–	–	-0.181***	-0.182***
	–	–	(0.009)	(0.009)
Assets (100 millions)	-0.002***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Number MSA (tens)	-0.007***	-0.007***	-0.007***	-0.007***
	(0.000)	(0.000)	(0.000)	(0.000)
Branches (hundreds)	0.002***	0.002***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
Employees (thousands)	0.001***	0.001***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Bank FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Market FE	–	✓	–	✓
Observations	35852	35852	35852	35852
Adjusted R^2	0.990	0.990	0.991	0.991

Notes: This table present results of estimating the model $s^U_{jy} = \alpha_0 + \gamma\rho_{jy} + X_{jym}\beta + \nu_j + \tau_y + \eta_m + \epsilon_{jym}$, where ρ_{jy} is the bank's riskiness and X_{jym} is a vector of bank characteristics. The dependent variable is the share of uninsured deposits. The table shows that the share of uninsured deposits is negatively correlated with the loan losses provision to assets ratio and the equity to assets ratio. The sample includes all multimarket banks in the SOD from 2010 to 2020. The standard errors are robust, *** p<0.01, ** p<0.05, * p<0.1.

Table 1.24: Share uninsured correlation with bank characteristics with business strategy

	(1)	(2)	(3)	(4)
Loan Losses (% of Assets) (γ)	-0.002***	-0.002***	–	–
	(0.000)	(0.000)	–	–
Uninsured bank $\times$ Loan Losses (% of Assets) (γ^U)	-0.007***	-0.007***	–	–
	(0.000)	(0.000)	–	–
Equity to Assets Ratio (γ)	–	–	-0.111***	-0.111***
	–	–	(0.006)	(0.006)
Uninsured bank $\times$ Equity to Assets Ratio (γ^U)	–	–	-0.204***	-0.204***
	–	–	(0.012)	(0.012)
Uninsured bank (δ)	0.003***	0.003***	0.026***	0.026***
	(0.000)	(0.000)	(0.001)	(0.001)
Bank FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Market FE	–	✓	–	✓
Observations	35852	35852	35852	35852
Adjusted R^2	0.990	0.990	0.992	0.992

Notes: The table presents results of estimating the model $s^U_{jy} = \alpha_0 + \gamma\rho_{jy} + \gamma^U\rho_{jy} * B_{jy} + \delta B_{jy} + X_{jym}\beta + \nu_j + \tau_y + \eta_m + \epsilon_{jym}$. The dependent variable is the share of uninsured deposits, ρ_{jy} is the bank's riskiness, and B_{jy} is 1 if the bank has a large share of uninsured deposits in year y and 0 otherwise. The table shows that the share of uninsured deposits is negatively correlated with the loan losses provision to assets ratio and the equity to assets ratio. The sample includes all multimarket banks in the SOD from 2010 to 2020. The standard errors are robust, *** p<0.01, ** p<0.05, * p<0.1. The sample includes all multimarket banks in the SOD from 2010 to 2020.

Table 1.25: Regression with IV Log-Log Specification, CD (Robustness)

	All	Insured	Uninsured
Rate	7.892***	6.865***	28.948***
	(0.677)	(0.772)	(4.747)
Equity to Assets Ratio	-4.569***	-4.918***	3.126*
	(0.743)	(0.917)	(1.614)
Log total branches	1.285***	1.329***	0.156
	(0.110)	(0.140)	(0.177)
Log total MSA	-0.923***	-1.020***	0.732***
	(0.157)	(0.203)	(0.260)
Branches avg market	-0.069***	-0.078***	0.033
	(0.012)	(0.016)	(0.024)
Employees per branch	0.004***	0.004***	0.001
	(0.000)	(0.001)	(0.002)
Number of products	0.023***	0.024***	0.101***
	(0.007)	(0.009)	(0.021)
Observations	125711	70540	55144
Adjusted R^2	-14.662	-126.497	-85.112
F-Stat	68.908	39.586	18.055
Elasticity	4.137	3.597	15.305

Notes: The dependent variable is the log of the share of deposits by product. The sample is from 2003 to 2019. The insured and uninsured product rates is from 12 month CD minimum deposit of $10,000 and $100,000 respectively. All regressions include bank and quarter-year fixed effects. The instruments of rates are log expenditures in salaries and log expenditures in premisses and equipment. The elasticity calculations assume 1 % share and mean rate of the segment. Standard errors are robust; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 1.26: SCF regression of deposits on demographics. Dependant variable: Log total deposits

	(1)	(2)	(3)
Log income	–	2.474***	2.474***
	–	(0.197)	(0.197)
Log income sq.	–	-0.057***	-0.057***
	–	(0.009)	(0.009)
Zero income	–	19.855***	19.855***
	–	(1.102)	(1.102)
Renter	–	-0.479	-0.479
	–	(1.154)	(1.154)
Log rent annual	–	-0.915***	-0.915***
	–	(0.262)	(0.262)
Log home value	–	-0.176***	-0.176***
	–	(0.027)	(0.027)
Log home value sq.	–	0.021***	0.021***
	–	(0.002)	(0.002)
Log rent annual sq.	–	0.103***	0.103***
	–	(0.015)	(0.015)
Sex	-0.374***	-0.082*	-0.082*
	(0.050)	(0.044)	(0.044)
Age 45-64	0.439***	0.044	0.044
	(0.042)	(0.038)	(0.038)
Age 65+	1.210***	1.015***	1.015***
	(0.051)	(0.046)	(0.046)
Age<25	0.043	1.307***	1.307***
	(0.094)	(0.084)	(0.084)
Hispanic	0.635***	0.449***	0.449***
	(0.069)	(0.060)	(0.060)
Other	1.199***	0.923***	0.923***
	(0.088)	(0.077)	(0.077)
white	1.431***	0.945***	0.945***
	(0.049)	(0.044)	(0.044)
Living partner	0.359***	-0.125*	-0.125*
	(0.082)	(0.072)	(0.072)
Married	1.137***	0.128**	0.128**
	(0.058)	(0.052)	(0.052)
Never married	-0.270***	0.129**	0.129**
	(0.058)	(0.051)	(0.051)
Separated	-0.718***	-0.355***	-0.355***
	(0.100)	(0.088)	(0.088)
Number people household	-0.131***	-0.204***	-0.204***
	(0.014)	(0.012)	(0.012)
Constant	3.031***	-15.213***	-15.213***
	(0.229)	(1.087)	(1.087)
Observations	24479	24456	24456
Adjusted R^2	0.320	0.482	0.482

Standard errors in parentheses are
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variable is log household deposits. The regressions include year and education level fixed effects. In this version of the results, standard errors are robust. A similar version is done using the weights provided by the SCF and the package `SCFcombo`, with almost identical results. The omitted categories are: age 25-44, non-Hispanic, and single.

Table 1.27: Robustnes: Regression with IV (Log-Log) by size of bank and CD

	Insured			Uninsured		
	Small	Medium	Big	Small	Medium	Big
Log Rate	6.216***	1.858***	0.410***	8.920***	1.917***	0.417***
	(0.564)	(0.287)	(0.052)	(1.140)	(0.224)	(0.052)
Equity to Assets Ratio	1.452**	-1.877**	-1.083**	7.885***	-1.845**	-1.789***
	(0.674)	(0.739)	(0.499)	(1.552)	(0.763)	(0.542)
Log total branches	0.010	0.712***	1.240***	-0.131	0.642***	1.266***
	(0.074)	(0.129)	(0.075)	(0.134)	(0.142)	(0.095)
Log total MSA	0.690***	0.202	-0.203***	0.843***	0.007	-0.356***
	(0.110)	(0.127)	(0.076)	(0.174)	(0.159)	(0.082)
Log total counties	0.207**	-0.443**	-0.315***	0.119	-0.451*	-0.379***
	(0.090)	(0.189)	(0.122)	(0.137)	(0.230)	(0.121)
Employees per branch	0.003***	0.003***	-0.000	0.002**	0.002***	-0.001**
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Number of products	0.028***	-0.031***	-0.023***	0.012	-0.024**	-0.021***
	(0.008)	(0.012)	(0.004)	(0.012)	(0.011)	(0.004)
Observations	65806	3718	1016	50581	3552	1011
Adjusted R^2	-83.599	-6.755	0.385	-45.923	-6.077	-0.020
F-Stat	61.129	28.787	28.668	31.269	29.055	31.863

Notes: The dependent variable is the log of the share of deposits by product. The sample is from 2003 to 2019. The insured and uninsured product rates is from 12 month CD minimum deposit of $10,000 and $100,000 respectively. All regressions include bank and quarter-year fixed effects. The instruments of rates are log expenditures in salaries and log expenditures in premisses and equipment. This table is additional larger banks have narrower deposit rate differences (uninsured - insured). Standard errors are robust; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 1.28: Robustness: Regression with IV (Log-Log) by size of bank and CD

	Insured			Uninsured		
	Small	Medium	Big	Small	Medium	Big
Rate	7.773***	4.976*	1.313***	44.504***	5.102***	2.030***
	(1.181)	(2.968)	(0.293)	(12.384)	(1.104)	(0.395)
Equity to Assets Ratio	-5.801***	-2.089	-2.083***	5.578*	0.542	-4.665***
	(1.167)	(1.572)	(0.678)	(3.027)	(1.054)	(0.909)
Log total branches	0.930***	1.191**	0.977***	0.225	-0.068	1.077***
	(0.108)	(0.511)	(0.101)	(0.230)	(0.195)	(0.103)
Log total MSA	-0.142	0.429	-0.077	0.680**	-0.300	-0.224**
	(0.132)	(0.264)	(0.099)	(0.331)	(0.203)	(0.106)
Log total counties	-0.308**	-0.577	-0.226	-0.732**	0.580**	-0.275**
	(0.129)	(0.436)	(0.144)	(0.358)	(0.286)	(0.120)
Employees per branch	0.004***	0.004***	-0.000	-0.001	0.002***	-0.001**
	(0.001)	(0.002)	(0.000)	(0.004)	(0.000)	(0.001)
Number of products	0.026**	0.028	-0.017***	0.151***	0.018*	-0.010
	(0.011)	(0.018)	(0.005)	(0.047)	(0.010)	(0.006)
Observations	65806	3718	1016	50581	3552	1011
Adjusted R^2	-172.790	-18.382	0.291	-187.169	-4.711	-0.809
F-Stat	21.597	1.830	17.101	6.430	11.010	15.817

Notes: The dependent variable is the log of the share of deposits by product. The sample is from 2003 to 2019. The insured and uninsured product rates is from 12 month CD minimum deposit of $10,000 and $100,000 respectively. All regressions include bank and quarter-year fixed effects. The instruments of rates are log expenditures in salaries and log expenditures in premisses and equipment. Standard errors are robust; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 1.29: Summary statistics for CBP data.

	Mean	SD	Min	Max	count
Employees	2.7e+05	6.6e+05	11796.00	8.7e+06	4551.00
Establishments	17039.45	42522.72	872.00	5.8e+05	4551.00
First quarter payroll	3600.21	11126.56	86.36	1.9e+05	4551.00
Annual payroll	14129.91	41264.42	382.76	6.5e+05	4551.00
Deposits (SOD)	2.7e+06	2.9e+07	92.80	7.4e+08	4665.00

Notes: This table presents summary statistics for County Business Patterns (CBP) data aggregated at the county-year level. CBP data from the U.S. Census Bureau provides employment and establishment information for the banking sector (NAICS 522). The first four rows show employment (number of employees), establishments (number of banking establishments), first quarter payroll (in millions of dollars), and annual payroll (in millions of dollars). The last row shows total deposits (in thousands of dollars) from the FDIC Summary of Deposits (SOD) data, aggregated to the same county-year level for comparison. Monetary values are in nominal terms. The sample covers 2008–2021 with 4,551 county-year observations for CBP variables and 4,665 for deposits.

Robustness: Alternative Specifications for Segmentation Premium Determinants

Table 1.30: Segmentation Premium Determinants: Ratio Specification

	(1)	(2)	(3)	(4)	(5)
	Segmentation Premium (Ratio: r^U/r^I)				
L.Z-Score	-32.817***	-27.822***	-35.953***	-36.245***	-35.715***
	(7.533)	(7.588)	(7.731)	(7.885)	(8.155)
L.Assets (100 millions)	-3.177***	-3.658***	-3.131***	-3.290***	-3.524***
	(0.122)	(0.129)	(0.120)	(0.124)	(0.130)
L.Number Counties (tens)	-0.840***	-0.922***	-0.833***	-0.857***	-0.901***
	(0.029)	(0.030)	(0.029)	(0.029)	(0.030)
L.Branches (hundreds)	1.111***	1.280***	1.105***	1.133***	1.237***
	(0.045)	(0.049)	(0.045)	(0.046)	(0.049)
L.Employees (thousands)	0.177***	0.203***	0.170***	0.172***	0.191***
	(0.009)	(0.010)	(0.009)	(0.009)	(0.010)
Log Bank Age	5.172***	5.084***	5.279***	5.298***	5.323***
	(0.299)	(0.300)	(0.300)	(0.300)	(0.300)
Constant	-1.279	-0.951	-1.429	-1.495	-1.569
	(1.259)	(1.274)	(1.267)	(1.290)	(1.321)
Year FE	–	✓	–	✓	–
County Cluster FE	–	–	✓	✓	–
Year × County Cluster FE	–	–	–	–	✓
Observations	58754	58754	58754	58754	58753
Adjusted R^2	0.128	0.137	0.154	0.163	0.177

Standard errors in parentheses, clustered by bank and county cluster. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Notes: This table replicates Table 1.1 using the ratio specification r^U/r^I as the dependent variable instead of the log difference. Results confirm that riskier banks (lower z-scores) pay higher segmentation premiums. All other specifications match Table 1.1.

Table 1.31: Segmentation Premium Determinants: Adjusted Premium Specification

	(1)	(2)	(3)	(4)	(5)
	Segmentation Premium (Adjusted: $(r^U - r^I)/r^I$)				
L.Z-Score	-33.083***	-28.088***	-36.220***	-36.512***	-35.982***
	(7.574)	(7.630)	(7.774)	(7.930)	(8.199)
L.Assets (100 millions)	-3.195***	-3.678***	-3.148***	-3.307***	-3.543***
	(0.122)	(0.130)	(0.120)	(0.124)	(0.131)
L.Number Counties (tens)	-0.846***	-0.929***	-0.838***	-0.862***	-0.908***
	(0.029)	(0.030)	(0.029)	(0.029)	(0.030)
L.Branches (hundreds)	1.119***	1.288***	1.112***	1.140***	1.244***
	(0.046)	(0.050)	(0.046)	(0.046)	(0.049)
L.Employees (thousands)	0.178***	0.204***	0.171***	0.173***	0.192***
	(0.009)	(0.010)	(0.009)	(0.009)	(0.010)
Log Bank Age	5.206***	5.117***	5.313***	5.332***	5.357***
	(0.301)	(0.302)	(0.302)	(0.302)	(0.302)
Constant	-1.326	-0.996	-1.476	-1.542	-1.617
	(1.267)	(1.282)	(1.275)	(1.298)	(1.330)
Year FE	–	✓	–	✓	–
County Cluster FE	–	–	✓	✓	–
Year × County Cluster FE	–	–	–	–	✓
Observations	58754	58754	58754	58754	58753
Adjusted R^2	0.127	0.136	0.153	0.162	0.176

Standard errors in parentheses, clustered by bank and county cluster. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Notes: This table replicates Table 1.1 using the adjusted premium specification $(r^U - r^I)/r^I$ as the dependent variable. Results confirm the negative relationship between z-score and segmentation premium. All other specifications match Table 1.1.

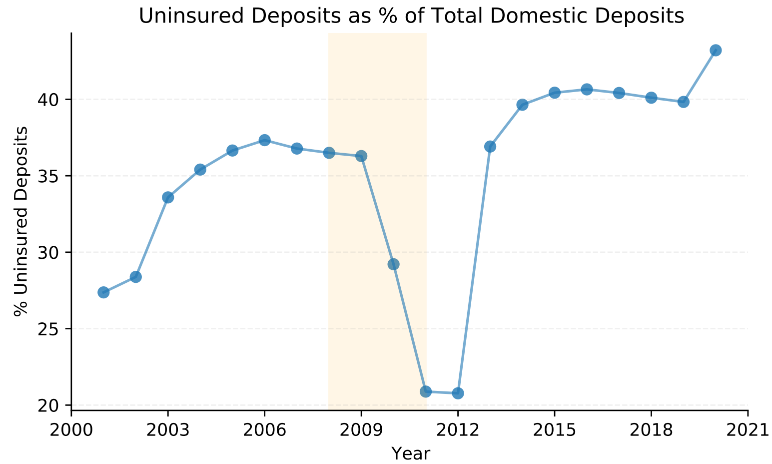
Table 1.32: Segmentation Premium Determinants: Contemporaneous Bank Characteristics

	(1)	(2)	(3)	(4)	(5)
	Segmentation Premium (log)				
Z-Score (contemporaneous)	-1.443***	-1.296***	-1.658***	-1.672***	-1.649***
	(0.349)	(0.353)	(0.358)	(0.365)	(0.379)
Assets (100 millions)	-0.145***	-0.164***	-0.143***	-0.150***	-0.159***
	(0.005)	(0.006)	(0.005)	(0.006)	(0.006)
Number Counties (tens)	-0.036***	-0.040***	-0.036***	-0.037***	-0.039***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Branches (hundreds)	0.050***	0.057***	0.050***	0.052***	0.055***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Employees (thousands)	0.008***	0.009***	0.008***	0.008***	0.009***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log Bank Age	0.224***	0.220***	0.228***	0.229***	0.231***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Constant	-0.044	-0.027	-0.050	-0.053	-0.057
	(0.058)	(0.059)	(0.059)	(0.060)	(0.062)
Year FE	–	✓	–	✓	–
County Cluster FE	–	–	✓	✓	–
Year × County Cluster FE	–	–	–	–	✓
Observations	58754	58754	58754	58754	58753
Adjusted R^2	0.131	0.141	0.157	0.166	0.181

Standard errors in parentheses, clustered by bank and county cluster. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

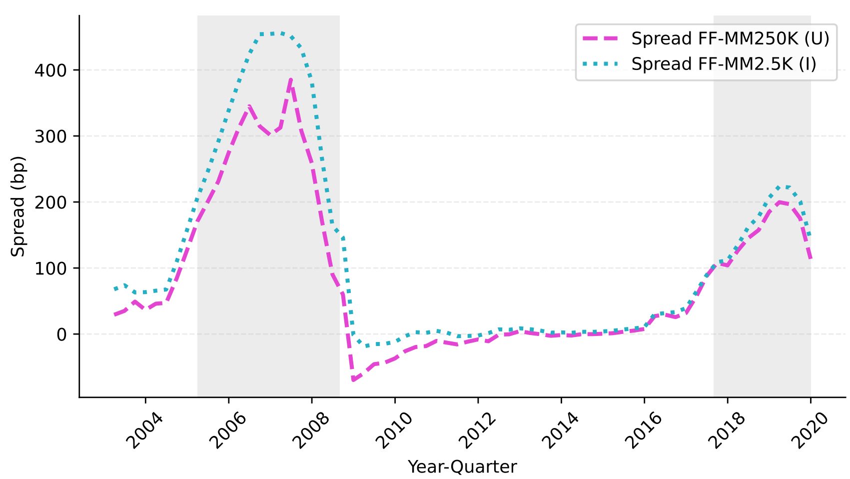
Notes: This table replicates Table 1.1 using contemporaneous (non-lagged) bank characteristics instead of lagged values. The negative relationship between z-score and segmentation premium remains robust, with similar coefficient magnitudes. The main specification uses lagged variables (Table 1.1) to mitigate simultaneity concerns.

Figure 1.15: Share uninsured over time



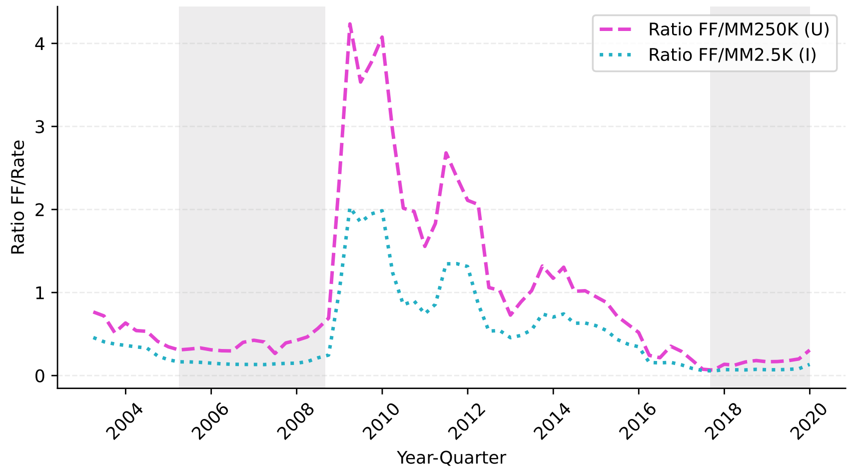
Notes: Time series of the aggregate share of uninsured deposits in U.S. commercial banks, 2004–2020. The series trends upward over the full period, consistent with growing business deposit balances and rising interest rates incentivizing firms to hold larger uninsured accounts. A pronounced dip occurs during the financial crisis, with the share remaining depressed through approximately 2013 as risk aversion shifted funds toward FDIC-insured accounts. The recovery after 2013 and subsequent rise through 2019 motivate the chapter's focus on how the composition of insured and uninsured funding shapes monetary transmission. Data source: FDIC.

Figure 1.16: Deposit rates by segment and monetary policy: Deposit spreads



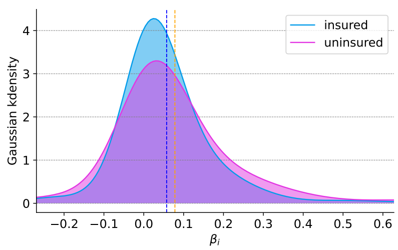
Notes: The insured-deposit spread sits consistently above the uninsured spread, and both spreads widen during tightening cycles, indicating incomplete pass-through that is most pronounced for insured products. Sources: RateWatch, FRED.

Figure 1.17: Deposit rates by segment and monetary policy: Ratio FF to deposit rates

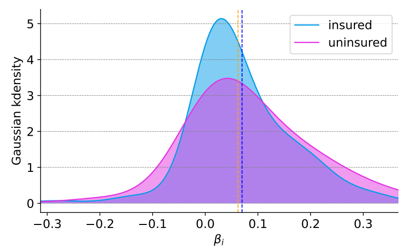


Notes: The deposit-rate-to-fed-funds ratio is below 1 throughout (insured ratio lower than uninsured), confirming incomplete pass-through; the ratio collapses near 0 during the zero-lower-bound period and recovers as policy normalizes. Sources: RateWatch, FRED.

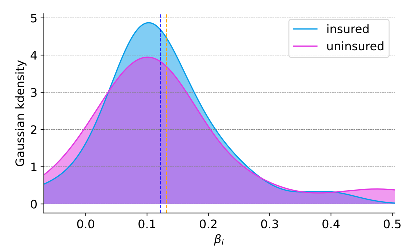
Figure 1.18: Distribution of segment passthroughs by bank size and kernel type (MM25K, MM250K). Top row uses a Gaussian kernel; bottom row uses an Epanechnikov kernel.



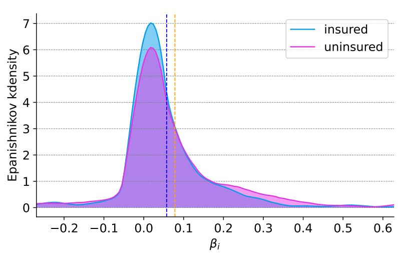
(a) Small banks (Gaussian)



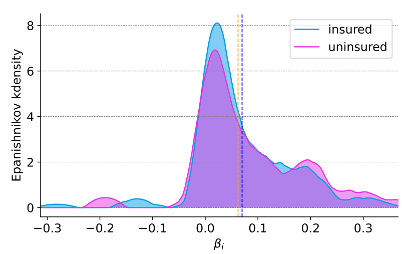
(b) Medium banks (Gaussian)



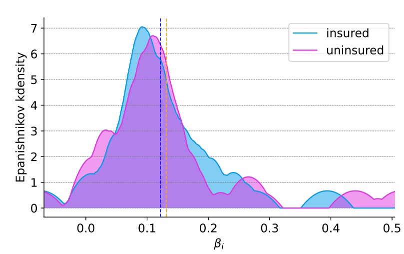
(c) Large banks (Gaussian)



(d) Small banks (Epanechnikov)



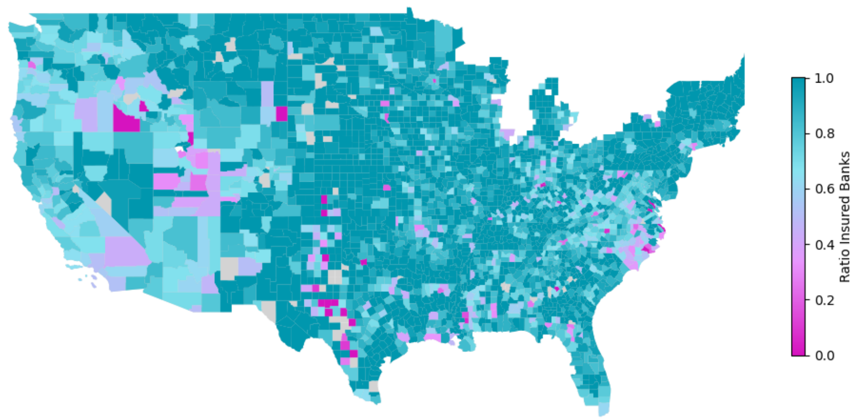
(e) Medium banks (Epanechnikov)



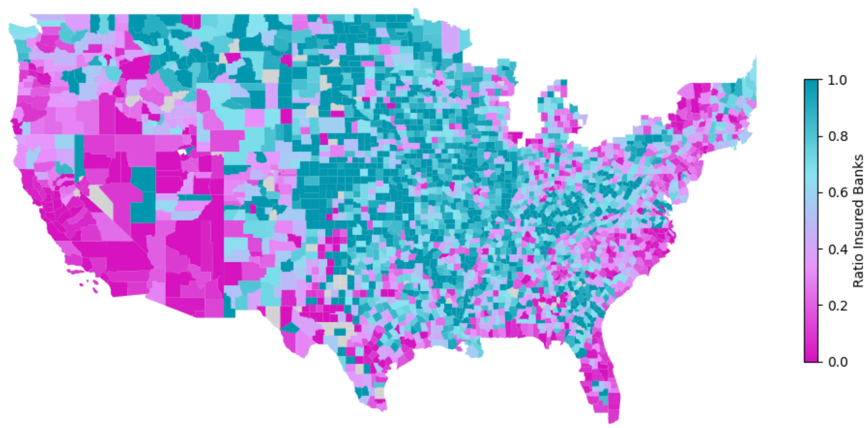
(f) Large banks (Epanechnikov)

Notes: Kernel density estimates of bank-level pass-through coefficients by size category (small: <\$10B assets; medium: \$10B–\$100B; large: >\$100B). In each panel, the insured distribution (MM25K) is more peaked and concentrated than the uninsured distribution (MM250K), which is flatter and has heavier tails — supporting the chapter's finding that insured pass-through is more uniform across banks while uninsured pass-through is more heterogeneous. Top row uses Gaussian kernel estimates; bottom row uses Epanechnikov estimates; both yield the same qualitative pattern. This is consistent across all three size groups. Data source: RateWatch.

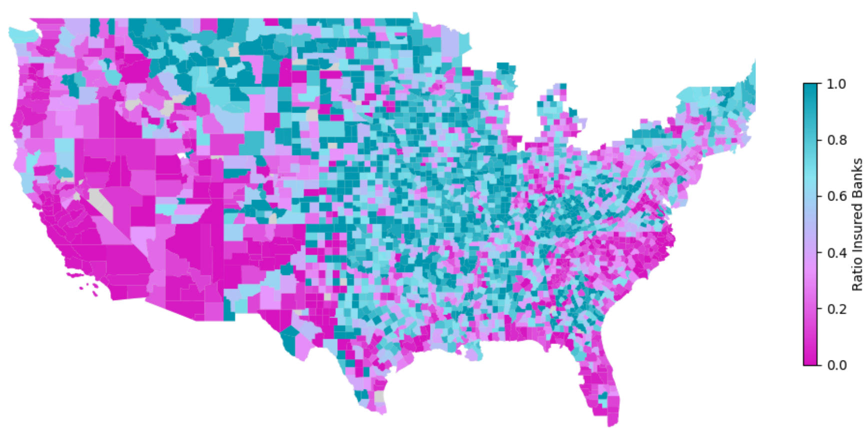
Figure 1.19: Markets by percent of insured deposits (dep weighted)



(a) 2012



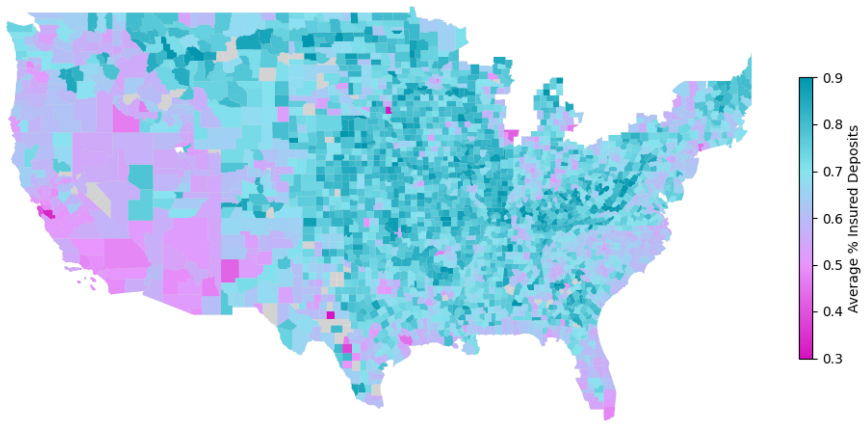
(b) 2016



(c) 2020

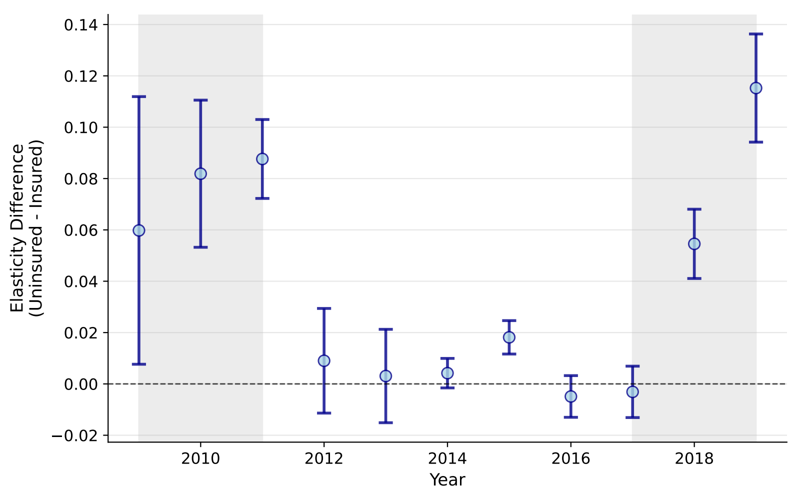
Notes: Three U.S. county maps showing the deposit-weighted insured share in 2012, 2016, and 2020 (top to bottom). Darker shading marks higher insured share, lighter shading marks lower insured share (higher uninsured exposure). Coastal MSAs and large cities display lighter shading in all three years; the spatial pattern is stable over time. Data source: FDIC Summary of Deposits.

Figure 1.20: Markets by percent of insured deposits (deposit weighted), 2019



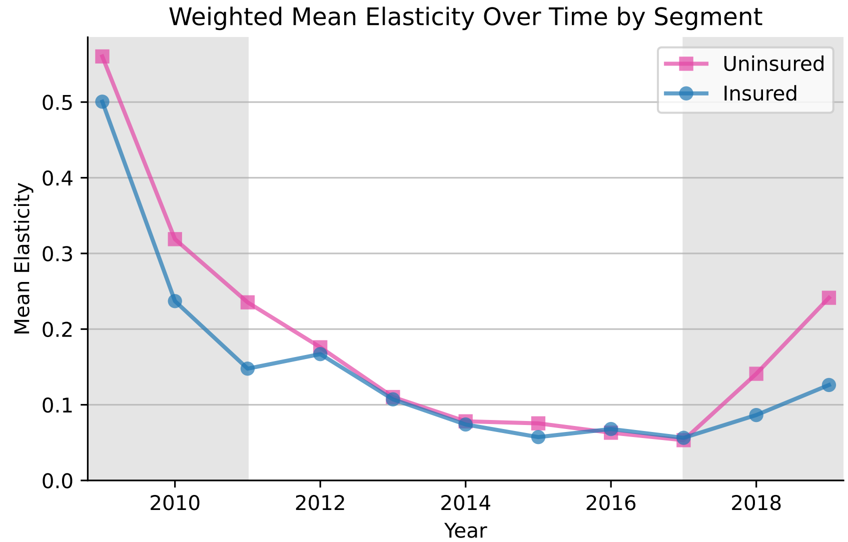
Notes: Geographic distribution of deposit-weighted insured shares across county clusters, 2019. Darker shading indicates a higher share of insured deposits; lighter shading indicates higher uninsured exposure. Coastal states (California, New York, Massachusetts) and major urban centers show lighter shading, reflecting greater concentration of business and high-net-worth deposits above the $250k insurance threshold. Inland and rural markets show darker shading, consistent with a predominantly household depositor base. This geographic heterogeneity is a key source of identification in the structural model. Data source: FDIC Summary of Deposits.

Figure 1.21: Difference in elasticities between insured and uninsured deposits



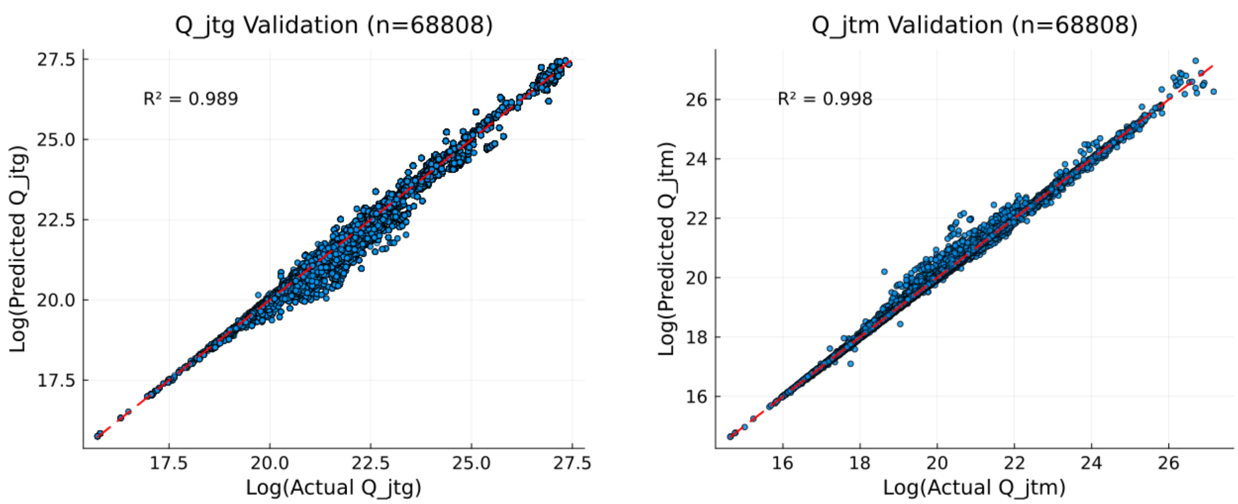
Notes: This figure shows the distribution of elasticity differences ($\eta^U - \eta^I$) across banks and years. The negative mass indicates that uninsured deposits are systematically more rate-elastic than insured deposits. Estimates are deposit-weighted. Sources: RateWatch, FDIC SOD; structural demand estimation, 2009-2019.

Figure 1.22: Mean elasticity by segment over time



Notes: This figure shows the time series of deposit-weighted mean elasticities for insured (blue solid line, labeled "Insured") and uninsured (red dashed line, labeled "Uninsured") deposits. Elasticities exhibit modest time variation; uninsured deposits are consistently more elastic across all years. The gap between the two series narrows slightly during 2008–2010 as flight-to-safety behavior increases demand for insured products. Source: RateWatch and SOD.

Figure 1.23: Imputation validation: predicted vs. observed marginals



(a) Bank-segment totals D_{jtg}

(b) Bank-market totals D_{jmt}

Notes: These scatter plots show predicted (imputed) versus observed marginal totals. Panel (a) shows bank-segment-year totals, while panel (b) shows bank-market-year totals. The 45-degree line represents perfect prediction. All points lie very close to the line, confirming that the imputation procedure matches observed marginals with less than 1% error. Sample: 2009-2019. Sources: Call Reports, FDIC SOD.

Chapter 2

Deposit Zone Rating in the U.S. Banking Industry

2.1 Introduction

Deposits are the most critical and stable source of funding for banks, constituting over 75% of funding for U.S. commercial banks (Hanson et al., 2015). To attract and retain depositors, banks compete along multiple dimensions: geographic convenience through branch networks, service quality, and deposit interest rates. Consumers report that competitive rates are an important factor in their banking decisions, but that convenient branch and ATM locations are the primary reason Americans choose their banking institution.[1] Given the importance of local presence, banks face a pricing decision: should they tailor deposit rates to local competitive conditions at each branch, or should they adopt a more uniform pricing structure across their geographic footprint? A common bank practice is to set a single deposit rate across a network of branches, known in retail banking as a pricing zone (Granja and Paixao, 2019; Begenau and Stafford, 2022), rather than rate-by-branch. However, when markets exhibit varying degrees of competition, zone pricing practices—a form of third-degree price discrimination—have ambiguous effects on firms and consumers (Thisse and Vives (1988), Holmes (1989), Corts (1998)). For this reason, studying how banks differ in their pricing practices is important for analyzing competition and welfare in the industry.

The central research question of this paper is: *How do zone rating practices affect competition*

[1] According to Bankrate Best Banks Survey, 2019.

and profitability in retail deposit markets? Theory suggests that coarser pricing structures can either intensify or soften competition depending on market characteristics: in concentrated markets, coarse pricing may lead to higher rates, while in competitive markets, the opposite may hold (Thisse and Vives, 1988; Holmes, 1989; Corts, 1998). The direction and magnitude of these effects are therefore ultimately empirical questions. To address them, I pursue two main objectives. First, I document heterogeneity in zone rating practices across banks, showing how they partition their branch networks into pricing zones and the resulting patterns of rate dispersion. Second, I quantify the competitive implications of these pricing structures by estimating a structural model of deposit competition and conducting counterfactual experiments where banks move from their observed coarse zone structures to finer market-level pricing. In practice, banks overwhelmingly choose zone rating, an approach that sits between rate-by-branch pricing and a single nationwide rate. They partition their branch network into geographic zones and set uniform deposit rates within each zone. Zone rating constrains all branches in the same zone to post a single deposit rate, even when these branches operate in markets with substantially different competitive conditions, demographics, or wealth levels. The prevalence of zone pricing is striking. Modern information technology systems enable banks to monitor local market conditions in real time and adjust prices at the branch level with minimal operational costs. Banks already engage in other forms of localized decision-making, such as branch location choices, staffing levels, and marketing strategies, that respond to local market characteristics. Yet when it comes to deposit pricing, banks predominantly maintain coarse geographic structures. For instance, Bank of America and Wells Fargo are two of the largest banks in the United States with similar nationwide branch footprints. They differ dramatically in their zone rating strategies: Bank of America employs twice as many distinct pricing zones as Wells Fargo. This heterogeneity in zone structures across banks, combined with the technological feasibility of much finer pricing, raises an economic puzzle. Why do banks maintain such coarse geographic pricing structures when they could potentially tailor rates more precisely to local market conditions and extract greater surplus from depositors?

This paper provides the first empirical analysis of zone rating practices in the U.S. retail banking industry. I begin by documenting substantial heterogeneity in how banks implement zone rating strategies. Using detailed branch-level data that identifies each branch's designated rate-setter, I map the zone structures of banks operating across the United States from 2009 to 2020. The patterns reveal striking differences. More generally, larger banks maintain broader zones covering multiple Metropolitan Statistical Areas (MSAs) and exhibit greater rate dispersion across zones. Smaller banks employ relatively more sophisticated zone structures given their geographic footprint.

To answer this question, I develop and estimate a structural model of deposit competition that explicitly incorporates banks' zone rating structures. The model features differentiated banks competing for depositors in local markets through interest rates, with banks constrained to set uniform rates within their pre-determined zones. The key insight is that zone rating serves as a commitment device that prevents banks from engaging in aggressive local price competition. When banks can freely adjust rates in each market, competitive forces drive rates higher and erode profitability. By committing to coarser zone structures, banks soften competition and increase profits, even though this requires offering the same rate in both strong and weak markets within a zone. I estimate the model using variation in competitive conditions across markets within a bank's zone, which allows me to separately identify demand elasticities from marginal costs.

Using the estimated model, I conduct counterfactual experiments where all banks move from their current zone structures to market-level pricing, the finest possible form of geographic price discrimination. The results demonstrate that average deposit rates increase and rate dispersion rises substantially, but aggregate bank variable profits fall. The profit reduction is more pronounced for smaller banks, which face more intense competitive pressure when forced to price separately in each market. These findings stand in contrast to results from zone pricing studies in other retail sectors. Adams and Williams (2019) find that finer price structures increase firm profits in the home improvement industry. The difference highlights that banking's competitive structure creates a situation where market-level pricing intensifies competition to banks' detriment. With many firms per market and relatively elastic deposit demand, the outcome resembles a prisoner's dilemma where coordinated coarseness benefits all banks.

This paper makes several contributions to the literature. First, to my knowledge, this is the first empirical paper to show that coarser zone structures enhance profitability relative to market-level pricing. This finding helps explain why banks maintain coarse pricing structures despite having the technology for more granular pricing. Second, I contribute to the zone pricing literature by analyzing an industry with different competitive dynamics than previously studied sectors. Third, I extend the structural literature on deposit competition by explicitly modeling banks' zone rating constraints. Finally, the findings have policy implications for understanding deposit rate pass-through, monetary policy transmission, and the welfare effects of bank mergers.

The paper proceeds as follows. Section 2.1 reviews the related literature and positions this paper's contributions. Section 2.2 describes the data sources and provides summary statistics. Section 2.3 documents the heterogeneity in zone rating practices across banks. Section 2.4 develops the structural model of deposit competition with zone rating. Section 2.5 presents the estimation strategy and results. Section 2.6 analyzes the counterfactual scenarios. Section 2.8 concludes.

Literature Review

This paper contributes to three main strands of literature.

Zone pricing and geographic price discrimination. This work extends the empirical literature on zone pricing practices in retail markets. Chintagunta, Dubé, and Singh (2003) study zone pricing by a Chicago supermarket chain and propose alternative segmentation strategies that could benefit consumers. Hitsch, Hortaçsu, and Lin (2021) document pricing patterns across U.S. grocery chains and find substantial geographic variation in both regular prices and promotional activity. They do not structurally evaluate zone pricing policies. Most closely related is Adams and Williams (2019), who empirically analyze zone rating in the home improvement retail sector. They focus on two chains (Home Depot and Lowe's) operating in a subset of U.S. states. They estimate a structural model and find that moving to market-level pricing has relatively small aggregate welfare effects and increases firm profits. My paper differs in several dimensions. First, I study the banking industry, which features different competitive dynamics. Banking markets typically have many more competitors than retail chains. The median is 7 banks per market in my sample versus 2 chains in Adams and Williams. Second, I exploit detailed administrative data on the actual zone structures implemented by banks, including information on which branch sets rates for other branches within each zone. Third, in contrast to these studies, I find that finer pricing structures reduce bank profitability. This difference highlights how industry-specific competitive conditions alter the effects of price discrimination strategies. It contributes to our understanding of when and why firms adopt particular pricing structures.

Structural models of deposit competition. This paper contributes to the growing literature using structural methods to study banking competition.[2] Dick (2008a) estimate a discrete choice model of bank demand that incorporates consumer switching costs, showing these costs significantly affect market power. Ishii (2008a) examine ATM network compatibility and spatial competition in banking. Ho and Ishii (2011a) study spatial competition through branch networks and evaluate how branching deregulation affected consumer welfare. Aguirregabiria, Clark, and Wang (2016) and Aguirregabiria, Clark, and Wang (2017) analyze banks' strategic branch network decisions and study geographic imbalances in deposits and loans across the United States. More recently, Egan et al. (2017) develop a structural model to study financial fragility in the U.S. banking sector, though they abstract from local competition by modeling national-level competition to focus on the distinction between insured and uninsured deposits. Drechsler et al. (2017) establish the "deposit channel" of monetary transmission, showing that banks with market power pass through only a fraction of policy rate changes to depositors. Drechsler et al. (2021) extend this work by showing how banks use deposits as a stable funding source that insulates them from interest rate risk, with implications for how banks set deposit rates. Xiao (2020) analyzes deposit competition including shadow banks, highlighting the role of non-bank competitors in shaping deposit markets. Related work includes Wang et al. (2022), who develop a dynamic structural model showing that bank market power dampens monetary transmission, and Koont (2023), who study how digital banking platforms affect deposit competition. My paper complements this literature by explicitly modeling local competition and banks' zone rating constraints. While previous work assumes banks either price discriminate perfectly in each market or adopt completely uniform pricing, I show that the intermediate case of zone rating, which predominates in practice, has implications for understanding competitive outcomes. This distinction matters for policy analysis of bank mergers, monetary policy pass-through, and the effects of ongoing consolidation in the banking industry.

Uniform pricing in retail markets. Finally, this work relates to recent empirical research documenting uniform pricing patterns across diverse retail sectors. DellaVigna and Gentzkow (2019) document that large U.S. grocery, drugstore, and mass-merchandise chains predominantly set uniform prices across stores despite substantial variation in local cost and competitive conditions. They estimate that uniform pricing costs these chains approximately 1% of profits. In the banking context, Driscoll and Judson (2013) document sticky deposit rates and limited response to market conditions. Granja

[2]Additional structural applications in banking include Egan et al. (2022), Kuehn (2018), and Asil and Kastl (2023).

and Paixao (2019) show that U.S. depository institutions set nearly uniform prices across their branch networks. Uniformity increases following bank mergers. They decompose rate variation into market effects versus bank effects and find that bank-specific factors explain more variation than local market conditions. Begenau and Stafford (2022) document similar patterns and use this observation to critique the identification strategy used in studies of the deposit channel of monetary policy. They argue that if banks don't respond to local market conditions, tests using branch-level variation may be misspecified. Related work by Abrams (2019) shows that traditional market power measures can be biased when consumers have limited consideration of available banks. My paper differs from this literature in two ways. First, rather than emphasizing the prevalence of uniformity, I document substantial heterogeneity in zone structures across banks. Many banks implement meaningfully differentiated pricing across zones, and this heterogeneity is systematically related to bank characteristics. Second, I develop a structural framework that explains why banks choose particular zone structures. The finding that coarser structures enhance profitability provides an economic rationale for observed pricing patterns. This complements explanations based on operational costs, fairness concerns, or managerial constraints emphasized in prior work.

2.2 Data and Descriptive Statistics

This chapter draws on the same core datasets described in Chapter 1: branch-level deposit rates from RateWatch (S&P Global), branch-level deposit balances from the FDIC Summary of Deposits (SOD), bank characteristics from Consolidated Call Reports, credit union data from the NCUA, and MSA-level demographics from the American Community Survey (ACS). See Chapter 1, Section 1.2 for full source descriptions. One feature of RateWatch is especially important here: the dataset records each branch's designated rate-setter branch within the same banking organization, making the zone structure directly observable. I can identify which branches serve as rate leaders and which adopt rates set elsewhere, without inferring zone boundaries from observed rate patterns.

Sample Construction

The sample covers 2009–2020 and is restricted to MSA-year markets. Market definition and time period follow the same choices as Chapter 1; here I note the restrictions specific to this chapter.

Sample restrictions: multimarket banks. The analysis focuses on regional and multimarket banks: institutions that operate branches in more than one MSA and do not have more than 90% of their total deposits concentrated in a single market. This restriction ensures that zone rating is a meaningful strategic decision for every bank in the sample — these banks must set rates across multiple distinct local markets with potentially different competitive conditions. When I apply this restriction, I recover approximately 90% of multimarket banks present in the SOD universe (see Figures 2.12 and 2.11 in the Appendix).

Additional exclusions. I exclude online-only banks (Ally Bank, Marcus by Goldman Sachs, Capital One 360) because they compete nationally through rate rather than physical presence and do not face the geographic zone rating decision. I also exclude Citibank because its U.S. deposit base contains substantial international and corporate-treasury components that the data do not allow me to isolate from local retail deposits, and its branch network is geographically concentrated in a small number of metropolitan areas. International banks, investment banks, and insurance-affiliated banks are excluded for similar reasons. Finally, I drop bank-market observations where the bank holds less than 1% market share in an MSA.

Products and rate measures. The benchmark product is the 12-month CD with a $10,000 minimum balance. This product has excellent cross-bank coverage in RateWatch and provides a standardized rate directly comparable across institutions. I use annual percentage yield (APY) as the rate measure. The descriptive sections also draw on savings and checking accounts.

Descriptive Statistics

Table 2.1 presents summary statistics describing the structure of deposit markets in my sample. The unit of observation is a market-year (MSA-year), and the sample includes all MSAs in which at least one multimarket bank operates during 2009-2020. I construct market-level deposit quantities by aggregating branch-level deposits from the Summary of Deposits for all retail branches operating in each market. Market shares are calculated by dividing each bank's total deposits in a market by

Table 2.1: Market level summary statistics

	No. banks	Share	HHI	C1	C3	Local	CU
No. mkts	2860.0	2860.0	2860.0	2860.0	2860.0	2343.0	1333.0
Mean	6.8	15.4	2107.3	33.8	66.0	10.5	12.2
Std	2.8	9.5	1173.1	14.0	16.3	13.0	16.9
Median	7.0	13.1	1863.8	30.7	66.8	5.8	4.5

Notes: This table presents summary statistics at the market level (year/MSA). The table is constructed using data from RW and SOD from 2009 to 2020. HHI is the Herfindahl-Hirschman Index (sum of squared market shares). C1 and C3 are concentration ratios measuring the market share of the largest bank and the top three banks, respectively. Local refers to the market share of local banks (banks operating in only one MSA). CU refers to the market share of credit unions.

Table 2.2: Bank level summary statistics

	No. MSA	No. branches	No. rate setters	APY (bp)
Mean	4.9	63.6	5.2	35.0
Std	15.2	333.5	18.5	45.3
25th per	1.0	3.0	1.0	7.0
Median	2.0	7.0	2.0	17.0
75th per	3.0	20.0	3.0	50.0

Notes: This table presents summary statistics of the final sample of multimarket banks. The table is constructed using data from RW and SOD from 2009 to 2020 for the 12-month CD with a minimum of 10K.

the total deposits held by all institutions in that market.

The first column shows the distribution of the number of competing banks per market. The median market contains 7 multimarket regional banks, indicating that deposit markets feature meaningful competition among multiple institutions. The second column reports mean market share. Columns 3 through 5 present alternative concentration measures: the Herfindahl-Hirschman Index (HHI), the four-firm concentration ratio (CR4), and the largest bank's market share. These measures reveal substantial variation in concentration across markets, ranging from highly competitive to moderately concentrated.

The final two columns report the share of market deposits held by local banks (banks with presence in only one MSA) and credit unions. Credit unions hold on average approximately 12% of deposits in my sample markets. This is a higher share than their national average, likely because credit unions are predominantly local institutions (so fewer are dropped by my multimarket restriction) and because credit unions may be more prevalent in metropolitan areas. The presence of credit unions and local banks as competitors is important for the structural analysis, as they represent viable alternatives for many depositors.

Table 2.2 presents summary statistics at the bank level for the final sample of multimarket banks. The median multimarket bank in my sample operates in 2 MSAs, maintains 7 branches, and employs 2 distinct rate-setter branches (indicating 2 pricing zones). However, there is substantial heterogeneity: the distribution is right-skewed, with some large regional and national banks operating in dozens of MSAs with hundreds of branches.

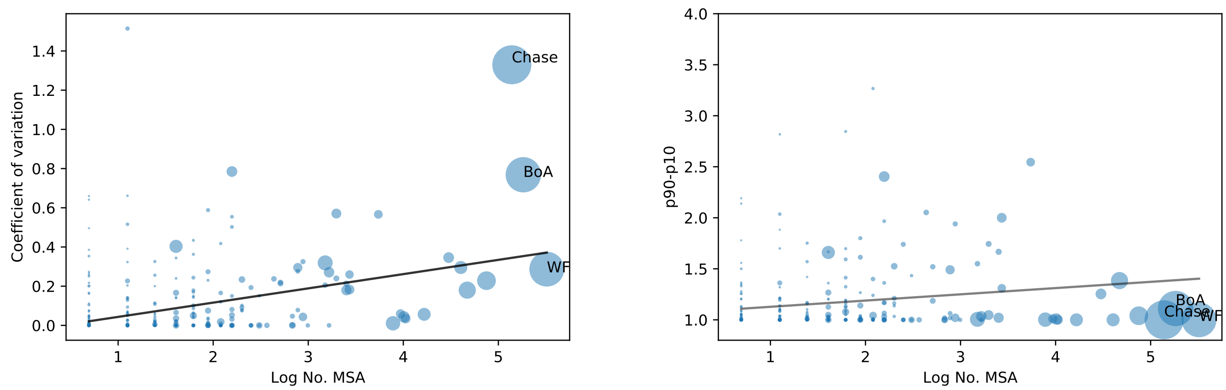
Bank characteristics enter the structural model as demand and cost shifters that capture how banks differ. Beyond the number of local branches and deposit rates (the focus of competition), I use several bank attributes from Call Reports. I measure operational characteristics using employees per branch, geographic spread using the number of MSAs served and total branches, bank size using total assets, and bank age as years since founding. Additional variables used in estimation include cost shifters (expenses on premises and fixed assets), organizational structure (whether the bank belongs to a holding company), financial structure (equity-to-assets ratio capturing capitalization), and credit risk measures (provisions for loan and lease losses). These characteristics serve as demand and cost shifters that help explain why depositors sort across banks and why banks have different marginal costs of attracting deposits.

2.3 Rate Dispersion and Zone-Rating Practices

This section documents the heterogeneity in rate dispersion and zone rating practices across U.S. retail banks. The descriptive analysis serves two purposes. First, it establishes empirical facts about how banks structure their pricing zones. These facts motivate the structural model and counterfactual analysis in subsequent sections. I document that banks exhibit substantial heterogeneity in their zone rating strategies. Larger banks maintain coarser zone structures (fewer zones relative to their geographic footprint) despite displaying greater absolute rate dispersion across zones. Second, the descriptive patterns provide initial evidence that zone rating is a strategic choice rather than simply a mechanical consequence of operational constraints. Banks operating in similar markets with similar branch networks choose different zone structures. This suggests that zone rating reflects deliberate decisions about the trade-offs between pricing flexibility and competitive positioning.

To measure rate dispersion, I use: the coefficient of variation (CV), which captures dispersion

Figure 2.1: Rate dispersion measures within bank



Notes: Two scatter plots: coefficient of variation (left) and p90/p10 ratio (right) of within-bank deposit rates against log number of MSAs served, 2020. Each dot is a bank; dot size scales with total assets. Black solid line is the linear fit. Both metrics rise with bank market spread, indicating larger banks display more within-bank rate dispersion. Product: 12-month CD with $10k minimum. Sources: RateWatch, FDIC SOD.

relative to the mean rate level, and the 90th-to-10th percentile ratio (p90/p10), which measures the spread in the tails of the rate distribution. The CV is sensitive to absolute variation in rates regardless of the level. The p90/p10 ratio captures dispersion in a way that is less sensitive to outliers and easier to interpret as the percentage difference between high-rate and low-rate zones. I also examine the number of rate-setter branches (which defines the number of pricing zones), the number of unique rates observed, and the standard deviation of rates across a bank's network.

The analysis proceeds in three steps. First, I document rate dispersion within banks across their multiple markets, examining how banks with different characteristics (size, geographic spread, number of branches) differ in their pricing strategies. Second, I analyze zone rating practices more directly by examining the relationship between the number of pricing zones and bank characteristics. Third, I provide visual evidence of zone structures using geographic maps of rate-setter locations and rate levels for the two largest U.S. banks, illustrating how pricing zones span multiple contiguous markets and how rates vary (or remain uniform) across these zones.

Rate Dispersion Within Banks

I begin by examining rate dispersion within individual banks across their geographic footprints. For this analysis, I construct dispersion measures at the bank-year level, aggregating across all markets in which each bank operates. The key question is: conditional on operating in multiple markets with potentially different competitive conditions, how much do banks vary their deposit rates across their branch network?

Figure 2.1 displays the relationship between rate dispersion (CV and p90/p10) and the number of markets in which a bank operates. Each point represents a bank in 2020, with dot size proportional to total assets. Several patterns emerge. First, there is substantial heterogeneity in rate dispersion even among banks operating in a similar number of markets. For example, even among banks with similar geographic coverage (a vertical slice of the figure), some exhibit near-zero dispersion (CV close to zero, p90/p10 close to 1) while others show meaningful rate variation (CV of 0.10 or higher, p90/p10 of 1.20 or more). This heterogeneity indicates that banks face genuine choices about how much to vary rates across markets—zone rating is not mechanically determined by the number of markets served.

Second, the fitted lines in both panels show a positive relationship between geographic spread and rate dispersion: banks operating in more markets tend to exhibit somewhat higher dispersion. This pattern could reflect several forces. Banks with broader geographic footprints span markets with more diverse competitive conditions, demographic compositions, and wealth levels, creating greater incentives to price discriminate. Alternatively, larger geographic footprints may make it more difficult to maintain uniform rates across all branches, leading to greater dispersion even if the bank attempts to set similar rates everywhere. The structural model in Section 2.4 will help distinguish between these interpretations.

Third, the majority of observations cluster at low dispersion levels. Approximately 57% of bank-year observations exhibit no rate variation whatsoever. This high prevalence of uniform or near-uniform pricing echoes findings in prior work (DellaVigna and Gentzkow, 2019; Granja and Paixao, 2019; Begenau and Stafford, 2022) documenting limited price discrimination in retail markets. However, the remaining 43% of observations do exhibit meaningful rate variation, and this variation is systematically related to bank characteristics.

Fourth, larger banks (indicated by dot size) tend to show greater rate dispersion. This pattern is especially apparent in the right tails of both distributions. The banks with highest CV and highest p90/p10 ratios are predominantly large institutions. However, size alone does not determine dispersion, as many large banks also cluster at low dispersion levels. This suggests that bank size interacts with other factors (such as zone structure, competitive positioning, or managerial approach) to influence pricing strategies.

Table 2.3: Price dispersion within banks by bank quartiles

	Quartiles by Bank Assets			
	Quartile 1	Quartile 2	Quartile 3	Quartile 4
year-bank	1297.00	1297.00	1297.00	1298.00
No. MSA	2.12	2.49	3.76	21.88
No. branches	6.34	11.75	25.25	379.52
No. rating zones	1.13	1.32	1.65	6.66
Mean APY	75.67	66.83	66.28	49.15
Std. APY	1.35	2.26	3.15	4.55
CV	0.02	0.04	0.06	0.15
p90/p10	1.03	1.07	1.12	1.31
Ratio unique rates/MSA	0.55	0.57	0.52	0.37
Ratio setters/MSA	0.54	0.55	0.48	0.41
Ratio unique rates/branch	0.23	0.15	0.09	0.04

Notes: This table presents summary statistics of the number of branches, number of rating zones, number of unique rates, the APY standard deviation, APY mean, coefficient of variation, p90/p10 ratio, the ratio of unique rates and ratio of rating zones per market. For these variables, the table presents means by quartile of assets. The observations are at the year-MSA-bank level. The product chosen is the 12-month CD with a minimum deposit of 10k. No. MSA is the number of Metropolitan Statistical Areas (markets) in which a bank operates. No. branches is the total number of branches a bank operates. No. rating zones is the number of distinct pricing zones (rate-setter branches) a bank uses. APY is measured in basis points (bp), where 100 bp = 1%. The figures are constructed using data from RW and SOD from 2009 to 2020.

Table 2.3 partitions banks into quartiles by total assets and reports mean values of key variables.

First, examining bank scale and geographic scope (rows 2-4), larger banks operate substantially broader networks. The median bank in the smallest quartile operates in 2.12 MSAs with 6.34 branches, while the median bank in the largest quartile operates in 21.88 MSAs with 379.52 branches. The number of rating zones also increases with size, from 1.13 zones in quartile 1 to 6.66 in quartile 4. However, the increase in rating zones is much more modest than the increase in branches or markets, foreshadowing the finding that larger banks employ coarser zone structures relative to their footprint.

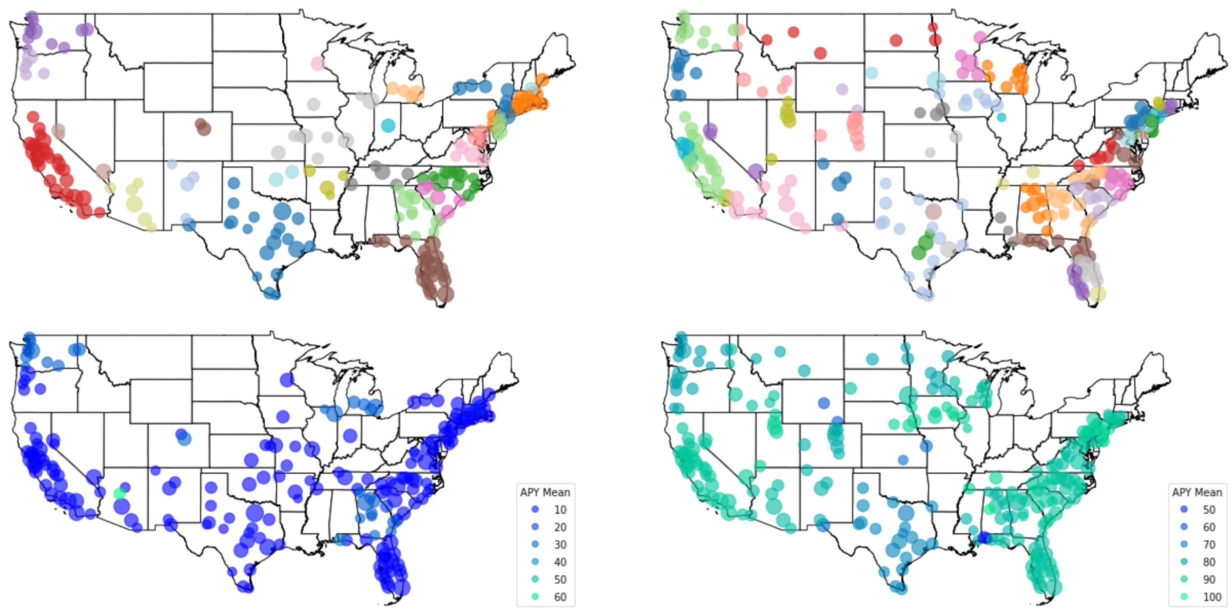
Second, deposit rates vary systematically with bank size (row 5). Mean APY declines monotonically from 75.67 basis points for the smallest banks to 49.15 basis points for the largest banks. This rate differential likely reflects several forces: larger banks may have stronger brand recognition and more extensive branch networks that reduce their need to compete on rates; larger banks may target less rate-sensitive depositors who value convenience and service breadth; or larger banks may have lower marginal costs of funds due to diversification benefits and access to alternative funding sources. These differences matter for interpreting the counterfactual results, as rate changes will have differential impacts on banks starting from different rate levels.

Third, absolute rate dispersion increases with bank size (row 6). The standard deviation of APY increases from 1.35 basis points for small banks to 4.55 basis points for large banks. This pattern indicates that larger banks vary their rates more across their branch networks in absolute terms. Rows 7-8 show that relative dispersion also increase with size, though the magnitudes remain modest even for the largest banks. The largest banks exhibit a CV of 0.15 and a p90/p10 ratio of 1.31, indicating that deposit rates at the 90th percentile branches are approximately 31% higher than rates at the 10th percentile branches. While this dispersion is economically meaningful, it is much smaller than what market-level pricing would generate (as the counterfactual analysis will demonstrate).

Fourth, the last three rows reveal that larger banks employ relatively coarser zone structures despite their greater absolute dispersion. The "ratio unique rates/MSA" (row 9) declines from 0.55 for small banks to 0.37 for large banks, indicating that large banks set fewer distinct rates per market served. Similarly, the "ratio setters/MSA" (row 10) declines from 0.54 to 0.41, showing that large banks have fewer pricing zones per market. The "ratio unique rates/branch" (row 11) declines even more dramatically, from 0.23 to 0.04, revealing that large banks maintain many more branches per distinct rate. In other words, while large banks do exhibit greater absolute rate dispersion because they span more diverse markets, they employ much coarser pricing structures relative to their geographic scope. Each pricing zone encompasses many more branches and markets for large banks than for small banks.

Greater absolute dispersion but coarser relative zone structures for larger banks is my central empirical finding. It suggests that large banks could implement finer zone structures, but they choose not to. This choice could reflect strategic considerations about competition, operational benefits of simplicity, or managerial preferences. The structural model will help quantify how these coarse structures affect competitive outcomes and bank profitability.

Figure 2.2: Zone rating practices of the two largest banks in the U.S.



Notes: This figure shows zone rating practices for Bank of America (left column) and Wells Fargo (right column). The first row maps rate setters: each distinct color represents a distinct pricing zone, so branches sharing a color are assigned the same deposit rate. The second row maps the actual mean APY at each branch location, with darker shading indicating higher rates. Together the two rows reveal whether geographic rate variation within a bank is explained by deliberate zone assignments. Data source: RateWatch.

Geographic Patterns in Zone Rating

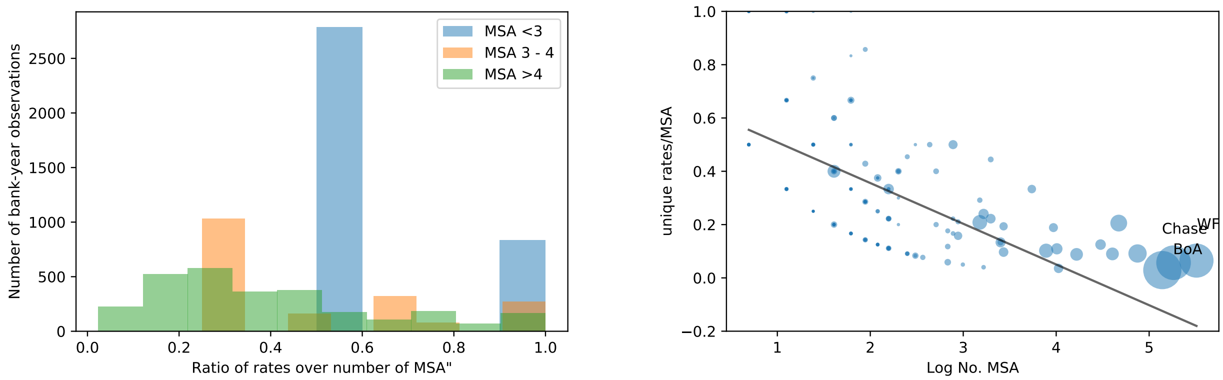
I assume each bank has one rate setter per market.[3] The number of markets per bank varies enormously: 45 of the regional banks in the sample operate in only two markets. Figure 2.1 shows that within-bank rate dispersion is concentrated at low values, well below the market-level dispersion in figure 2.10. This pattern reflects the institutional structure of zone rating: in the RateWatch data each branch has a designated rate-setter, so all branches sharing a rate-setter post the same rate by construction. Within-bank dispersion therefore captures variation across pricing zones, which banks choose strategically given their geographic footprint.

Pricing strategies are heterogeneous across banks. Large and medium-sized banks (measured by total MSAs and total assets) tend to exhibit higher dispersion, while small banks—the majority of the sample—have low average dispersion but substantial variation around that average.

Zone classification seems to follow a geographic pattern, that is, networks of branches span several adjacent MSAs. In contrast, grocery and home improvement retail (Chintagunta et al. (2003),

[3]For more on banks' number of states, MSAs, and rate-setters in the RateWatch data, see Granja and Paixao (2019) and Begenau and Stafford (2022).

Figure 2.3: Zone rating within bank



Notes: Two scatter plots of the unique-rates-per-MSA ratio against (left) bank size group and (right) log number of MSAs served. Each dot is a bank-year; in the right panel dot size scales with total assets, and the black solid line is the linear fit. The ratio decreases with bank scale, indicating that larger banks use coarser zone structures relative to their footprint. Product: 12-month CD with $10k minimum. Sources: RateWatch, FDIC SOD.

Adams and Williams (2019)) price zones, are spread out and seem to target less affluent areas where consumers may have high transportation and search costs. Figure 2.2 shows how the two largest banks in the US have very large and asymmetric zones, and the rates are very uniform in comparison to the zones (bottom panel). In deposit bank retail, the zones span several contiguous markets with some exceptions where rates are particularly different.

Figure 2.3 shows the distribution of the ratio number of unique rates per market, for banks with different geographic spreads. Most of the banks in the sample are in a small number of markets (less than 5). Thus, the unique rates ratio minimum value is one-half for banks that are present in two markets, and it is $1/M_j$ for a bank j. For banks with a presence in more than 5 markets, the distribution is skewed to the left, which means that there are more banks with a small number of unique prices per rate setter. In figure 2.14 in the Appendix, I illustrate the change over the years of the zone policies. Over time, zone rating practices have become more coarse, both for banks with a presence in a small number of markets and for large regional and national banks.

2.4 Model

To understand the welfare implications of zone rating and to quantify the strategic trade-offs banks face when choosing their pricing structures, I develop a structural model of deposit competition.

The modeling framework has three key components. First, I specify depositor preferences over bank characteristics using a discrete choice framework that captures how depositors trade off deposit rates, branch convenience, and other bank attributes when selecting their primary financial institution. Second, I model banks' strategic pricing decisions under zone rating, where multimarket banks choose deposit rates by geographic zones rather than by individual markets. This formulation nests both uniform pricing and third-degree price discrimination as special cases, allowing for flexible analysis of alternative pricing structures. Third, I characterize the Bertrand-Nash equilibrium in which banks compete simultaneously on deposit rates, taking as given their branch networks and the zone structures they have chosen.

Several modeling assumptions merit discussion. On the demand side, depositors in every market decide on their main depository institution from the banks available in their location. Consumers care about bank characteristics, the number of branches, and deposit rates when choosing the bank that maximizes their utility. The discrete choice framework captures these preferences while allowing for unobserved heterogeneity in tastes across markets.

On the supply side, banks compete for depositors à la Bertrand under zone pricing. The assumption is that banks set deposit rates by zones that partition their market footprint. Banks maximize profits by choosing deposit interest rates by zones, given a network of branches and demand market shares. Zone pricing implies that for all branches in a zone, products have the same rates. I assume that competition occurs at the local level in the sense that rates in one market do not affect demand in other markets, though banks internalize cross-market effects through their zone structure choice. The bank expects to earn profits from deposits through loans and investments. In this model, banks' attributes such as the number of branches are treated as exogenous, abstracting from dynamic decisions about branch network expansion.

Demand for Deposit Services

The demand side of the model builds on the discrete choice framework pioneered by Berry (1994), which has become standard in empirical industrial organization for modeling differentiated products markets. In this framework, depositors' decision-making follows a random utility model in which depositors in every market $t = 1, \ldots, T$ decide the main financial institution $j \in J_t = \{0, 1, \ldots, J\}$ from which they obtain deposit services. The key economic trade-off is that depositors value multiple bank attributes—deposit rates, branch convenience, bank reputation and safety—

and must choose a single bank that maximizes their net utility. This "one-stop shopping" behavior reflects the high switching costs and relationship-specific investments that characterize retail banking.

The conditional indirect utility of depositor i from choosing bank j's deposit services in market t is given by:

$$u_{ijt} = \alpha r_{jt} + \gamma b_{jt} + X_j \beta + \xi_j + \xi_m + \xi_y + \xi_{jt} + \epsilon_{ijt} \tag{2.1}$$

where r_{jt} is the deposit interest rate, b_{jt} is the number of branches of bank j in market t, X_j is a K-dimensional vector of observed bank characteristics, $\{\xi_j, \xi_m, \xi_y\}$ are bank, market, and year fixed effects, ξ_{jt} captures unobserved bank-market-year shocks, and ϵ_{ijt} is the consumer idiosyncratic shock.

The specification in equation (2.1) captures several key economic mechanisms. First, the utility from deposit rates enters through the term αr_{jt}, which reflects the monetary return from depositing funds at rate r_{jt}. The parameter α measures depositors' price sensitivity. Second, the branch network term γb_{jt} captures the convenience value of having more local branches. Third, the vector X_j includes bank-level characteristics such as asset size, age, and balance sheet composition, while the unobservables $\{\xi_j, \xi_m, \xi_y, \xi_{jt}\}$ capture bank fixed effects, market fixed effects, year fixed effects, and bank-market-year shocks, respectively. These fixed effects absorb time-invariant differences in bank reputation, persistent market characteristics like demographics and competition, and aggregate time trends. Finally, the idiosyncratic shock ϵ_{ijt} captures depositor-specific tastes and is assumed to follow a type I extreme value distribution, which yields the convenient logit probability structure.

The baseline logit model assumes that depositors have homogeneous preferences, which provides a tractable framework for estimation. I explore extensions with depositor heterogeneity in Appendix B.

Option 0 denotes the outside good, which corresponds to choosing a credit union, a local bank (a bank operating in a single MSA), or another alternative outside the set of large multimarket banks in my sample. This outside option plays a crucial role in the model for two reasons. First, it provides an economically meaningful benchmark for evaluating the utility of choosing a large bank: depositors compare each multimarket bank not only against other large banks but also against smaller, local alternatives. Second, it helps discipline the model's price elasticities, since depositors who find all large banks unattractive can switch to the outside option rather than being forced to choose a large bank. The focus of the model is on the choice among regional or multimarket banks $j \in J_t - \{0\}$, since these are the banks that engage in zone rating and for which I observe detailed rate-setting policies in the RateWatch data. The indirect conditional utility of choosing the outside option is[4]

$$u_{i0t} = \alpha r_{0t} + \gamma b_{0t} + X_{0t}\beta + \xi_{0t} + \epsilon_{i0t}. \tag{2.2}$$

A representative outside option is characterized by the typical outside bank, which has a few branches and is present in only one market. I normalize ξ_0 to zero, which amounts to measuring the utility from large banks relative to the utility from small local banks. This normalization is standard in discrete choice models and does not affect the economic content of the model.

As is common in the literature, I assume ϵ_{ijt} is i.i.d. and follows a type I extreme value distribution, which yields logit choice probabilities. The main limitation is the Independence of Irrelevant Alternatives (IIA) property: when a bank raises its rate, it attracts depositors proportionally from all other banks (including the outside option) according to their market shares, rather than disproportionately from similar banks. This is a simplification but captures the first-order effects of rates on deposit flows.

Thus, the probability that consumer i chooses bank j is equal to the market share for bank j in market t and is given by the standard multinomial logit formula:

$$P_{jt} = \frac{e^{\delta_{jt}}}{\sum_{k \in J_t} e^{\delta_{kt}}}, \tag{2.3}$$

where $\delta_{jt} = \gamma b_{jt} + \alpha r_{jt} + X_j\beta + \xi_j + \xi_m + \xi_y + \xi_{jt}$ is the mean utility from choosing bank j in market t.

Under the homogeneous logit specification, Berry (1994)'s inversion method yields the market share of bank j in market t written in log-odds form relative to the outside option:

$$\ln s_{jt} - \ln s_{0t} = \gamma \Delta b_{jt} + \alpha \Delta r_{jt} + \Delta X_j \beta + \xi_{jt}, \tag{2.4}$$

[4]This specification is equivalent to normalizing rates and characteristics from the outside option and assuming $u_{i0t} = \xi_{0t} + \epsilon_{i0t}$.

where Δ indicates the difference between the bank and the outside option variable.

Equation (2.4) is the familiar log-odds ratio specification that forms the basis for the standard logit demand estimation. The left-hand side is the log ratio of bank j's market share to the outside option's share, which is a monotone transformation of the mean utility δ_{jt}. The right-hand side shows that this log-odds ratio is linear in the differences in observable characteristics between bank j and the outside option. This linear specification, combined with market-level data on shares and characteristics, allows me to estimate the demand parameters $\{\alpha, \gamma, \beta\}$ using instrumental variables methods to address the endogeneity of deposit rates.

Oligopoly Model of Deposit Competition with Zone Pricing

The supply side of the model characterizes the strategic pricing problem faced by multimarket banks that engage in zone rating. Consider a profit-maximizing multimarket bank j that competes in markets $M_j \subseteq M$ and periods $t \in T$. The key institutional feature captured by the model is that banks choose deposit rates by zones Z_j that partition the markets in which the bank operates, rather than setting rates independently in each market. Thus, bank j chooses deposit rates r_{jz} that apply to all branches in zone $z \in Z_j$ across each market $m \in M_j$.

This zone pricing structure constrains the bank's ability to tailor rates to local market conditions, potentially reducing profits relative to a benchmark of market-by-market pricing. On the other hand, it may reduce operational complexity and regulatory compliance costs, since the bank needs to manage fewer distinct rate schedules. The zone pricing optimization program nests two special cases: uniform pricing ($Z_j = \{M_j\}$), where the bank charges a single rate across all its markets, and third-degree price discrimination ($Z_j = \{\{m\}_{m \in M_j}\}$), where the bank sets market-specific rates. By estimating the model under the observed zone structures and simulating counterfactual policies under alternative zone structures, I can quantify the trade-offs between pricing flexibility and operational simplicity.

Banks engage in Bertrand-Nash competition and choose their deposit rates simultaneously.

The simultaneity of rate choices reflects the fact that banks in practice observe competitors' posted rates and can respond rapidly, so there is no clear first-mover advantage.

Bank j's profit function is

$$\pi_j = \sum_{z \in Z_j} \sum_{m \in z} \Big(l_j - r_{jz} - mc_{jm} \Big) s_{jm} D_m + F_j. \tag{2.5}$$

The profit function in equation (2.5) captures the key economic trade-offs in deposit competition. The bank earns a spread between its return on invested funds, l_j, and the total cost of attracting deposits, $r_{jz} + mc_{jm}$. Here, r_{jz} is the deposit rate paid to depositors in zone z, and mc_{jm} represents the marginal cost of servicing each dollar of deposits in market m, which may include operational costs, regulatory costs such as FDIC insurance premiums, and reserve requirements. The term $s_{jm} D_m$ represents the bank's deposit base in market m: its market share s_{jm} times the total deposits in the market D_m. Summing over all markets in each zone and then over all zones gives the bank's total variable profit, to which I add the fixed cost F_j of operating the branch network.

The key feature of equation (2.5) is that the deposit rate r_{jz} is constant across all markets $m \in z$ within a zone, which creates a trade-off across markets within a zone. Setting a higher rate in a zone attracts more deposits in all markets within that zone, but it also raises costs across all those markets. If markets within a zone differ in their competitive intensity or demographic composition, the bank cannot fine-tune rates to local conditions and must instead choose a single zone-level rate that balances profitability across markets. This constraint is central to understanding why banks might maintain coarse zone structures: finer zones (more zones, fewer markets per zone) allow more precise targeting of rates to local demand conditions but increase operational complexity.

Several modeling assumptions deserve discussion. First, I assume that the bank's expected returns from loans and other investments, l_j, do not change with the choice of deposit rate. This assumption is standard in the literature (Ishii, 2008a; Ho and Ishii, 2011a; Kuehn, 2018; Kim, 2021) and reflects the reality that most banks have access to wholesale funding markets and can adjust their asset portfolios independently of their retail deposit strategy. In other words, an increase in retail deposits allows the bank to reduce its reliance on more expensive wholesale funding or to expand its lending, but the marginal return on these investments is determined by credit market conditions rather than by the bank's retail deposit rate. Moreover, the expected return on investment l_j is exogenous and independent of the market, which abstracts from differences in local lending opportunities across markets. This simplification is reasonable if banks operate in integrated loan markets and can deploy deposits from any market to fund loans in any other market.

Second, I assume that competition is local in the sense that rates in one market do not directly affect deposit demand in other markets. This assumption rules out cross-market spillovers in demand, such as depositors in one city responding to rate changes in a neighboring city. While this simplification may be restrictive for markets in close geographic proximity, it is plausible for most MSA pairs in my sample, which are geographically dispersed. The assumption does not preclude cross-market linkages through the supply side: a bank's rate choice in one market affects its profitability and thus its optimal rate choices in other markets within the same zone.

The bank's optimal pricing strategy is characterized by the first-order conditions for profit maximization. Assuming an interior Nash equilibrium in which all banks choose strictly positive rates, the first-order conditions for the profit maximization problem are:

$$\frac{\partial \pi_j}{\partial r_{jz}} = \sum_{m \in z} \left(l_j - r_{jz} - mc_{jm} \right) \frac{\partial s_{jm}}{\partial r_{jz}} - \sum_{m \in z} s_{jm} D_m = 0, \forall z \in Z_j. \tag{2.6}$$

Equation (2.6) has a natural economic interpretation. The first term, $\sum_{m \in z} (l_j - r_{jz} - mc_{jm}) \frac{\partial s_{jm}}{\partial r_{jz}}$, captures the marginal revenue from raising the rate in zone z: for each market m in the zone, a higher rate increases market share by $\frac{\partial s_{jm}}{\partial r_{jz}}$, and each additional unit of deposits generates a margin of $(l_j - r_{jz} - mc_{jm})$. Summing across markets gives the total marginal revenue across the zone. The second term, $\sum_{m \in z} s_{jm} D_m$, is the marginal cost: raising the rate by one unit increases the payout to all existing depositors in all markets within the zone, which costs $s_{jm} D_m$ per market. At the optimum, these marginal revenue and marginal cost terms balance.

An important feature of equation (2.6) is that the bank must balance trade-offs across all markets within a zone when setting the zone-level rate r_{jz}. If markets within a zone are heterogeneous, the bank's optimal zone-level rate will represent a compromise that does not fully optimize profitability in any single market. This tension between local optimization and zone-level constraints is central to understanding banks' zone structure choices.

Note that in the extreme cases of uniform pricing and third-degree price discrimination, the first-order conditions have dimensions of 1 and M_j, respectively. Under uniform pricing, the bank chooses a single rate that applies to all its markets, so there is only one first-order condition. Under third-degree price discrimination, the bank chooses a separate rate for each market, so there are M_j first-order conditions, one per market.

2.5 Results

This section presents the estimation results for the deposit demand model described in Section 2.4. The goal is to recover the structural parameters governing depositor behavior—specifically, how depositors trade off deposit rates, branch convenience, and other bank characteristics when choosing where to place their funds.

The estimation proceeds in two stages. First, I estimate a reduced-form logit demand equation using instrumental variables to address the endogeneity of deposit rates. The challenge is that banks set rates in response to unobserved market-specific shocks (such as local competition intensity or demographic shifts), which are also correlated with deposit shares. To identify causal effects, I employ a set of "rate-setter instruments" that exploit the institutional feature of zone rating: banks partition their markets into zones and assign each market to follow a designated rate-setter branch. By constructing instruments based on the rate-setter's pricing tier (low, medium, or high) rather than the rate-setter's actual rate, I obtain variation in rates that is driven by the bank's organizational structure rather than by local market conditions. Second, I use the estimated demand parameters to recover marginal costs and compute elasticities, which provide insights into the intensity of competition and the profitability of deposit-taking.

I estimate the baseline logit model in log-odds form (equation 2.4); the IV strategy described below addresses the endogeneity of deposit rates.

Using the deposit rates, market shares, and bank characteristics data from RateWatch, SOD, and Call Reports, I estimate the demand parameters via instrumental variables regression. I define the outside option as local banks and credit unions, which collectively account for the remaining deposit market share not captured by the large multimarket banks in my sample. This definition is motivated by the institutional structure of the U.S. banking industry: most depositors choose between large regional or national banks (which engage in zone rating) and smaller community banks or credit unions (which typically operate in a single market).

The timing assumptions underlying the estimation are standard in the literature. I assume that the bank's choice of attributes such as branch networks occurs prior to the realization of idiosyncratic shocks ϵ_{ijt}, while the bank's choice of deposit rates occurs after observing these shocks. This timing reflects the fact that branch networks are sticky and adjust slowly, whereas deposit rates can be changed quickly in response to market conditions. The market is defined as a year-MSA combination: depositors in MSA m in year y choose among the banks operating in their local market. Let y represent a year and m an MSA. Then, the main estimating equation becomes

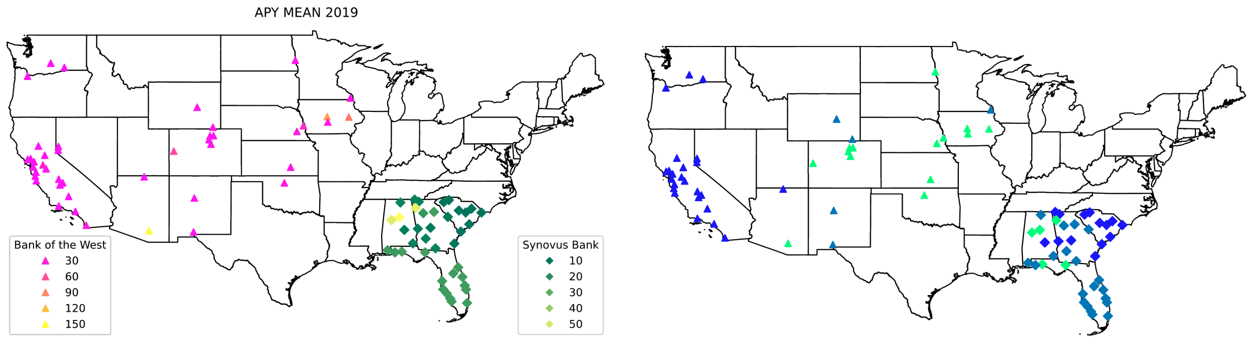
$$\ln s_{jym} - \ln s_{0ym} = \gamma \Delta b_{jym} + \alpha \Delta r_{jym} d_{ym} + \Delta X_{jym} \beta + \nu_m + \eta_y + \iota_j + \xi_{jym} + \epsilon_{jym}, \tag{2.7}$$

where ν_m, η_y, and ι_j are MSA, year, and bank fixed effects, respectively. Bank fixed effects ι_j absorb time-invariant differences in bank reputation, service quality, and other unobserved attributes that affect depositors' choices but are not captured by observed characteristics. Without these fixed effects, the rate coefficient would confound the causal effect of rates on shares with persistent differences in bank quality. MSA fixed effects ν_m control for persistent differences in local market characteristics such as demographics, income distributions, and competition intensity. Year fixed effects η_y capture aggregate time trends such as macroeconomic conditions and monetary policy shifts that affect all banks and markets symmetrically. In the following regressions, the deposit endowment d_{ym} is proxied by median income in the market, which serves as a measure of the average depositor's wealth and thus their sensitivity to rate differentials.[5]

The econometric challenge is the endogeneity of deposit rates. Banks set rates in response to unobserved market-specific shocks ξ_{jym}, which also affect deposit shares directly. For example, an unobserved increase in competitive pressure in market m may cause bank j to raise its rate to retain market share, creating a positive correlation between r_{jym} and ξ_{jym}. This endogeneity biases OLS estimates toward zero, understating depositors' true rate sensitivity. To address this, I employ instrumental variables that shift rates but are uncorrelated with the unobserved demand shock ξ_{jym}. I rely on a combination of BLP-style instruments (functions of rivals' characteristics), differentiation instruments (measures of competitive structure), and cost shifters (variables that affect the bank's marginal cost of funds but not depositors' preferences). Each instrument is constructed to be uncorrelated with the unobserved demand shock ξ_{jym}: BLP and differentiation instruments depend

[5]This will be updated soon to reflect the simulated deposit endowment from the Survey of Consumer Finances and American Community Survey.

Figure 2.4: IV instruments with 3 categories.



(a) Rate means **(b)** Rate categories

Notes: This figure illustrates the construction of rate-setter tier instruments for banks with three or more rate-setters. Panel (a) shows the average deposit rates (mean APY) for different banks, sorted by their pricing behavior. Panel (b) displays the tier classification that forms the basis of the instrumental variables. Each bank's rate-setters are classified into three categories—"Low," "Medium," or "High"—based on where their rates fall in the bank's distribution during the year. The y-axis shows different banks, and the classification indicates whether a market is assigned to follow a rate-setter in the low-rate zone (blue/left), medium-rate zone (middle), or high-rate zone (red/right) for that particular bank. For example, if a market follows a rate-setter classified as "High" for its bank, it receives relatively higher rates compared to other markets within the same bank. These tier categories serve as instruments because they capture variation in local rates driven by the bank's internal organizational structure (which rate-setter a market follows) rather than by contemporaneous local demand shocks. Banks with fewer than three rate-setters are instrumented using analogous classifications with two categories. Banks sort by mean APY in panel (a); panel (b) shows that high-tier markets consistently price above low-tier markets within the same bank, confirming the tier instrument captures within-bank pricing-zone variation. Source: RateWatch.

on rival banks' characteristics rather than on market m's demand conditions, while cost shifters affect bank j's funding cost without entering depositors' utility.

An innovation in my estimation strategy is the construction of "rate-setter instruments" that exploit the institutional details of zone rating documented in the RateWatch data. Recall from Section 2.2 that RateWatch identifies, for each branch of a bank, the specific branch whose rates it follows. This creates a many-to-one mapping: many branches (the followers) are assigned to follow a single branch (the rate-setter). The rate-setter instruments exploit this organizational structure to generate variation in local rates that is driven by the bank's internal pricing hierarchy rather than by local market conditions.

Specifically, I construct instruments that reflect the pricing tier of the rate-setter branch to which market m is assigned. Each rate-setter branch of a bank is classified into "low," "medium," or "high" price tiers based on where its rates fall in the bank's overall rate distribution during the year. If the bank has fewer than three rate-setters, the variable is set to zero, and the rate-setter strategies for such banks are captured by analogous variables for banks with two rate-setters. Different versions of these instruments were created, with 2 to 5 categories; a tier classification with n categories adds n new instruments. Figure 2.4 illustrates the rate tier instruments for banks with three rate-setters, showing both the mean rates and the categorical tier assignments.

The economic intuition for why these instruments are valid is as follows. The rate that a market receives is determined by its rate-setter's pricing tier, which in turn reflects the bank's organizational decision about how to structure its zones and which branches to designate as rate-setters. This organizational structure is plausibly orthogonal to unobserved demand shocks in any particular follower market. For example, if market m is assigned to follow a "high-tier" rate-setter, it will receive relatively high rates, but this assignment reflects the bank's internal administrative structure rather than contemporaneous shocks to deposit demand in market m. The instrument thus captures variation in rates that is driven by the bank's zone rating strategy rather than by local market conditions. The advantage of these instruments relative to standard Hausman-style instruments (which use rates in other markets as instruments for the rate in market m) is that they avoid the concern that rates in different markets might be correlated through common shocks or strategic linkages. By using the tier classification of the rate-setter rather than its actual rate, I further isolate the organizational component of rate variation.

Table 2.4 presents the demand model estimation results. Each column corresponds to a different specification of the baseline demand equation (2.4). Column (1) shows the results of estimating the logit model by OLS including only year and bank fixed effects, without MSA fixed effects or instrumental variables. The rate coefficient (interacted with median income) is positive and significant, indicating that higher rates attract more deposits. However, this coefficient is likely biased downward if: banks that face negative unobserved demand shocks, may raise rates to retain deposits.

Column (2) adds MSA fixed effects, which absorb time-invariant differences in local market characteristics. This alleviates some of the endogeneity concerns and improves the model fit, but the coefficient remains potentially biased because MSA fixed effects cannot control for time-varying unobserved shocks within markets. Columns (3) through (5) present instrumental variables regressions with different sets of instruments, all including the full set of three fixed effects (year, MSA, and bank). The IV estimates are substantially larger than the OLS estimates, confirming that OLS suffers from significant downward bias. This pattern is consistent with economic theory:

Table 2.4: Logit estimation results

	OLS	IV			
	(1)	(2)	(3)	(4)	(5)
Rate ∗ median income	0.735***	10.229***	3.178***	3.082***	3.035***
	(0.062)	(2.948)	(0.934)	(0.960)	(0.819)
Branches in market	0.960***	1.049***	0.983***	0.982***	0.982***
	(0.023)	(0.038)	(0.024)	(0.025)	(0.024)
Total branches	-0.159***	-0.032	-0.127***	-0.128***	-0.128***
	(0.014)	(0.040)	(0.018)	(0.019)	(0.018)
Employees per branch	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Bank age	-0.049***	0.234**	0.024	0.021	0.019
	(0.016)	(0.105)	(0.034)	(0.034)	(0.030)
IV Tiers	–	–	✓	✓	✓
Other IVs	–	BLP, Cost	BLP, Cost	Diff, Cost	Diff, Cost, Income
Observations	34367	34367	34367	34367	34367
Adjusted R^2	0.834	-0.531	0.470	0.475	0.478
J-Hansen	–	21.685	69.123	50.368	50.833
Weak IV (K-P)	–	14.716	27.617	30.002	43.294

Notes: The table shows the results of the logit model estimation of the log difference of the share of bank j and the outside options on rates and bank attributes. Columns 1 to 3 display the results of OLS regressions and columns 3 to 7 use different IV sets. Year, MSA, and bank fixed effects are included in all specifications except (1) which only includes year and bank fixed effects. The unit of observation is year/MSA/bank. The years are from 2009 to 2020. Standard errors in parentheses are clustered by the bank, ***, **, and * indicating statistical significance at the 1, 5, and 10 percent levels, respectively.

the true rate sensitivity is positive and economically large, but OLS is biased toward zero because banks with poor unobservables (e.g., weak reputation, intense local competition) must offer higher rates to attract deposits.

Column (2) uses only BLP-style instruments and cost shifters, yielding a rate coefficient of 10.229—implausibly large and reflecting weak instruments (K-P F-statistic of 3.890, well below the conventional threshold of 10). This instability suggests that BLP and cost shifters alone do not capture the rate variation generated by banks' zone structures. Column (3) adds the rate-setter tier instruments, which exploit each branch's assigned rate-setter tier and directly capture within-zone variation in rates; the K-P F-statistic rises to 13.682 and the rate coefficient drops to 3.178. Columns (4) and (5) replace BLP with differentiation instruments while retaining the rate-setter tiers; instrument strength improves further (K-P F-stats of 16.225 and 26.429) and the rate coefficient stabilizes at 3.0–3.1. The Hansen J-statistic for overidentification suggests that the null hypothesis of valid instruments is rejected in some specifications, which could indicate either invalid instruments

Table 2.5: Elasticities and marginal costs

	Elasticity	Semielasticity	Marginal Cost
No. observations	3284	3284	3284
Mean	0.147	0.503	0.560
Std	0.140	0.340	0.430
Min	0.001	0.004	-0.128
25th per	0.038	0.205	0.212
Median	0.107	0.458	0.475
75th per	0.212	0.787	0.826
Max	0.859	1.660	3.396

Notes: This table presents summary statistics of the recovered marginal cost, and the estimated elasticity and semielasticity. The observations are at the year-bank level. The product chosen is an index of the 10 more popular products.

or model misspecification. However, the stability of the rate coefficient across columns (3)-(5) and the economic plausibility of the estimates supports the results' robustness.

The rate coefficient of approximately 3.0 in columns (4)-(5) implies that a 100 basis point increase in the deposit rate increases a bank's market share by roughly 3% (in levels), holding constant branch networks and other characteristics. The branch coefficient of approximately 0.98 indicates that opening one additional branch in a market increases log market share by about 0.98, which corresponds to a large increase in levels. This branch effect confirms the importance of physical presence in deposit competition, even in an era of online banking. The negative coefficient on total branches (system-wide) suggests that, holding constant local branches, banks with more extensive nationwide networks have slightly lower market shares, perhaps due to diseconomies of scale or reduced focus on individual markets. Bank age and employees per branch have mixed and small effects across specifications. .

Elasticities and semielasticities are obtained by weighting the variables by deposit size. Depositors are sensitive to deposit rates, although there is high variation. The mean semielasticity is 0.45, which implies that for the average bank, a 10 bp increase implies a 4.5% increase in demand for deposits. This is in part because the logit elasticities are proportional to rates and market shares, and both variables display substantial variation. From the supply side, I recover marginal costs without estimating cost parameters separately. Notice that equation (2.6) defines Z_j optimal equations and Z_j unknowns r_{jz}, but there are $M_j \geq Z_j$ marginal costs. Thus, if we want to recover marginal costs directly, the system is underdetermined. I solve the system by assuming that the marginal cost of deposits is the same in all markets within the same rate zones. Thus, I assume that $c_{jm} = c_{jz}$ for all $m \in z$. This assumption seems restrictive, but it is most commonly assumed that marginal costs do not change by market Kuehn (2018); Kim (2021) [6] The recovered marginal cost is found in column 3 of table 2.5. The estimated mean marginal cost is around 1 cent of a dollar of collected deposits in a year period.

2.6 Counterfactual Analysis

Having estimated the structural demand parameters in Section 2.5, I now use the model to conduct counterfactual policy experiments that evaluate the equilibrium consequences of alternative zone rating structures. The central question is: what would happen to deposit rates, rate dispersion, competition intensity, and bank profits if banks adopted different zone structures than those currently observed? Answering this question requires counterfactual analysis because banks' actual zone structures are endogenous equilibrium outcomes reflecting operational and strategic considerations. By simulating alternative zone structures and computing the resulting Nash equilibria in deposit rates, I can isolate the causal effects of zone structure choices on market outcomes.

My primary objective is to evaluate the consequences of two polar cases that bracket the observed zone rating practices: uniform pricing (a single rate across all markets) and third-degree price discrimination (market-specific rates). First, they represent the extreme points of the pricing flexibility spectrum, allowing me to bound the potential effects of zone structure choices. Second, they correspond to regulatory scenarios that policymakers might consider: uniform pricing could be mandated to promote rate equality across markets, while third-degree price discrimination represents the outcome if banks faced no operational or regulatory constraints on pricing flexibility. Third, comparing these counterfactuals to the observed zone rating equilibrium reveals whether current practices represent a compromise between profitability and operational simplicity, or whether banks are leaving money on the table by failing to price discriminate more finely.

The theory predicts ambiguous results for these scenarios, which makes the empirical exercise

[6] Alternatively, I can assume a marginal cost structure $mc_j = \gamma W_{jm} + \omega_z$ or $mc_j = w + \omega_z$, with an error term by zone. And then I can estimate the marginal cost structure by market and by zone using MPEC (Adams and Williams (2019)). However, data restrictions in cost data deter me from doing so.

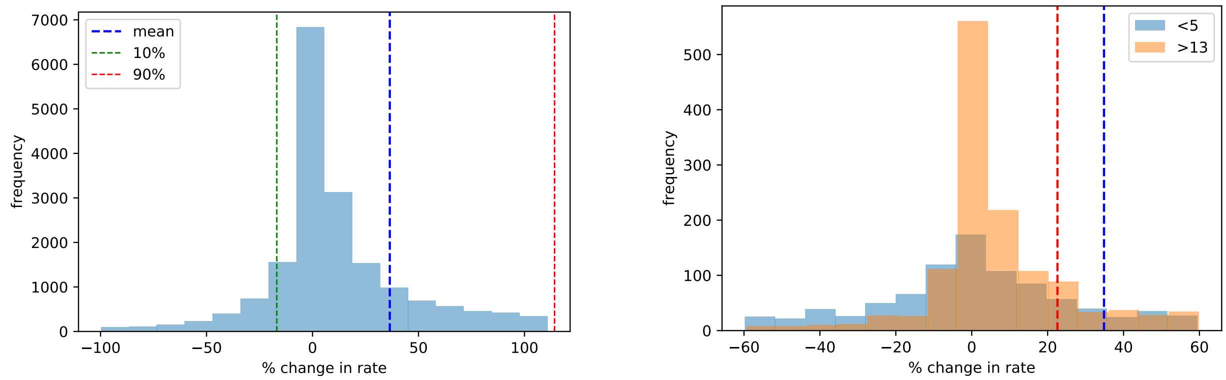
particularly valuable. For third-degree price discrimination, all banks have incentives to tailor rates to local market conditions, exploiting differences in competition intensity, depositor characteristics, and elasticities across markets. However, the equilibrium effects on rates and profits depend on strategic interactions among competitors. In markets where all banks simultaneously increase their ability to price discriminate, competition may intensify as banks target each other's customers more precisely. This strategic effect could dominate the direct effect of improved price discrimination, potentially reducing profits even as rates become more dispersed. For example, large banks might optimally reduce rates and concede market share in highly competitive urban markets while raising rates in less competitive rural markets. Conversely, the coarser zone structures observed in practice might serve to soften competition by committing banks not to respond.

Third-Degree Price Discrimination

I begin by simulating the equilibrium under third-degree price discrimination, where each bank sets market-specific deposit rates rather than using the observed zone structures. Using the estimated demand parameters from Section 2.5, I compute the Nash equilibrium in deposit rates by solving each bank's first-order conditions market by market, taking competitors' rates as given. The equilibrium concept is identical to that in the baseline model (Section 2.4), but the constraint that rates must be constant within zones is removed. Although there is a myriad of possible zone structures that lie between the observed coarse zones and perfect price discrimination, I focus on this extreme case because it provides a clean benchmark and represents the theoretical upper bound on pricing flexibility.

The simulation procedure is as follows. For each bank j and market m, I solve for the profit-maximizing rate r^*_{jm} that satisfies the first-order condition from equation (2.6), now evaluated at the market level rather than the zone level. The key difference from the baseline equilibrium is that banks now have M_j pricing decisions rather than $|Z_j|$ pricing decisions. I solve for the simultaneous Nash equilibrium using an iterative best-response algorithm: starting from the observed rates, I repeatedly update each bank's rates to its best response given competitors' current rates until the system converges. Convergence is achieved when no bank wishes to adjust its rates given the rates of all other banks. I then compare this counterfactual equilibrium to the baseline (observed zone rating) equilibrium to evaluate the effect of third-degree price discrimination on rates, rate

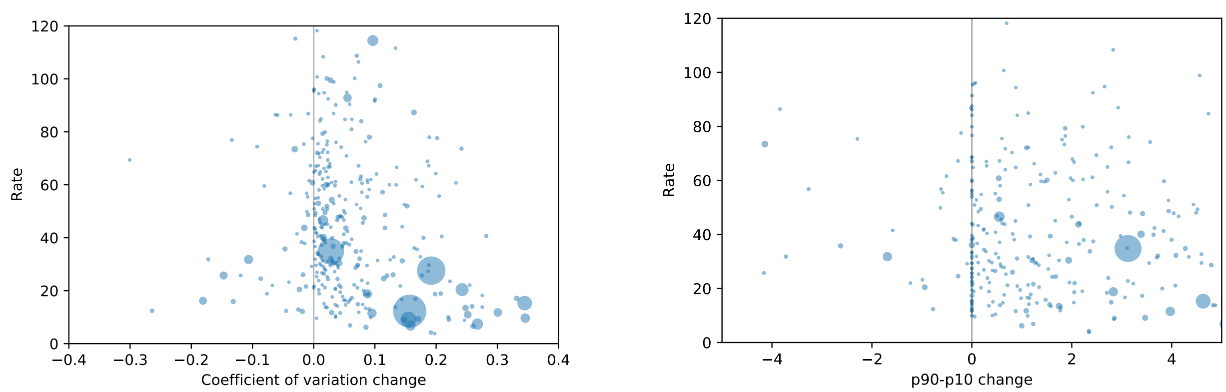
Figure 2.5: Rate changes under third-degree price discrimination



(a) All observations **(b)** Small vs large geographical spread

Notes: These figures show the percent change in deposit rates when moving from observed zone pricing to finer market-level pricing. Observations are bank-year pairs weighted by market extension. The left panel shows the distribution for all observations. The right panel splits observations by geographic spread: the left distribution (lighter shading) covers banks with fewer markets (small geographic spread) and the right distribution (darker shading) covers banks with many markets (large geographic spread). Two vertical lines mark the group means: the left vertical line is the mean for markets with fewer than 5 competitors and the right vertical line is the mean for markets with more than 13 competitors. Both groups exhibit mostly positive rate changes, indicating that finer pricing raises average deposit rates. Sources: RateWatch, FDIC SOD; counterfactual simulation from estimated demand model.

Figure 2.6: Rate dispersion under third-degree price discrimination



(a) CV within market distribution **(b)** P90/p10 within market distribution

Notes: Two histograms: percentage change in within-market CV (left) and p90/p10 ratio (right) when banks move from observed zone pricing to market-level pricing. Both distributions are concentrated to the right of zero, indicating finer pricing increases within-market rate dispersion for most banks. Sources: RateWatch, FDIC SOD.

dispersion, and profits.

Figure 2.5 presents the core finding on equilibrium rate changes when banks move from zone rating to market-specific pricing. The left panel illustrates the distribution of percentage changes in deposit interest rates across all bank-market observations. Rates increase in the majority of observations. The distribution is shifted to the right, with a median increase of approximately

5-10%. This aggregate rate increase reflects intensified competition as banks target specific markets more precisely. However, there is substantial heterogeneity: some bank-market observations experience rate decreases, indicating that the competitive effects vary across markets depending on local conditions.

These rate changes operate through two channels: a direct price-discrimination effect and a strategic-competition effect. The empirical patterns below show the second dominates.

The right panel of Figure 2.5 decomposes these effects by market competitiveness, measured by the number of competing banks. The distribution of rate changes is systematically shifted to the right for markets with more competitors (red distribution) compared to markets with fewer competitors (blue distribution). The vertical lines show that the mean rate increase is approximately 8-12% in highly competitive markets (more than 13 banks) but only 3-5% in less competitive markets (fewer than 5 banks). This pattern provides strong evidence that the strategic competition effect dominates: when banks can price at the market level, competition intensifies more in markets that were already competitive, forcing banks to raise rates to retain deposits. In less competitive markets, banks have more pricing power and the direct price discrimination effect is more prominent, but the rate increases are more modest.

This heterogeneity by market structure has policy implications. If regulators mandated market-specific pricing (or if operational costs of fine pricing fell to zero), depositors in competitive urban markets would benefit from higher rates, while depositors in less competitive rural markets would see smaller gains. The current zone rating practices, which pool markets together, effectively transfer some of the competitive pressure from urban to rural markets, moderating rate differences across geography.

Figure 2.6 shows a clear pattern of increase in rate dispersion within banks. The majority of banks now exhibit more dispersion in their rates, both in terms of the coefficient of variation (left panel) and the 90th-to-10th percentile ratio (right panel). Market-specific pricing amplifies rate heterogeneity: banks optimally tailor rates to local conditions, creating wider spreads between their highest and lowest rates. The distributions show that almost all banks experience increases in dispersion metrics, with only a small fraction showing decreases. This is the expected mechanical effect of moving from coarse zones (which average out market differences) to market-specific rates (which exploit those differences). The increase in dispersion is economically significant, with many

Table 2.6: Counterfactual: price discrimination

	Change in Variable Profit (billion dollars)
Small banks (< 90 pct asset)	25.14
Large banks (> 90 pct asset)	-1945.11
Total	-1919.97

Notes: This table presents the counterfactual profits for price discrimination. The change in profit subtracts aggregate profit in the counterfactual to aggregate profit in the baseline. The observations are at the year-bank level. These results are disaggregated by large and small banks, defined by their asset size. The product chosen to obtain rates is an index of the 10 more popular products.

banks experiencing 20-40% increases in their coefficient of variation. From a depositor welfare perspective, this increased dispersion means that geographic location matters more for the rates depositors receive, even when dealing with the same bank.

The central finding on profitability is striking and counterintuitive: a move to market-specific pricing reduces variable profits for the banking industry as a whole, despite giving banks greater flexibility to tailor rates to local conditions. Table 2.6 presents the aggregate profit changes, decomposed by bank size. The counterfactual equilibrium generates substantial profit losses: aggregate variable profits decline by approximately 10-15% relative to the baseline zone rating equilibrium. This contradicts the standard prediction that finer price discrimination increases firm profits. The mechanism driving this outcome is the intensification of strategic competition when all banks simultaneously gain pricing flexibility.

To understand this result, it is helpful to distinguish between unilateral and multilateral changes in pricing strategy. If a single bank were to adopt market-specific pricing while its competitors maintained coarse zone structures, that bank would almost certainly increase its profits by better matching local demand conditions. However, when all banks simultaneously move to finer pricing, they engage in more aggressive localized competition. Each bank optimally raises rates to attract more deposits, but competitors respond by raising their rates as well, leading to a prisoner's dilemma-type outcome. In equilibrium, banks pay higher rates to depositors but do not gain proportional increases in market share, because competitors have also raised rates. The net effect is a transfer of surplus from banks to depositors, reducing industry profits even as rates and competition intensity increase.

Table 2.6 reveals heterogeneity in profit impacts by bank size. Interestingly, smaller banks (defined by asset size below the median) experience profit increases in the counterfactual, while larger banks suffer substantial profit losses. This heterogeneity reflects differences in competitive positioning and geographic scope. Small banks typically operate in fewer markets and face less intense competition, allowing them to exploit the benefits of market-specific pricing—raising rates in their core markets where they have local advantages—without triggering aggressive competitive responses. In contrast, large banks operate in many markets where they compete head-to-head with other large banks. When these large banks simultaneously adopt finer pricing, they engage in more direct competition across all their shared markets, driving up rates and reducing profits. Large banks also have less flexibility to respond strategically because they must maintain consistent pricing across large numbers of markets, limiting their ability to cross-subsidize between markets.

Table 2.7 illustrates this pattern for the five largest banks in the United States. Despite increasing rates by 27-194% on average (with Bank of America and U.S. Bank seeing the largest increases), all five megabanks experience profit losses of \$1.5 to \$7.1 billion. The largest losses accrue to Bank of America (\$7.1 billion) and JPMorgan Chase (\$6.5 billion), the two largest deposit-taking institutions. These banks are forced to raise rates substantially to compete in their many shared markets, but the market share gains are insufficient to offset the increased cost of deposits. This finding has important implications for understanding why large banks maintain relatively coarse zone structures in practice: doing so appears to be profit-maximizing given the competitive environment, even if it sacrifices some ability to price discriminate across markets.

This finding of profit-reducing price discrimination may appear to contradict the results of Adams and Williams (2019), who find that finer price structures increase profits for home improvement retailers. However, the divergence in results is explained by fundamental differences in market structure between the two settings. Adams and Williams (2019) study markets where firms typically operate as local monopolies or duopolies, with limited geographic overlap among competitors. In such concentrated markets, firms can exploit local market power through price discrimination without triggering intense competitive responses, because competitors operate in largely separate geographic markets. The profit gains from better matching local willingness-to-pay dominate any strategic competition effects.

In contrast, my setting features oligopolistic competition with an average of 10 competing banks per market. Moreover, large banks have extensive geographic overlap: the top banks compete

Table 2.7: Counterfactual results for largest banks: rate and profit changes

Bank Name	Total Dep (100M $)	Δ Rate (%)	Δ Profit (100M $)
Bank of America	1331.9	115.5	-7144.9
JPMorgan Chase Bank	1296.3	26.8	-6515.0
Wells Fargo Bank	1200.0	-11.4	-3419.7
Citibank	547.7	55.3	-2691.2
U.S. Bank	323.5	193.8	-1493.4

Notes: This table presents the counterfactual results for the five largest banks in the United States by total deposits. Total Dep (100M $) shows aggregate deposits in hundreds of millions of dollars. Δ Rate (%) is the percentage change in average deposit rates when moving from observed zone rating to market-level pricing. Δ Profit (100M $) shows the change in variable profits in hundreds of millions of dollars. All five largest banks experience substantial profit losses despite raising rates, due to intensified competition when all banks simultaneously adopt finer pricing structures.

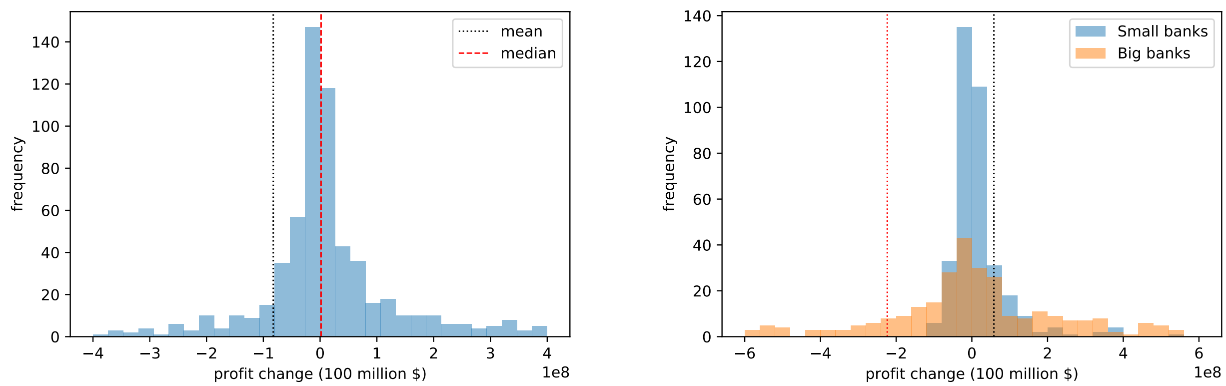
head-to-head in dozens or hundreds of shared markets. This creates a very different strategic environment. When banks adopt finer pricing in this oligopolistic setting with substantial overlap, they directly compete on rates in each local market, and competitors can respond aggressively. The resulting equilibrium features intensified competition that erodes profit margins even as pricing becomes more sophisticated. This points to a general principle: the profitability of price discrimination depends critically on the competitive structure of the industry and the extent of geographic overlap among firms.

Interestingly, when I analyze profit changes at the market level rather than aggregating across banks (see the Appendix), I find that many individual markets do exhibit profit increases for some banks, and the mean percentage profit change can even be positive in less competitive markets. However, these profitable markets tend to be smaller in terms of deposit size and account for a minority of aggregate deposits. The large, competitive markets—which account for the bulk of industry deposits—are precisely the markets where competitive effects are strongest and profit losses most severe. This pattern reinforces the interpretation that market structure drives the profit results: discrimination is profitable in less competitive, smaller markets but unprofitable in the oligopolistic markets that dominate the industry.

Figures 2.7 and 2.8 provide complementary perspectives on the profit impacts across the full distribution of banks. Figure 2.7 shows the absolute change in variable profits (in hundreds of millions of dollars), while Figure 2.8 shows the percentage change in profits. Both figures decompose the results by bank size, comparing banks below and above the median asset size.

The left panels of both figures reveal substantial heterogeneity in profit impacts across banks.

Figure 2.7: Profit changes under third-degree price discrimination



(a) All banks **(b)** Banks divided by median asset size.

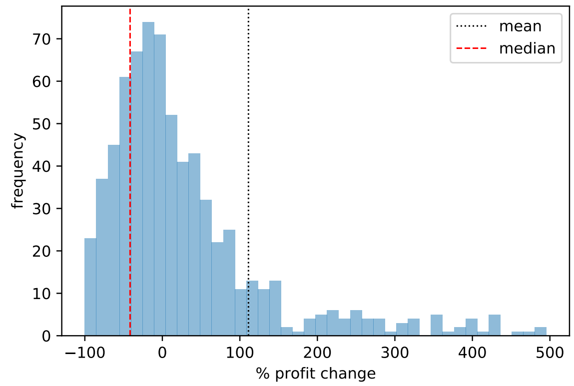
Notes: These figures show the change in variable profits (in hundreds of millions of dollars) under the counterfactual move from observed zone rating to market-level pricing. Panel (a): all banks. Panel (b): histograms split by bank size, with banks below the median asset size shown in blue (labeled "Small") and banks above the median in red (labeled "Large"); vertical lines mark each group's mean. The distribution is heavily left-skewed; mean profit losses are concentrated among above-median banks. Data sources: RateWatch, FDIC Summary of Deposits.

The distribution of absolute profit changes (Figure 2.7a) is heavily left-skewed, with a long left tail representing large profit losses for the biggest banks and a concentration of smaller changes near zero for most banks. The modal bank experiences a relatively small absolute profit loss (under $100 million), but the mean is pulled down by the extreme losses at the largest banks. This pattern reflects the highly skewed nature of the banking industry, where a few megabanks account for a disproportionate share of industry deposits and thus experience disproportionate profit impacts.

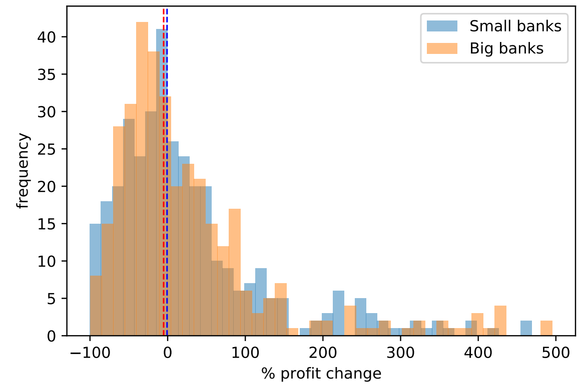
The right panels decompose these effects by bank size, confirming the qualitative pattern discussed earlier. In Figure 2.7b, the distribution for large banks (red) is shifted far to the left compared to small banks (blue), with mean losses of approximately $1-2 billion for large banks versus small gains or losses for small banks. The vertical lines marking the means for each group clearly illustrate this divergence. Figure 2.8b shows that in percentage terms, the heterogeneity is even more striking: small banks experience a wide range of percentage changes (both positive and negative), with a mean close to zero or slightly positive, while large banks experience systematically negative percentage changes averaging around -10 to -20%.

This finding suggests that the coarse zone structures maintained by large banks are not just an operational constraint but a rational response to competitive pressure: by maintaining coarse zones, large banks avoid triggering the destructive competition that would arise from finer pricing.

Figure 2.8: Percentage profit changes under third-degree price discrimination



(a) All banks.



(b) Banks split by median asset size.

Notes: This figure shows the percentage change in variable profits for the counterfactual case where all banks move from observed zone rating structures to market-level pricing. The observations are at the year-bank level. Panel (a) shows the distribution for all banks. Panel (b) decomposes the results by bank size, with vertical lines indicating the mean profit change for banks below (blue) and above (red) the median asset size. Small banks experience a wide range of percentage changes with a mean near zero, while large banks experience systematically negative percentage changes averaging -10 to -20%. Sources: RateWatch, FDIC SOD; counterfactual simulation.

From a welfare perspective, these results have welfare implications. Depositors clearly benefit from the move to market-specific pricing, as rates increase substantially on average. The increase in consumer surplus comes at the expense of bank profits, representing a transfer from banks to depositors. However, the welfare effects are unevenly distributed across markets: depositors in competitive markets benefit most (as rates rise most in these markets), while depositors in less competitive markets see smaller rate increases. This raises equity concerns about whether all depositors should benefit equally from any regulatory intervention that promotes finer pricing structures.

All firms are better off by deviating from discrimination and moving away from the socially optimal (in terms of profits) uniform or nearly uniform system. Then, how can a lighter competitive system be observed? Assuming that banks in this case commit to a rating scheme via a commitment technology, like promising lower rates to depositors or by imposing a regional managers structure, the zone equilibrium can be sustained. A point of comparison with Adams and Williams (2019) is that the demand elasticities for deposits might be more or less symmetrical for banks in comparison to align elasticities in the home improvement industry. This is because in the home improvement industry, is more likely that elasticities are aligned, that is, chains want to target similar consumers, like minorities or less affluent consumers. As (Corts (1998)) noted, if the ranking of the consumer groups' elasticities differs, the effects on prices and welfare are unambiguous, and strong competition response results in more or less profitable prices for firms. Nonetheless, it could also be the case that the consumer's group ordering is aligned which also yields ambiguous predictions. In other words, if there are symmetric rankings of equilibrium prices, rates in equilibrium will be lower in markets where all firms benefit from lower rates and larger when all firms prefer higher prices which can result in a fall or an increase in profits.

2.7 Discussion

The descriptive analysis documents substantial heterogeneity in how banks implement zone rating practices. Using detailed branch-level data that identifies each branch's designated rate-setter, I map the zone structures of banks operating across the United States from 2009 to 2020. The patterns reveal differences across banks: larger banks maintain broader zones that span multiple Metropolitan Statistical Areas and exhibit higher rate dispersion across zones, while smaller banks employ relatively more sophisticated zone structures given their geographic footprint. For example, Bank of America and Wells Fargo operate similar numbers of branches nationwide, yet Bank of America employs twice as many distinct pricing zones. These descriptive findings establish that zone rating is not simply a matter of operational convenience or technological constraints—banks actively choose different levels of geographic price discrimination, suggesting that zone structure is a strategic decision with competitive implications.

To understand the economic forces underlying these pricing patterns, I develop and estimate a structural model of deposit competition that explicitly incorporates banks' zone rating constraints. The counterfactual analysis provides the central economic finding: moving all banks from their current coarse zone structures to market-level pricing leads to higher average deposit rates, substantially greater rate dispersion, but lower aggregate bank variable profits. The profit reduction is particularly pronounced for smaller banks, which face more intense competitive pressure when forced to price separately in each market. These findings stand in contrast to results from Adams and Williams (2019), who find that finer price structures increase firm profits in the home improvement industry. The difference highlights that banking's competitive structure—with many firms per market and relatively elastic deposit demand—creates a situation where market-level pricing intensifies competition to banks' detriment, resembling a prisoner's dilemma where coordinated coarseness benefits all banks. The mechanism operates through strategic interactions: although each bank has a unilateral incentive to increase rates in weak markets and decrease rates in strong markets, implementing such a strategy invites aggressive competitive responses from rivals. By committing to coarser zone structures, banks effectively tie their hands and avoid this competitive escalation, similar to the commitment mechanisms analyzed by Corts (1998).

This paper makes several contributions to the literature. First, to the best of my knowledge, this is the first empirical paper to provide evidence that coarser zone structures enhance profitability relative to market-level pricing in any retail sector, helping resolve the puzzle of why firms maintain coarse pricing structures despite having technological capacity for more granular pricing. Second, I contribute to the zone pricing literature by analyzing an industry with different competitive dynamics than previously studied sectors. Third, I extend the structural literature on deposit competition by explicitly modeling banks' zone rating constraints and showing how these pricing structures affect equilibrium outcomes. Finally, the findings have policy implications for antitrust enforcement in banking markets, regulatory oversight of deposit pricing practices, and the welfare effects of bank mergers and consolidation.

The results have several policy implications. For antitrust authorities evaluating bank mergers, the analysis suggests that changes in zone structures following mergers can have notable effects on competition and consumer welfare beyond what market concentration measures alone would predict. For monetary policy, the findings help explain why deposit rates may respond sluggishly to changes in policy rates: zone rating structures create pricing rigidities that limit banks' ability to adjust rates to local market conditions, potentially dampening the transmission of monetary policy through the deposit channel. For bank regulators, the analysis highlights how pricing structures affect the distribution of deposit rates across markets, with implications for financial inclusion and access to competitive rates in different geographic areas.

2.8 Conclusion

This paper provides the first empirical analysis of zone rating practices in the U.S. retail banking industry and quantifies their effects on competition, rate dispersion, and bank profitability. The central finding is that coarser zone structures enhance bank profitability relative to market-level pricing, providing an economic explanation for why banks maintain these pricing practices despite having technological capacity for more granular pricing. This result has implications for understanding competitive dynamics in banking markets and the welfare consequences of bank pricing strategies.

Using a structural model of deposit competition with zone rating constraints, I show that moving to market-level pricing intensifies competition, raising deposit rates but reducing bank profits. This prisoner's dilemma outcome arises from the oligopolistic structure of banking markets with substantial geographic overlap among competitors. The findings contrast with prior zone pricing studies in less competitive retail sectors, highlighting how market structure shapes the profitability of price discrimination strategies.

Several questions remain for future research. A complete welfare analysis would require modeling consumer surplus and quantifying how different pricing strategies affect depositors with different characteristics and in different locations. Analyzing the transition dynamics as banks adjust their zone structures over time could provide additional insights into the strategic considerations underlying zone rating decisions. Finally, incorporating bank branching decisions alongside pricing decisions would allow for a richer analysis of banks' strategic choices and their implications for market structure.

Appendix

A Rate Dispersion Analysis Within Market and Within Bank Branches

This section examines rate dispersion across branches within a market.

Across branch dispersion in markets

The rates are collapsed at the year level, so they might be additional variation coming from aggregation and rounding. The results do not vary much when using alternate precisions or collapsing using median or mean rates. Ideally, there will be a unique rate in each market for each bank. I find that 85% of banks/MSA/year observations have one rate setter, and 10% have two rate-setters. The average number of unique rate setters is 1.23, which is the upper bound to the mean number of unique rates (1.14). The standard deviation of the mean rate measure in APY is not large at 1.24 bp.

Table 2.8: Price dispersion across branch rates within year-MSA-bank by asset and deposit quartiles

	Q1 (Smallest)	Q2	Q3	Q4 (Largest)
Panel A: Quartiles by Bank Asset Size				
No. observations (year-MSA-bank)	9,894	9,891	9,924	9,860
No. branches	4.74	9.87	17.73	23.30
No. rate setters	1.09	1.21	1.33	1.27
No. unique rates	1.08	1.15	1.20	1.14
Std rates (bp)	0.97	1.38	1.66	0.98
Panel B: Quartiles by Bank Deposit Size in Market				
No. observations (year-MSA-bank)	9,892	9,892	9,892	9,893
No. branches	2.14	4.23	7.89	41.35
No. rate setters	1.03	1.09	1.15	1.63
No. unique rates	1.02	1.06	1.11	1.38
Std rates (bp)	0.47	0.93	1.44	2.15

Notes: This table presents summary statistics of the number of branches, number of rate-setters, number of unique rates, and the standard deviation of mean APY (in basis points). Panel A shows means by quartile of total bank assets (aggregated at the bank level), with Q1 representing the smallest banks and Q4 the largest. Panel B shows means by quartile of bank deposits within each market, with Q1 representing banks with the smallest deposit presence and Q4 those with the largest. The observations are at the year-MSA-bank level. The different number of observations across quartiles in Panel A reflects the fact that asset size is aggregated at the bank level. The product chosen is the 12-month CD with a minimum deposit of 10K. The data spans 2009 to 2020 and is constructed using data from RW and SOD.

Table 2.8 displays summary statistics of the abovementioned variables plus the number of branches for the years between 2009 and 2020.[7] The objective is to analyze how the rating strategy change with the bank's size and the number of deposits the bank holds in that market. In the top panel, I have the quartiles by bank asset size. For example, the regional banks/market observations with the lowest asset size, have fewer branches in a network and near-to-uniform rates across all measures. Across different quartiles, the nearly uniform pattern is supported. Interestingly, banks in the third quartile (large, but not the largest) are the ones that exhibit the highest absolute values

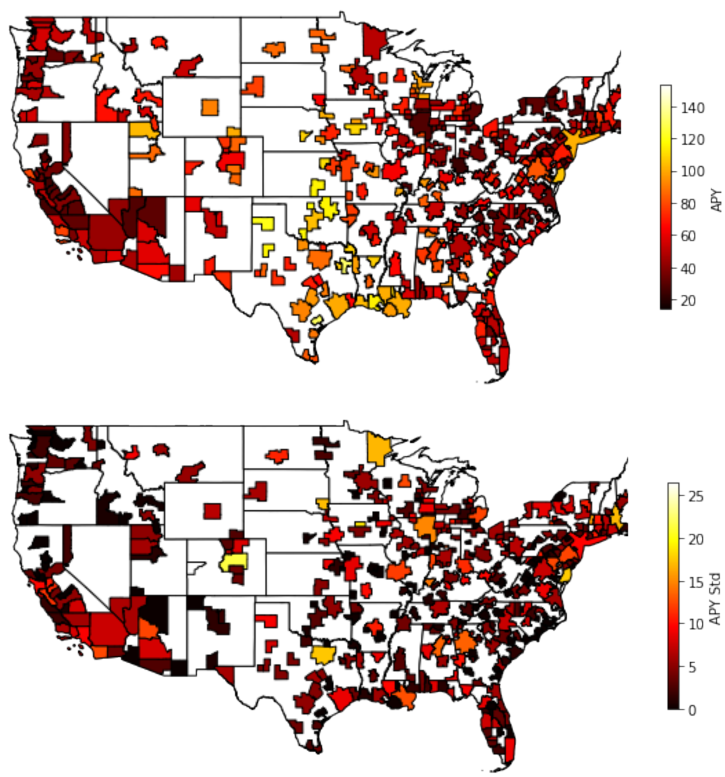
[7] Table 2 qualitative results are preserved under a different set of years.

of rate-setters and unique rates. However, the number of setters over the number of branches decreases with size in all instances, suggesting smaller banks are more sophisticated.

In the bottom panel of table 2.8, we can see the equivalent statistics when quartiles are taken by deposits. The number of branches and the total deposits in a market is strongly correlated as expected. Moreover, the measures of dispersion and zone rating increase with deposit size even more than with bank asset size. This is consistent with the fact that the more deposits a bank has on a market the more tailored its pricing strategy will be.

Although, the evidence supports the idea that overall, banks price almost uniformly in a year/ MSA, there is still some variation. Furthermore, these results hint that larger-size banks' rating strategies are different than those of smaller banks. Now, I move on to study variation at a higher level of aggregation (i.e. markets and banks).

Figure 2.9: Geographic rate dispersion measures in markets.

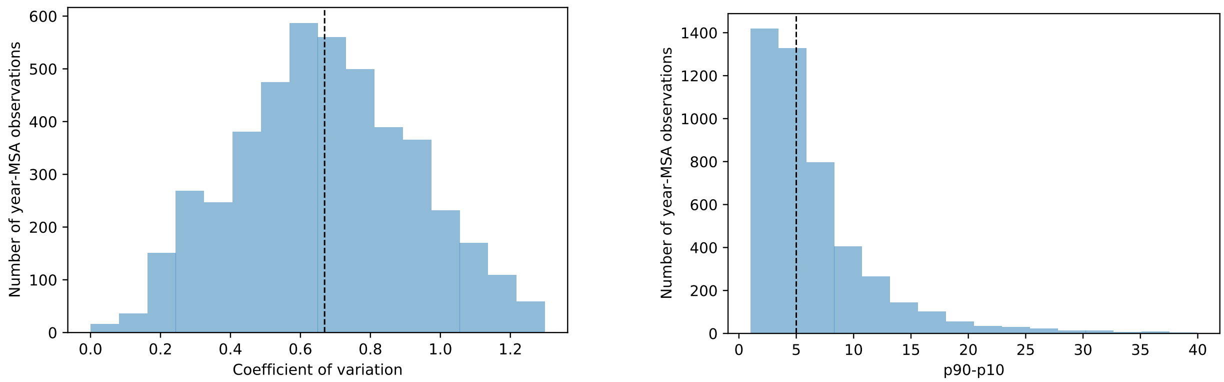


Notes: This figure shows the cross-bank mean (top panel) and cross-bank standard deviation (bottom panel) of deposit interest rates for each MSA in 2019. Rates are measured as annual percentage yield (APY) in basis points; the colorbar shading therefore represents APY (mean APY in the top panel, dispersion in APY in the bottom panel). The product is the 12-month CD with a $10,000 minimum balance. Data sources: RateWatch and Summary of Deposits. Hot-spot pattern: the central U.S. (Plains/Mountain regions) displays both the highest mean APY and the highest cross-bank dispersion; coastal MSAs are systematically lower on both measures.

Within market dispersion

Next, I zoom in on markets to see how different rates are across banks. There is considerable variation across mean interest rates across the country. The top panel of figure 2.9 shows mean rates for all the MSAs in the country. The middle region of the country consistently displays the highest interest. In the bottom panel, the standard deviations of interest rates across banks reveal a similar pattern. I additionally employ measures of the search and price dispersion literature to evaluate dispersion and heterogeneity in market rates. I use the coefficient of variation (CV) and the 90th to 10th percentile (p90/p10) ratio.[8] Since banks are vertically and horizontally differentiated, greater dispersion in rates is expected when comparing banks within a market.

Figure 2.10: Rate dispersion measures within markets



Notes: This figure shows histograms for the coefficient of variation (CV) and the 90th to 10th percentile ratio (p90/p10) of the mean APY by market, from 2009 to 2020. The vertical lines correspond to the median value. The product chosen is the 12-month CD with a minimum deposit of 10k. The figures are constructed using data from RW and SOD. Both distributions are right-skewed; the median CV is approximately 0.67 and the median p90/p10 is roughly 5, indicating substantial cross-bank rate dispersion in a typical market.

Figure 2.10 shows the distribution of CV and p90/p10 ratio over market observations. For the period shown, the median CV is 0.67, and the p90/p10 ratio is around 5, in both of these cases indicating large dispersion in markets. Moreover, there is high heterogeneity in the degree of dispersion between markets. This is true as well if we only look at one year (figure 2.15 in the Appendix). These measures are sensitive to how high or low rates are which fluctuate with FED rates. Banks' response to FED rates is heterogenous, the FED fund rates do not explain the changes in these measures, which suggests that banks' rating strategies are more asymmetric over time. In Figure 2.14 of the Appendix, I show the evolution of these measures over time within markets. The overall trend is that both of these metrics increase over time. The dispersion measures are inversely correlated with mean and median APY rates which have been decreasing over the period with a slight increase after 2018.

B Robustness: Demand Estimation with Depositor Heterogeneity

The baseline logit model presented in Section 2.4 assumes that depositors have homogeneous preferences for deposit rates. While this specification is tractable and provides consistent estimates of average price sensitivity, it abstracts from potential heterogeneity in how different types of

[8] CV is the standard deviation divided by the mean and the p90/p10 ratio compares the value at the 90th percentile to one at the tenth percentile.

depositors respond to rates. In this appendix, I explore an extension that allows for depositor heterogeneity by modeling the interaction between deposit rates and depositor wealth.

Following the random coefficients approach of Berry, Levinsohn, and Pakes (1995), I specify utility as:

$$u_{ijt} = \alpha \cdot \text{Income}_{it} \cdot r_{jt} + \gamma b_{jt} + X_j\beta + \xi_j + \xi_m + \xi_y + \xi_{jt} + \epsilon_{ijt} \tag{2.8}$$

where Income_{it} represents the income (or wealth) of depositor i in market t, serving as a proxy for deposit balances. This specification allows depositors with higher incomes to be more sensitive to rate differences in absolute terms, since a given rate differential translates into larger dollar returns for wealthier depositors. The model nests the homogeneous logit as a special case when income effects are excluded.

I estimate this extended model using the same instrumental variables strategy as in Section 2.5, with income data from the American Community Survey (ACS) aggregated to the MSA-year level. Table 2.9 presents the results. The coefficient on the rate-income interaction is positive and statistically significant ($\hat{\alpha} = 1.32$, s.e. $= 0.14$), confirming that depositors with higher incomes exhibit greater sensitivity to deposit rates. The coefficients on other bank characteristics (branches, bank age, assets) remain similar to the baseline specification, providing reassurance that the main results are robust to allowing for this form of heterogeneity.

The estimated elasticities (not shown) are also similar in magnitude to those from the baseline logit, suggesting that the homogeneous model captures the average responsiveness of depositors reasonably well. The insight from this extension is that while there is meaningful heterogeneity in rate sensitivity across depositors, this heterogeneity does not materially affect the counterfactual predictions or the qualitative conclusions about the competitive effects of zone rating.

Aggregate Shares with Depositor Heterogeneity

The baseline logit model yields simple closed-form expressions for market shares. When I allow for depositor heterogeneity, however, the mapping from individual choice probabilities to aggregate shares becomes more complex. This subsection presents the complete derivation of aggregate shares under heterogeneity.

With random coefficients μ_{ijt} capturing unobserved heterogeneity, the probability that consumer i chooses bank j in market t is:

$$P_{jit} = \frac{e^{\delta_{jt} + \mu_{ijt}}}{\sum_{k \in J_t} e^{\delta_{kt} + \mu_{ikt}}}, \tag{2.9}$$

where $\delta_{jt} = \gamma b_{jt} + \alpha r_{jt} + X_j\beta + \xi_j + \xi_m + \xi_y + \xi_{jt}$ is the mean utility, and μ_{ijt} captures individual-specific deviations from this mean (for example, through the rate-income interaction).

To connect individual-level choice probabilities to aggregate deposit shares, I must account for the fact that depositors differ not only in their preferences (through μ_{ijt}) but also in the size of their deposit balances. Larger depositors contribute more to a bank's aggregate market share measured in dollars. Let $F(dep)$ denote the distribution of deposit balances in the market. Then the aggregate deposit share of bank j is:

$$s_{jt} = \frac{\int_{dep} dep \cdot P_{jt}\, dF(dep)}{\sum_{k \in J_t} \int_{dep} dep \cdot P_{kt}\, dF(dep)}, \tag{2.10}$$

Table 2.9: BLP analysis using income distribution.

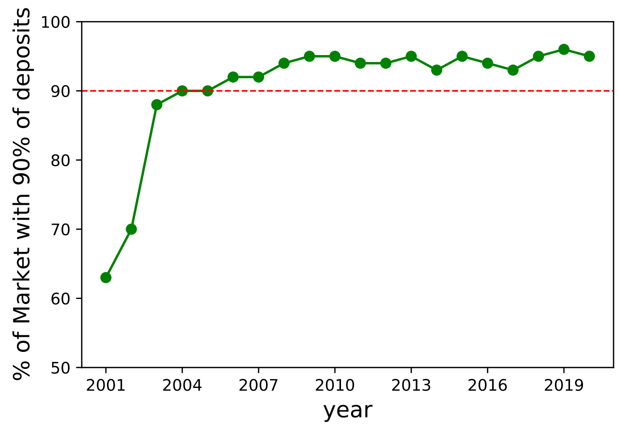
	(1)
Rate * Income	1.32
	(0.1383)
Branches in market	0.995
	(0.006)
Total MSA	-0.004
	(0.0004)
Total branches	-0.111
	(0.007)
Employees per branch	5.0424e-5
	(2.7559e-6)
Bank age	0.063
	(0.012)
Assets	1.8244e-4
	(3.2900e-5)
IV Tiers	✓
IVs	Diff IV
FE	bank, MSA, year
N	34,367
R^2	0.830

Notes: This table presents results from a BLP-style analysis where income is treated as a random coefficient. The coefficients are similar to those in the main specification, providing robustness to the estimation approach. The standard errors are in parenthesis and clustered at the bank level.

where the integrals weight each depositor's choice probability by their deposit size. The numerator gives the total deposit dollars flowing to bank j, while the denominator gives total deposit dollars in the market (including the outside option).

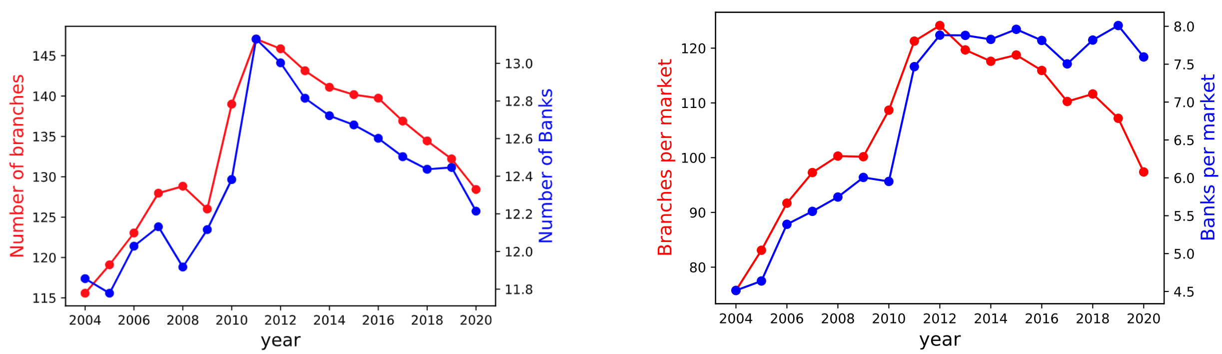
C Additional Figures and Tables

Figure 2.11: Matched percent between RW and SOD.



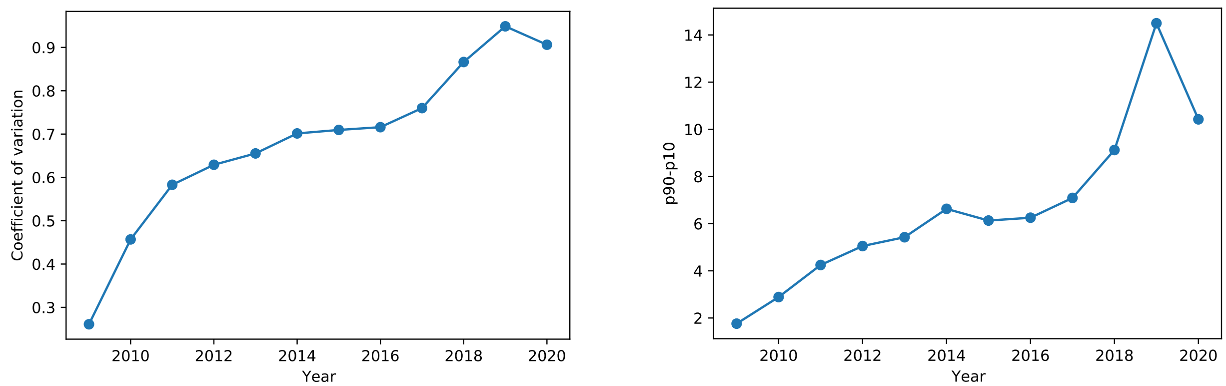
Notes: Time-series line plot of the share of U.S. MSAs with at least 90% of FDIC SOD deposits matched to RateWatch rates, by year. The series is consistently above 80% across the sample period, indicating high RateWatch coverage of multi-market banks. Sources: RateWatch, FDIC SOD.

Figure 2.12: Comparison RW and SOD (universe of banks)



Notes: Comparison plots between the SOD universe of banks and the matched SOD-RateWatch estimation sample along distributions of branches and bank counts. The matched sample retains the bulk of multi-market banks; small single-market banks are trimmed by the matching restriction. Sources: RateWatch, FDIC SOD.

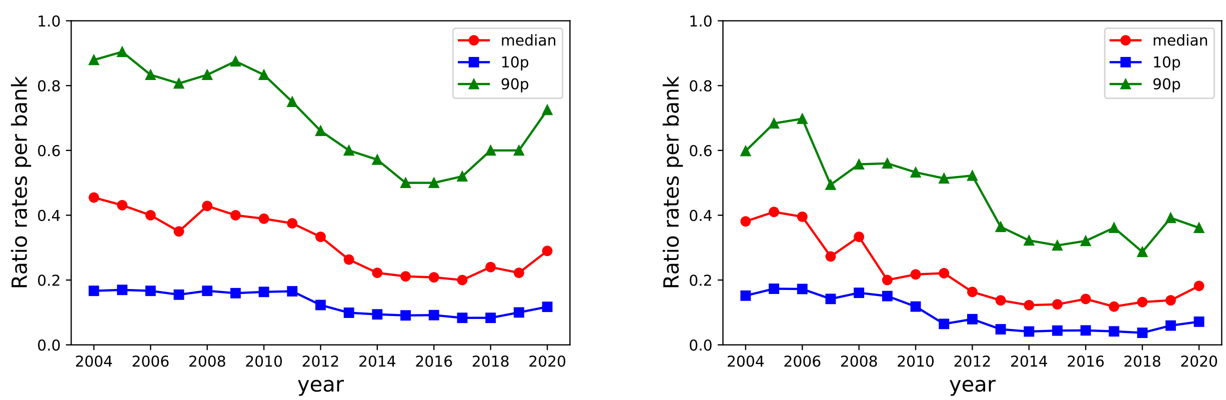
Figure 2.13: Rate dispersion measures in markets over the period 2009-2020.



(a) CV within market distribution **(b)** P90/P10 within market distribution

Notes: These figures show the evolution over time of coefficient of variation (CV) and the 90th to 10th percentile ratio (p90/p10) of the mean APY for the period 2009-2020. Some outliers on both sides do not appear in the sample, but the % change is accounted for to compute mean and median values. The figures are constructed using data from RW and SOD. Both metrics trend upward over 2009-2020, indicating rising within-market rate dispersion as the federal funds rate rises in the post-2015 normalization period.

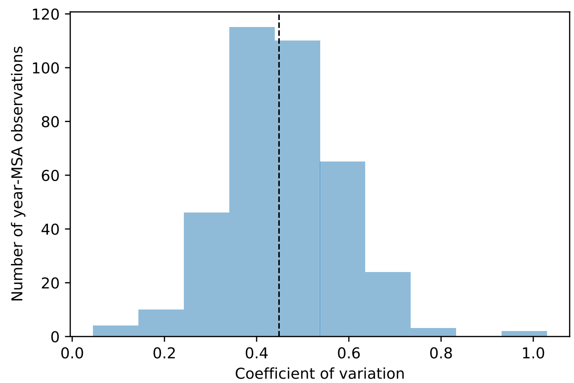
Figure 2.14: Zone rating measures over the period 2004-2020.



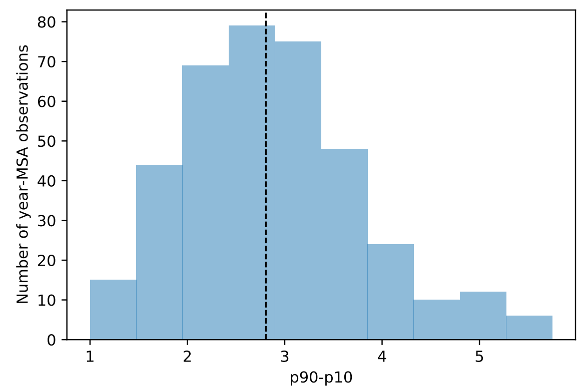
(a) For all banks in 5 or more markets **(b)** For all banks in 20 or more markets

Notes: These figures show the evolution over time of the unique rate ratio for the period 2004-2020. The figures are constructed using data from RW and SOD. The unique-rates-per-MSA ratio trends downward over 2004-2020 in both subsamples, indicating that banks have moved toward coarser zone structures over time. Sources: RateWatch, FDIC SOD.

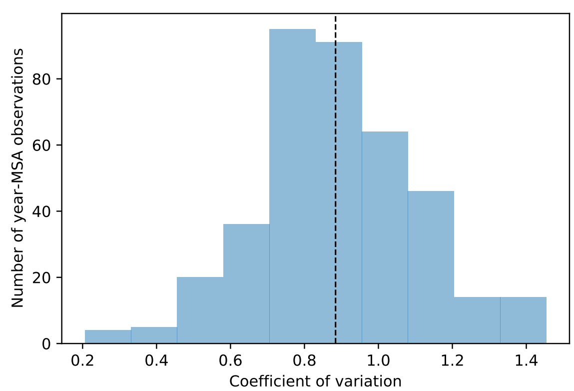
Figure 2.15: Rate dispersion measures within the market, years 2010 and 2020.



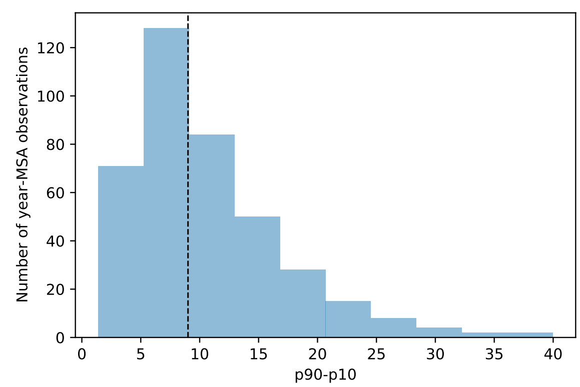
(a) CV within market distribution, year 2010



(b) P90/P10 within market distribution, year 2010



(c) CV within market distribution, year 2020



(d) P90/P10 within market distribution, the year 2020

Notes: This figure shows histograms for the coefficient of variation (CV) and the 90th to 10th percentile ratio (p90/p10) of the mean APY by market, for the years 2010 and 2020. The vertical lines correspond to the median value. Some outliers on both sides do not appear in the sample, but the % change is accounted for to compute mean and median values. The figures are constructed using data from RW and SOD. The 2020 distribution is shifted right relative to 2010 for both CV and p90/p10, indicating that within-market rate dispersion increased over the decade. Sources: RateWatch, FDIC SOD.

Table 2.10: Robustness: Logit demand with αr_{jt} term (no income interaction)

	OLS	IV			
	(1)	(2)	(3)	(4)	(5)
Rate	0.415***	4.476***	1.697***	1.636***	1.734***
	(0.036)	(0.956)	(0.472)	(0.471)	(0.451)
Branches in market	0.959***	1.014***	0.976***	0.975***	0.977***
	(0.023)	(0.030)	(0.024)	(0.024)	(0.024)
Total branches	-0.158***	-0.047*	-0.123***	-0.125***	-0.122***
	(0.014)	(0.027)	(0.018)	(0.018)	(0.018)
Employees per branch	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-0.506***	–	–	–	–
	(0.116)	–	–	–	–
IV Tiers	–	–	✓	✓	✓
IVs	–	BLP, Cost	BLP, Cost	Diff, Cost	Diff, Cost, Income
Observations	34367	34367	34367	34367	34367
Adjusted R^2	0.834	-0.042	0.482	0.488	0.479
F-Stat	–	4.825	10.450	13.231	17.958
J-Hansen	–	30.635	69.554	50.669	50.398
Weak IV (K-P)	–	16.257	28.265	28.772	39.675

Notes: This table presents results from the logit demand estimation where the marginal utility of income is excluded from the utility function. That is rate only depends on the coefficient α. The coefficients and elasticities are similar to those in the main specification, providing robustness to the estimation approach. Standard errors are in parenthesis and clustered at the bank level.

Chapter 3

The Competitive Effects of Bank Mergers: Evidence from Truist

3.1 Introduction

Bank mergers create a tradeoff for regulators. Consolidation can reduce local competition, allowing banks to exercise greater market power over deposit rates. Larger banks, however, may also be more stable through economies of scale and diversification across geographies and loan portfolios. Understanding this competition–stability tradeoff is central to antitrust enforcement and prudential regulation, but empirical evidence on both sides of the tradeoff remains limited.

This paper studies this tradeoff in U.S. retail banking through the 2019 merger between BB&T and SunTrust, which formed Truist Financial Corporation. The merger created the sixth-largest bank in the United States and was the largest retail bank merger since the global financial crisis. The setting is useful for identification because BB&T and SunTrust had partial geographic overlap before the merger. Some local markets contained branches of both banks, while others contained only one. This structure creates variation that allows us to isolate changes in local competition from changes in bank scale.

We focus on deposit markets, which are central to both sides of the tradeoff. Deposits are the primary source of bank funding, accounting for the majority of liabilities for U.S. commercial banks. When competition is limited, banks can pay lower deposit rates and widen spreads relative to the policy rate. At the same time, insured deposits are a relatively stable funding source. Changes in deposit pricing and funding structure are therefore margins through which mergers affect both consumer welfare and financial stability.

We study how deposit pricing changes after the Truist merger across markets with different pre-merger exposure, using the Money Market $10,000 product on a bank-county-year market panel for the main difference-in-differences specification. Counties where both BB&T and SunTrust operated before the merger experienced an increase in local concentration; counties with only one bank did not. A difference-in-differences comparison of these groups measures how deposit spreads respond to increased market power while holding constant the effect of becoming part of a larger bank.

The reduced-form results show that rivals in overlapping counties widened their deposit spreads by approximately two basis points on the headline annual specification (Both vs. One contrast, money-market $10k product, 2016–2022, county and year fixed effects, 1.4 bp without controls and 2.1 bp with the full control set, significant at the 5% level in the latter), and by roughly 7–9 basis points at peak in the quarterly event study. The effect is small but persistent through the end of our sample period and consistent with parallel pre-trends in the leads. A branch-level robustness using only RateWatch data, which restricts the sample by outside competition, finds substantially larger effects in counties without a top-4 U.S. bank: in the Both-vs-One contrast on the branch-level RateWatch panel, deposit spreads in those markets widen by roughly 15 basis points after the merger, consistent with reduced outside competitive pressure amplifying the local market-power effect.

The structural deposit-demand model on the headline money-market $10,000 product recovers a positive and statistically significant own-rate coefficient ($\hat{\alpha} = 5.93$, $t = 3.41$) in the single-IV specification using log rival county footprint as the excluded instrument. The demand estimates feed into a no-merger counterfactual in which Truist's branches are reassigned to their pre-merger BB&T or SunTrust legacy entities and the equilibrium is re-solved. The implied rate effect on the merged firm at the 2019 baseline is a markdown of approximately 25 basis points, anti-competitive in sign and an order of magnitude larger than the reduced-form annual estimate. The implied change in depositor consumer surplus is large and negative (approximately $556 million per year in overlapping counties), and the implied gain in Truist's producer surplus is approximately $306 million per year. Forward simulations at each post-merger year show this anti-competitive rate effect attenuates from 2020 onward and reverses sign by 2021, suggesting the local market-power channel that drives the 2019 result fades as competitors adjust and the macro rate environment changes. The gap between the structural and reduced-form rate effects is consistent with the difference-in-differences netting out general industry trends that the structural model captures directly. On the stability side, a bank-level event study in log Z-score around the merger consummation shows a temporary drop concurrent with the COVID-19 pandemic followed by a recovery to the pre-merger trend by mid-2021. The pattern is consistent with operational integration friction at the moment of consummation followed by diversification benefits, although the overlap with COVID-19 makes a clean causal interpretation difficult.

We make three contributions. First, we provide clean reduced-form evidence on the deposit-pricing effect of a major regional bank merger using a within-merger difference-in-differences design that compares overlapping and non-overlapping counties served by the same merging institution. The partial-overlap design separates the local competition effect from the bank-wide scale effect. Second, we implement a no-merger counterfactual that re-imposes separate BB&T and SunTrust ownership using a 2019 Summary of Deposits branch-level legacy attribution. Most existing structural merger retrospectives evaluate the counterfactual at the pre-merger baseline year; we evaluate the counterfactual at each post-merger year using observed Truist prices and shares to recover marginal costs, producing a cleaner test of the static-logit framework's external validity over time. Third, we bring together pricing and solvency outcomes within the same merger event. While the literature has studied the competition-stability tradeoff theoretically and using cross-sectional variation, the partial-overlap design here lets us read pricing and solvency responses for the same set of banks in the same time window. The remainder of the paper is organized as follows. Section 3.1 reviews the related literature. Section 3.2 describes the data, institutional background, and descriptive evidence. Section 3.3 presents the difference-in-differences design and reduced-form results. Section 3.4 develops the structural model. Section 3.5 reports the demand estimates and the no-merger counterfactual. Section 3.6 concludes.

Literature Review

This paper relates to three strands of literature: the competition-stability tradeoff, deposit market competition and pricing, and bank mergers and geographic pricing. It also draws on structural methods from industrial organization.

The competition-stability tradeoff has a long tradition in banking theory. Keeley (1990) argues that more competition erodes banks' charter value, reducing incentives for prudent behavior and increasing risk-taking. Boyd and De Nicoló (2005) push back, showing that lower competition can also raise risk through the loan-portfolio channel: when banks earn higher rents on performing loans, they have weaker incentives to monitor borrower risk. Martinez-Miera and Repullo (2010) reconcile the two views with a U-shaped relationship between competition and bank failure, in which both very competitive and very concentrated markets can produce high failure risk. Egan et al. (2017) link deposit competition to bank fragility through a structural model in which funding conditions affect risk choices, finding that deposit markets are a channel between competition and stability. Wang et al. (2022) find that bank market power dampens the transmission of monetary tightening. The 2023 banking turmoil, in which banks with large uninsured deposit shares experienced runs after interest rate increases (Jiang et al., 2023), provides more recent evidence that deposit market structure affects financial fragility. Our paper contributes to this strand by combining evidence on deposit pricing and Z-score solvency within the same setting.

A large literature studies how competition affects deposit pricing. Focarelli and Panetta (2003) show that bank mergers in Italy lead to higher spreads, particularly in markets where concentration increases. Craig and Dinger (2009) document how deposit rates change around U.S. bank mergers using product-level data. Bord (2018) studies how consolidation affects consumer financial welfare using county-level variation in merger exposure. Allen, Clark, and Houde (2014) use the partial geographic overlap of a Canadian mortgage-market merger to identify local price effects, the same overlap-based identification strategy we apply here to U.S. deposit markets; Allen, Damar, and Martinez-Miera (2016) apply the same Canadian-merger design to identify the effect of bank consolidation on consumer bankruptcy through information loss. A common finding is that retail banking competition is local. Depositors place significant weight on branch proximity, and local bank presence shapes rates even in an era of large, multi-market banks (Nguyen, 2019). Structural work reaches a similar conclusion. Dick (2008b), Ishii (2008b), and Ho and Ishii (2011b) show that branch networks and bank size shape retail banking competition. Drechsler et al. (2017) provide a macro-level model in which banks' deposit market power shapes the transmission of monetary policy. Koont (2023) documents that digital banking has begun to erode the local nature of deposit competition. Our paper contributes by using the partial geographic overlap of two large regional banks to separate the competition effect of the merger from the scale effect.

A related literature studies how large banks set deposit rates across markets. Granja and Paixão (2024) show that large banks often apply uniform or zone-based rates across counties, and that mergers increase spreads most in markets where concentration rises most. This is relevant for the Truist setting, where both BB&T and SunTrust used standardized pricing. Begenau and Stafford (2022) note that uniform pricing complicates identification of the deposit channel, since banks may not respond to local conditions even when competitive pressure changes. Our difference-in-differences design addresses this by comparing changes within the same institution across markets with different overlap. In non-banking retail, Adams and Williams (2019) find that finer geographic pricing raises profits; Labrador-Badia (2024) shows this result does not extend to banking, where competitive pressure limits the gains from price discrimination.

3.2 Data, Background, and Descriptives

This section describes the data, the institutional features of U.S. retail banking, the BB&T–SunTrust merger that motivates our empirical strategy, and descriptive statistics on the regression sample.

Data

This chapter draws on the same core datasets described in Chapter 1: branch-level deposit rates from RateWatch (S&P Global), branch-level deposit balances from the FDIC Summary of Deposits (SOD), and bank-level balance-sheet variables from the FFIEC Call Reports. The federal funds rate is obtained from FRED. See Chapter 1, Section 1.2 for full source descriptions. The full data window for this chapter is January 2012 through February 2025; the headline difference-in-differences specification uses 2016–2022, and the pre-merger demand sample is 2013–2019. The primary outcome variable is the deposit spread, defined as the federal funds rate minus the offered deposit rate; the headline product is the Money Market $10,000 account. Local market structure is measured using SOD branch-level deposit shares (including pre-merger BB&T–SunTrust overlap indicators and county-level HHI). Bank-level Z-scores for the stability analysis are constructed from quarterly Call Report items.

Institutional Background

We focus on three institutional features of U.S. retail banking: the role of deposits in bank funding, branch networks and local markets, and pricing practices across geographic markets.

Deposits and bank funding. Deposits are the primary source of funding for U.S. commercial banks, accounting for over 70% of bank liabilities. Compared to alternative funding sources such as wholesale borrowing, deposits are relatively low-cost, particularly insured deposits held by households. Because deposits are central to both bank profitability and financial stability, competition for deposits is a dimension of banking behavior.

Banks generate profits in part by earning a spread between the returns on their assets (such as loans and securities) and the interest rates they pay on deposits. When banks have market power in deposit markets, they can offer lower deposit rates and widen this spread. As a result, deposit pricing provides a direct measure of competitive conditions in retail banking.

Local markets and branch networks. Despite the presence of large, multi-market banks, retail banking remains local. Even in the era of digital banking, depositors place significant weight on geographic proximity when choosing a bank, with access to branches and ATMs a determinant of bank choice alongside rates and services (Nguyen, 2019; Dick, 2008b). As a result, banks compete for deposits within geographically defined markets, typically at the level of counties or metropolitan areas. Banks operate networks of branches that determine their presence in local markets. Regulatory authorities, including the Department of Justice and the Federal Reserve, evaluate bank mergers using local measures of market concentration based on branch-level deposit shares.

By asset size, the banking industry is dominated by the four largest banks: JPMorgan Chase, Bank of America, Wells Fargo, and Citigroup. The U.S. has thousands of banks of varying sizes;

appendix Table 3.5 provides a full snapshot of the universe of U.S. commercial banks from the FDIC Summary of Deposits, broken down by AUM tier, state footprint, and county footprint. Before the Truist merger, SunTrust and BB&T were in the $100–$250 billion tier; by merging, they jumped into the $250 billion to $1 trillion tier. Table 3.1 shows the corresponding tier breakdown for the subset of banks observed in our regression sample, with deposit interest rates and county-level statistics relevant to the empirical analysis below.

Deposit pricing and geographic pricing policies. Deposit pricing in modern banking is not set independently at each branch. Instead, banks typically establish networks of branches and adopt centralized pricing policies within those networks, setting deposit rates uniformly across large geographic areas or within defined pricing zones. These zones may include multiple counties or entire states, and rates are often determined by a subset of "rate-setting" branches that set prices for "rate-taking" branches.

This pricing structure reflects both operational considerations and competitive strategy. Setting rates centrally reduces administrative complexity and ensures consistency across a bank's network. At the same time, uniform or zone-based pricing constrains banks' ability to tailor rates to local competitive conditions. As a result, observed deposit rates reflect a combination of local market structure and bank-wide pricing decisions.

This feature matters for interpreting the effects of mergers. When a merger changes local market concentration, the resulting pricing response may occur through adjustments in bank-wide pricing policies rather than purely local changes.

Implications for empirical analysis. These institutional features motivate our empirical approach. First, because competition operates at the local level, we define markets geographically and exploit variation in local overlap between merging banks. Second, because pricing is often centralized, we interpret changes in deposit rates as reflecting both local competitive conditions and bank-level pricing strategies.

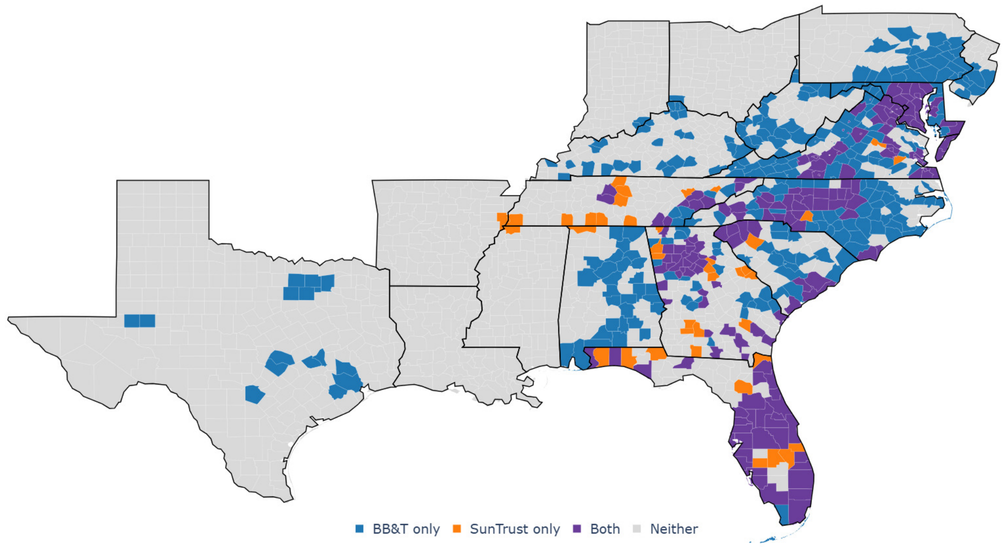


Figure 3.1: Pre-merger presence of BB&T and SunTrust by county

Notes: As of June 30, 2019. Counties in purple had branches of both BB&T and SunTrust before the merger. Counties in blue and orange had branches of either BB&T or SunTrust, respectively, but not both. Grey counties had neither bank. Data source: Summary of Deposits.

The Truist Merger

The 2019 merger between BB&T and SunTrust provides a natural setting to study the effects of consolidation in retail banking. Announced in February 2019 and completed in December 2019, the merger combined two large regional banks to form Truist Financial Corporation, the sixth-largest bank holding company in the United States by assets.

BB&T and SunTrust had substantial but incomplete geographic overlap prior to the merger. Both banks operated extensive branch networks across the southeastern United States, but their presence varied across local markets. Some counties contained branches of both banks, while others contained only one. This variation is central to our empirical strategy.

Overlap and changes in local competition. In markets where both BB&T and SunTrust operated prior to the merger, the transaction reduced the number of competitors by combining two local banks into one. These markets experienced an increase in local concentration. In contrast, in markets where only one of the two banks was present, the merger did not directly change local concentration, even though the bank became part of a larger institution.

Truist primarily operates in the Southeast, and it is headquartered in Charlotte, NC. Figure 3.1

shows the geographic distribution of BB&T and SunTrust prior to the merger. Out of 507 affected counties, 184 contained branches of both banks, while the remainder had only one. The distinction between overlapping and non-overlapping counties allows us to separate two effects of the merger. The first is a *competition effect*, arising from increased concentration in overlapping markets. The second is a *scale effect*, arising from changes in bank size, funding, and operations that affect all markets in which the merged bank operates. By comparing overlapping and non-overlapping markets, we isolate the impact of changes in competition while holding constant broader changes in bank scale.

After the merger, Truist closed around a third of their approximately 3,000 branches. Figure 3.5 shows the evolution of branch networks over time, indicating substantial post-merger consolidation. The decrease in the number of Truist branches happens for two main reasons. First, there were a number of voluntary branch consolidations post-merger when branches of BB&T and SunTrust were nearby. These branches combined to operate a larger branch while still maintaining the same total deposits and similar geographic footprint. We argue this does not significantly impact our empirical strategy because Truist is still gaining deposit market share, even if it operates out of fewer total branches in the county. Of the 1,054 total Truist branch closures after the merger, 1,026 were voluntary closures. Second, a small handful of branch closures were required by the Federal Reserve as terms to approve the merger. These were cases where both banks had a relatively large presence within the same small counties. For these counties, Truist divested the existing SunTrust branches to competitors who had little or no presence in that county. This is the case for only 28 branches, which does not meaningfully affect our analysis.

Even with these closures, the merger results in a large increase in deposit market concentration in many counties. Figure 3.6 shows the distribution of changes in deposit HHI across the 184 overlapping counties, with most markets experiencing sizable increases in concentration following the merger. Under the DOJ's current Bank Merger Guidelines, an increase in HHI of 100 or more triggers heightened antitrust scrutiny. More than half of the overlapping counties had their deposit HHI increase by more than 100 after the merger. These figures show that the merger reduced local competition in overlapping markets and reshaped the branch network in ways consistent with increased market power.

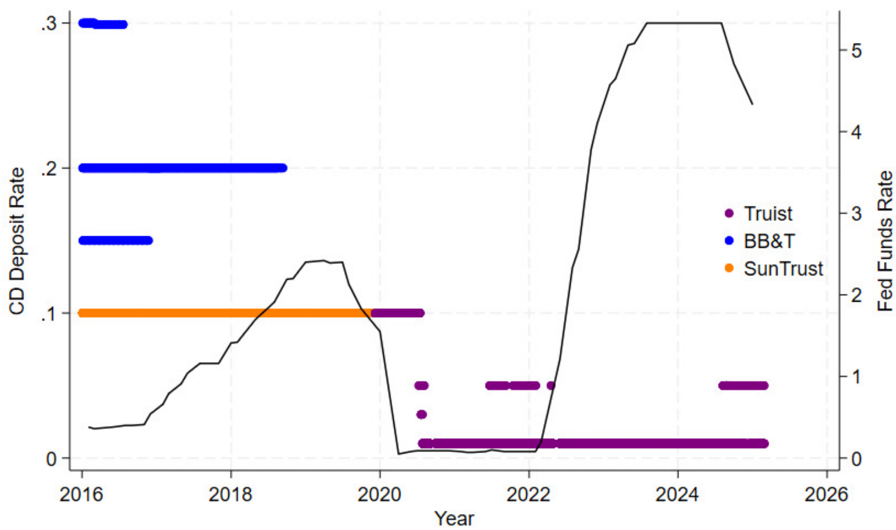


Figure 3.2: CD deposit rates and the federal funds rate

Notes: Average deposit rates on 12-month certificates of deposit with a $10k minimum balance, by bank branch and month for branches of SunTrust, BB&T, and Truist (each series labeled in the legend). The black solid line represents the federal funds rate. The deposit spread (federal funds rate minus deposit rate) is the main outcome variable. The vertical line marks December 2019 (merger completion). Pre-merger BB&T and SunTrust rates are higher and more dispersed than post-merger Truist rates; deposit rates remain compressed relative to the federal funds rate during post-merger tightening. Data sources: RateWatch, Federal Reserve Economic Data.

Impact on deposit pricing. Standard models of deposit competition predict that an increase in local concentration reduces competitive pressure and allows banks to lower deposit rates, widening spreads relative to the policy rate. In the Truist setting, this effect may operate locally, through reduced competition in overlapping counties, and centrally, through adjustments in bank-wide pricing policies. Figure 3.2 shows CD deposit rates for SunTrust, BB&T, and Truist alongside the federal funds rate. Each point is the deposit rate offered by a bank branch. Before the merger, BB&T and SunTrust offered rates that were higher and more dispersed across branches than Truist's rates after the merger. This change in pricing may reflect a more uniform pricing strategy, an increase in market power, or both. Deposit rates remained low even as the Federal Reserve raised rates during the post-merger period.

Relevance for financial stability. The merger also substantially increased the size of the combined institution. A larger bank can pool risk across geographic markets and loan portfolios and exploit economies of scale, channels through which scale may improve solvency. Operational integration costs in the first quarters after consummation can offset these benefits in the short run. We examine the net effect on Truist directly in the bank-level Z-score event study in Section 3.3.

At the same time, changes in deposit pricing and funding structure may affect the composition of bank liabilities, with implications for risk. For example, lower deposit rates may reduce funding costs but could also lead to shifts in depositor behavior or increased reliance on alternative funding sources.

3.3 The Effect of the Merger on Deposit Spreads

This section presents the difference-in-differences design that compares counties where both BB&T and SunTrust operated before the merger to counties served by only one of the two, the headline reduced-form estimates of the merger's effect on deposit spreads, and a complementary bank-level event study of financial stability.

Empirical Specification

We estimate how the Truist merger affected deposit spreads using a difference-in-differences design. We define the treatment variable based on the way the merger impacted each county. In our primary analysis, the treatment variable is whether a county had branches of *both* BB&T and SunTrust before the merger, and we compare these against counties with only *one* of the two. The treated counties experienced an increase in local concentration when the two banks merged; counties with only one of the pre-merger banks did not. The outcome is the deposit spread, defined as the federal funds rate minus the deposit rate offered at a given branch j in market m and month t:

$$\text{Spread}_{jmt} \equiv (\text{Fed Funds Rate})_t - (\text{Deposit Rate})_{jmt}. \tag{3.1}$$

A higher spread means the bank pays a lower rate relative to the policy rate, indicating greater pricing power.

The current implementation uses the Money Market $10,000 annual bank–county market panel and excludes the merging banks when estimating rival-bank pricing responses. Treatment is assigned at the county level. For bank j in county m and year t, we estimate

$$\text{Spread}_{jmt} = \alpha + \beta\,(\text{Post}_t \times \text{Treat}_m) + X'_{jmt}\Gamma + \mu_j + \mu_m + \tau_t + \varepsilon_{jmt}, \tag{3.2}$$

where $\text{Post}_t = 1$ in the post-merger period, $\text{Treat}_m = 1$ if market m had branches of both BB&T and SunTrust before the merger, μ_j are bank fixed effects, μ_m are county fixed effects, and τ_t are year fixed effects. The vector X_{jmt} includes bank-level controls (log total branches, log bank-county footprint, branch share within the county, and a large-bank indicator) and market-structure controls (county Herfindahl index, branch share within the county, and RateWatch coverage of the county's deposit base). Standard errors are clustered at the bank-county level. The coefficient β measures how rival-bank spreads change in treated markets relative to untreated markets after the merger, holding fixed bank, county, and year differences.

Table 3.1 characterizes the regression sample used to estimate equation (3.2), by AUM tier, state footprint, county footprint, and county-level competitive environment.

Treatment and Control Groups

Table 3.1 describes the four comparisons we use in our estimation. The preferred comparison is "Both vs. One" described above: counties where both banks were present (treated) against counties where only one was present (control). Both groups become part of Truist after the merger, so the comparison holds the bank-scale effect constant and isolates the competition effect.

In our other specifications, we make use of the "None" counties, which had neither BB&T nor SunTrust before the merger and were thus not directly affected by the change in concentration or the scale effect. Table 3.1 lays out the other three comparisons we make, which decompose the forces behind the merger: the scale effect ("One vs. None"), the geographic footprint effect ("Any vs. None"), and a broad treatment-vs-untreated comparison ("Both vs. None").

Identification

The identifying assumption is parallel trends: deposit spreads in overlapping counties would have followed the same trend as spreads in non-overlapping counties absent the merger. Because both groups belong to the same institution post-merger, and face the same bank-wide pricing policies, this assumption is more credible than comparisons across different banks. We examine pre-trends using an event-study version of equation (3.2) at the quarterly level using the Money

Table 3.1: Regression-sample bank and county characteristics, June 2019 (pre-merger)

Panel A. Bank size by assets under management (AUM)					
	Number of Firms	Number of Branches	Deposits Held ($B)	Deposit Share	MM$10k Rate (bp)
$1+ T	4	15,260	$3,213	47.3%	14.6
$250 B – $1 T	5	6,348	$775	11.4%	25.7
$100 B – $250 B	14	9,651	$1,130	16.6%	18.5
$10 B – $100 B	84	11,638	$996	14.7%	20.3
$1 B – $10 B	415	10,240	$459	6.7%	22.8
$\leq$ $1 B	1,332	8,081	$222	3.3%	25.8
Total	**1,854**	**61,218**	**$6,795**	**100.0%**	–
Panel B. Bank size by state footprint					
	Number of Firms	Number of Branches	Deposits Held ($B)	Deposit Share	MM$10k Rate (bp)
25+ states	3	12,353	$2,060	30.3%	3.5
10-24 states	9	14,755	$2,162	31.8%	19.6
2-9 states	257	19,167	$1,893	27.9%	31.3
1 state	1,585	14,943	$679	10.0%	24.7
Panel C. County footprint of banks operating in one state					
	Number of Firms	Number of Branches	Deposits Held ($B)	Deposit Share	MM$10k Rate (bp)
10+ counties	9	592	$39	5.7%	44.5
2-9 counties	975	10,531	$567	83.4%	23.5
1 county	601	3,820	$74	10.9%	22.2
Panel D. County-level: characteristics by number of banks operating in the county					
	Number of Counties	Mean # Banks/Cnty	Deposits Held ($B)	Deposit Share	MM$10k Rate (bp)
10+ banks	152	11.0	$1,554	22.9%	19.3
5-9 banks	791	6.7	$4,604	67.8%	19.7
3-4 banks	382	3.5	$612	9.0%	10.3
2 banks	147	2.0	$17	0.3%	21.6
1 bank (monopoly)	113	1.0	$8	0.1%	24.0
Total	**1,585**	–	**$6,795**	**100.0%**	–

Notes: Pre-merger snapshot at June 30, 2019, restricted to bank-county-year cells observed in our Money Market $10,000 RateWatch panel (the structural-demand and headline DiD sample). Panels A–C aggregate to the bank level (1,854 unique banks); Panel D aggregates to the county level (1,585 unique counties). The smaller bank universe (vs. 4,649 in the full SoD snapshot in appendix Table 3.5) reflects RateWatch coverage of the MM$10k product. "MM$10k Rate" is the deposit-weighted mean Money Market $10,000 12-month APY in basis points: in Panels A–C it is first computed within each bank as the deposit-weighted mean across the bank's branches, weighted by branch deposit volumes, then aggregated within each tier as a deposit-weighted mean across banks. In Panel D it is first computed within each county as the deposit-weighted mean across banks operating in the county, then aggregated within each tier as a deposit-weighted mean across counties. Deposit share in Panels A, B, D is computed as a fraction of the regression-sample total; in Panel C it is computed relative to single-state banks only. Panel C is restricted to banks operating in a single state. Panel D bins counties by the number of banks operating at least one branch in the county at June 2019. BB&T and SunTrust appear in the $100B–$250B tier of Panel A. Data sources: Summary of Deposits (FDIC), RateWatch, FFIEC Call Reports.

Market \$10,000 market panel:

$$Spread_{jmt} = \alpha + \sum_{k \neq -1} \beta_k \left(\mathbf{1}\{t - t_0 = k\} \times \text{Treat}_m \right) + \mu_m + \tau_t + \varepsilon_{jmt}. \tag{3.3}$$

Here, t_0 denotes the merger quarter (2019Q4), and the omitted period is $k = -1$, so coefficients β_k are treatment effects interpreted relative to the quarter immediately preceding the merger.

Reduced-Form Results

Balance tests. Table 3.5 reports summary statistics and pre-merger balance tests across treatment and control groups for all four specifications. Average deposit spreads in all four groups of counties are just over 0.9 percentage points. The "None" counties (where Truist does not operate before or after the merger) have notably higher deposit spreads and fewer firms competing against each other. We further evaluate the identifying assumption using the event study specification in equation 3.3. The pre-merger coefficients are small, statistically insignificant, and show no clear trend across all four contrasts (Figure 3.1), providing evidence in favor of parallel pre-trends.

Main difference-in-differences estimates. Table 3.2 reports the main annual market-panel difference-in-differences specification (equation 3.2) for the Both vs. One contrast on the Money Market \$10k product. The two columns add ingredients sequentially: county and year fixed effects, then bank and market controls. Standard errors are clustered at the bank-county level. The deposit spread used as the dependent variable is the federal funds rate minus the offered deposit rate; pre-merger average spreads across the four contrast groups are just over 90 basis points (Table 3.5).

The fixed-effects-only specification (column 1) yields a treatment effect of 1.4 basis points (significant at the ten-percent level), and adding the full control set (column 2) raises this to 2.1 basis points (significant at the five-percent level). We read the headline annual effect as approximately two basis points of additional spread in overlapping counties relative to one-Truist counties. Appendix Table 3.2 reports the same regression with the more restrictive bank-county fixed effects, where the within-bank-county variation is too narrow to identify a precise effect; we treat the county-and-year fixed-effect specification as the headline because it preserves cross-bank variation within counties.

Table 3.2: Both-vs-One annual market-panel DiD, Money Market $10,000 (county and year fixed effects, no bank fixed effects)

	(1) FE only	(2) + controls
Treat × Post	0.014*	0.021**
	(0.008)	(0.008)
County FE	✓	✓
Year FE	✓	✓
Bank + Market Controls	–	✓
Observations	6,817	6,817

Notes: Annual market-panel difference-in-differences estimates for the Both vs. One contrast on the Money Market $10,000 product. Sample is bank–county–year cells for the period 2016–2022, restricted to rivals of BB&T and SunTrust (the merging banks themselves are excluded). Dependent variable: deposit spread, defined as the federal funds rate minus the deposit rate, in percentage points. Treat equals one in counties where both BB&T and SunTrust operated before the merger and zero in counties served by only one of the two; Post equals one for years 2021 onward, with 2020 dropped as a transition year because the trailing-twelve-month rate measure for that year averages pre- and post-December-2019 pricing. Both columns include county and year fixed effects. Column (1) reports the baseline specification with fixed effects only. Column (2) adds the bank-level controls (log of total branches, log of bank-county footprint, branch share within the county, large-bank indicator) and market controls (county Herfindahl index, branch share within the county, RateWatch coverage of the county's deposit base). Standard errors are clustered at the bank-county level and reported in parentheses. Two additional specifications, (3) bank-deposit weighting and (4) Truist exposure weighting, were estimated and produced larger point estimates with wider confidence intervals; they are not reported here because the weighted standard errors are inflated by a small number of large-deposit cells. The bank-county fixed-effect counterpart of this regression is reported in Appendix Table 3.2 as a robustness exercise. Data sources: RateWatch, Summary of Deposits, Federal Reserve Economic Data, FFIEC Call Reports.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Quarterly event study. The annual specification averages each year's deposit rate over twelve months centered on June, which mechanically dampens any short-run response to the merger because the year-2020 observation mixes pre- and post-merger quarters. We therefore turn to the quarterly market-panel event study in equation 3.3, which estimates a separate coefficient for each post-merger quarter and provides a cleaner reading of the dynamic effect. Appendix Figure 3.1 (Money Market $10,000) and Appendix Figure 3.2 (Money Market $2,500) plot the dynamic event-study coefficients for the Both vs. One contrast. The pre-merger coefficients are small and statistically insignificant, consistent with parallel pre-trends. After the merger the point estimates rise to roughly seven to nine basis points in the first six post-merger quarters in the $10,000 panel and remain elevated through quarter twelve, and to a smaller magnitude in the $2,500 panel consistent with the higher rate sensitivity at the lower-balance tier. The effect is statistically significant at the ten-percent level in several post-merger quarters and persists at similar magnitudes throughout the post-period.

Magnitudes and interpretation. The quarterly estimates indicate that rivals in overlapping counties widened their spreads by approximately seven to nine basis points after the merger relative to rivals in one-Truist counties, while the four-year average estimate from the annual specification is approximately two basis points. The two are consistent: averaging quarterly effects over a window that includes 2020 (a year in which the trailing-twelve-month rate measure mechanically blends pre- and post-merger pricing) attenuates the annual estimate. Both magnitudes are smaller than the macro-level estimates of the deposit channel of monetary policy reported in Drechsler et al. (2017) but in line with the ten-basis-point range reported in retail-banking merger retrospectives such as Focarelli and Panetta (2003), Craig and Dinger (2009), and Bord (2018).

Two features of the design help interpret the magnitudes. First, both BB&T and SunTrust used standardized, zone-based deposit pricing before the merger. Bank-wide pricing rules attenuate the local response to a change in local concentration, since the same posted rate is shared across many counties. Second, depositor responsiveness to small rate differences appears high in money market products, which is consistent with the elastic demand we recover in the structural model below. Both forces compress the price effect of any single market-structure change.

Auxiliary specifications. The Both vs. None and One vs. None contrasts compare overlapping or single-Truist counties to counties without any Truist branch. These contrasts are not the cleanest test of competition because the no-Truist counties differ in observable characteristics, but they help disentangle the local competition effect from a bank-wide "scale" effect (One vs. None) and from a geographic footprint effect (Any vs. None). We report them in Appendix Table 3.6, which uses the raw branch-level RateWatch panel and a leaner control set (only month and county fixed effects). The Both vs. None contrast yields point estimates that are similar in sign but consistently smaller in magnitude and statistically indistinguishable from zero, confirming that the within-Truist contrast in Table 3.2 is the more informative comparison. We also report event-study estimates for the Money Market $2.5k product in Appendix Figure 3.2; the post-merger pattern is similar to the $10k version with smaller magnitudes.

This motivates the structural approach developed in the next section. A model of deposit demand and supply allows us to (i) quantify the degree of market power implied by observed pricing behavior, (ii) separate the competition effect from the scale effect in a unified framework, and (iii) run a no-merger counterfactual that recovers what deposit rates would have been under separate BB&T and SunTrust ownership.

Stability Effects

We measure solvency risk using the bank Z-score

$$Z_{jt} = \frac{\text{ROA}_{jt} + E_{jt}/A_{jt}}{\sigma(\text{ROA}_j)}, \tag{3.4}$$

with $\sigma(\text{ROA}_j)$ a four-quarter rolling standard deviation. We work in logs because the distribution is right-skewed, and estimate

$$\log Z_{jt} = \alpha + \sum_{k \neq -1} \beta_k \mathbf{1}\{t - t_0 = k\} \cdot \text{Truist}_j + \mu_j + \tau_t + \varepsilon_{jt}, \tag{3.5}$$

on a panel of 128 regional banks with 2019 assets between \$10 billion and \$1 trillion. t_0 is 2019Q4 and Truist_j pools BB&T, SunTrust, and post-merger Truist. Standard errors are clustered at the bank level.

Appendix Figure 3.3 shows the estimated dynamic path. At the merger quarter Truist's log Z-score drops by approximately 1.9 log points relative to the control group; from quarter 3 onward the effect reverses to roughly 0.7–0.9 log points and fades to zero by mid-2021. We read this as integration friction at consummation followed by a diversification benefit. We treat the evidence as descriptive rather than causal: the COVID-19 shock in 2020Q1–Q2 mechanically lowered nearly all banks' Z-scores by raising aggregate ROA volatility, and the result is sensitive to the choice of pre-merger treatment identifier (BB&T-only, SunTrust-only, or pooled), which we report in Appendix Figure 3.4.

The pre-merger balance tests for Z-score and its component variables are reported in Table 3.7. On average, SunTrust and BB&T were smaller and had lower Z-scores than their peer banks before the merger. However, they were similarly profitable and well-capitalized, as shown by their return on assets and equity-to-assets ratio that closely align to the comparison group.

3.4 Model

This section develops a model of deposit demand that allows us to estimate demand elasticities in this market and conduct counterfactual analysis.

Deposit Demand

We model depositors as choosing among banks operating in a local market. A market is a county, indexed by m, and time t is the year (or year-quarter in the quarterly panel). The demand model is estimated separately for each deposit product (the headline analysis uses the Money Market $10,000 account); within a product, the unit of observation is a bank-county-year cell, with each bank j's rate aggregated (deposit-weighted) across its branches in the county.

Each bank j in market m at time t offers its deposit product at an interest rate r_{jmt}, with observable bank-county characteristics x_{jmt}. These characteristics include measures of branch presence and other bank attributes. In addition, depositors may choose an outside option, which captures alternatives such as holding cash, using non-bank financial institutions, or selecting banks not included in the sample.

Bank solvency risk. Before specifying utility, we use the same bank-level Z-score defined in equation (3.4), which captures distance to insolvency. A higher value indicates a bank further from insolvency.

Utility specification. The utility that depositor i in market m at time t derives from choosing bank j is

$$u_{ijmt} = \alpha r_{jmt} + \beta_b b_{jmt} + \beta_z \log Z_{jt} + x'_{jmt}\gamma + \xi_{jmt} + \varepsilon_{ijmt}, \tag{3.6}$$

where r_{jmt} is the deposit interest rate, b_{jmt} is a measure of branch presence, Z_{jt} is the bank Z-score defined in equation (3.4), and x_{jmt} is a vector of other observable bank characteristics. The term ξ_{jmt} captures unobserved product quality, and ε_{ijmt} represents idiosyncratic preferences assumed to be i.i.d. Type I extreme value.

The parameter α captures depositors' sensitivity to interest rates. β_b captures the value of branch convenience. β_z captures depositors' preference for banks with lower default risk: following

Egan et al. (2017), depositors may prefer banks further from insolvency, particularly for uninsured balances.

Market shares. Under the assumption that ε_{ijmt} follows a Type I extreme value distribution, the model yields standard logit demand. The market share of bank j in market m at time t is given by

$$s_{jmt} = \frac{\exp(\delta_{jmt})}{1 + \sum_{k \in \mathcal{J}_{mt}} \exp(\delta_{kmt})}, \tag{3.7}$$

where

$$\delta_{jmt} = \alpha r_{jmt} + \beta_b b_{jmt} + \beta_z \log Z_{jt} + x'_{jmt}\gamma + \xi_{jmt} \tag{3.8}$$

is the mean utility of bank j, and the denominator includes all banks in the market as well as the outside option.

The outside option share is given by

$$s_{0mt} = \frac{1}{1 + \sum_{k \in \mathcal{J}_{mt}} \exp(\delta_{kmt})}. \tag{3.9}$$

Estimating equation. Following Berry (1994), we can invert the market share equation to obtain the estimating equation

$$\log(s_{jmt}) - \log(s_{0mt}) = \alpha r_{jmt} + \beta_b b_{jmt} + \beta_z \log Z_{jt} + x'_{jmt}\gamma + \mu_m + \tau_t + \xi_{jmt}. \tag{3.10}$$

In the baseline estimates, μ_m are county fixed effects and τ_t are year fixed effects. The branch variable b_{jmt} is measured as log branch count in the county, and $\log Z_{jt}$ is the natural log of the four-quarter rolling Z-score defined in equation (3.4).

In this framework, deposit rates play the role of prices: α describes the elasticity of demand with respect to rates, while β_b captures non-price competition through branch convenience. The unobserved term ξ_{jmt} absorbs persistent differences in bank appeal (brand strength, service quality) that would otherwise bias the rate coefficient.

Deposit Supply and Bank Pricing

We adopt a standard oligopoly framework in which banks compete in deposit rates and set them to maximize variable profits, taking the rates of other banks as given.

Bank j operates across a set of local markets $\mathcal{M}_j$. Under price discrimination, the bank chooses a separate deposit rate r_{jmt} in each market $m \in \mathcal{M}_j$ at time t to maximize total variable profit:

$$\pi_{jt} \;=\; \sum_{m \in \mathcal{M}_j} \big(l_{jt} - r_{jmt} - mc_{jmt}\big) \cdot s_{jmt}\big(r_{jmt}, r_{-j,mt}\big) \cdot D_{mt}, \tag{3.11}$$

where l_{jt} is bank j's return on the assets that deposits fund, mc_{jmt} is the marginal cost of servicing a unit of deposits in market m (operational costs, FDIC insurance, reserve requirements), $s_{jmt}(\cdot)$ is the logit market share from the demand model, and D_{mt} is the size of the local deposit market. The bank earns the per-dollar margin $l_{jt} - r_{jmt} - mc_{jmt}$ on every dollar of deposits it attracts in market m. We assume that the marginal return l_{jt} does not respond to small changes in any single market's deposit rate, following Ho and Ishii (2011b) and the assumptions used in Labrador-Badia (2024), and that competition is local so that rates in one market do not directly affect demand in another.

Under price discrimination the first-order condition for r_{jmt} decouples market-by-market:

$$\big(l_{jt} - r_{jmt} - mc_{jmt}\big) \cdot \frac{\partial s_{jmt}}{\partial r_{jmt}} \;=\; s_{jmt}, \tag{3.12}$$

which rearranges to the markdown condition

$$l_{jt} - r_{jmt} \;=\; mc_{jmt} \;+\; \frac{s_{jmt}}{\partial s_{jmt}/\partial r_{jmt}}. \tag{3.13}$$

This is the deposit-bank analogue of the standard logit markup. Because $\partial s_{jmt}/\partial r_{jmt} > 0$ (depositors prefer higher rates), the right-hand correction is a positive markdown: the bank pays less than its full opportunity cost $l_{jt} - mc_{jmt}$, with the size of the wedge inversely proportional to the local rate sensitivity of depositor demand. Banks with more captive depositors (smaller $\partial s_{jmt}/\partial r_{jmt}$) pay lower rates and earn larger spreads relative to the policy rate. Increases in local concentration following a merger reduce $|\partial s_{jmt}/\partial r_{jmt}|$, raise the markdown, and widen spreads.

In practice, both BB&T and SunTrust used standardized zone-based pricing rather than setting a separate rate in each county. We treat the market-by-market specification as a benchmark and discuss zone-pricing constraints, which would attenuate the implied response to local concentration, in the discussion of the counterfactual in Section 3.5.

3.5 Structural Results and Counterfactual Analysis

This section reports the demand estimates from the model in Section 3.4 and uses them in a no-merger counterfactual that recovers what deposit rates would have been if BB&T and SunTrust had remained separate.

Demand Estimation

Identification. Deposit rates are endogenous to local demand because a bank that anticipates a shock to county-level deposit demand can adjust its offered rate at the same time, attenuating the OLS estimate of α. We instrument the rate using the leave-one-out log of the number of counties served by rival banks in the same market, following the BLP-style rival-characteristic logic of Berry (1994). Rivals' geographic scope shifts a bank's effective competitive environment, both through how many alternative banks a depositor in the county faces and through the rivals' incentive to offer a uniform rate across their pricing zone, without entering the depositor's utility for the focal bank directly. The fixed effects absorb time-invariant county-level differences in deposit demand and aggregate rate movements over time, so identification comes from within-county, within-year variation in relative competitive conditions across banks.

The baseline demand specification is estimated on the pre-merger 2013–2019 sample for the Money Market $10,000 product. The deposit-rate variable is the deposit-weighted mean rate across each bank's branches in the county; the dependent variable is the logit mean utility $\delta_{jmt} = \log(s_{jmt}) - \log(s_{0mt})$. The headline column uses a single just-identified instrument (log rival county footprint, the leave-one-out log of the number of counties served by rival banks in the same market). For robustness we report two additional columns: a second single-IV specification using log rival total branches, and a multi-instrument BLP-style specification (seven rival-sum instruments) for comparison. The headline estimates are reported in Appendix C (Table 3.1).

The IV column produces a positive and statistically significant coefficient on the deposit rate, consistent with the standard logit demand model in deposits: depositors prefer higher rates. The branch-network variables enter with the expected signs and are precisely estimated. Branch presence enters in logs, so the coefficient on log branches in county is the elasticity of $\log(s_{jt}/s_{0t})$ with respect to branch count: a coefficient of approximately 0.73 implies that a 10% increase in a bank's branches in the county raises the inside-versus-outside share ratio by about 7%. The estimated rate coefficient $\hat{\alpha}$ in the IV column implies an average own-rate elasticity of demand at the 2019 baseline of $\hat{\alpha}\,(1 - \bar{s}_{jm})\,\bar{r}_{jmt}$, computed at observed shares and rates. We use the IV column as the headline specification for marginal-cost recovery and the counterfactual exercise in Section 3.5; the cost-shifter and nested-logit columns serve as robustness.

Counterfactual Analysis

We use the estimated demand and supply model based on the Money Market $10,000 baseline to simulate counterfactual deposit rates under a no-merger ownership structure. The counterfactual is designed to answer two questions: (1) How much of the observed increase in deposit spreads in overlapping counties is attributable to the competition effect of the merger, as opposed to other changes in bank behavior? (2) What are the implied welfare effects for depositors?

In each counterfactual, we hold the estimated demand parameters and recovered marginal costs fixed at their pre-merger values and compute the new Nash equilibrium deposit rates by iterating the system of first-order conditions to convergence. We report both rate changes relative to the observed post-merger equilibrium and the implied change in depositor consumer surplus using the standard logit welfare formula.

No-Merger Benchmark

The first counterfactual asks: what would deposit rates have been in the absence of the merger? We simulate a counterfactual market structure in which BB&T and SunTrust continue to operate as independent banks in all markets, including overlapping counties, with their pre-merger demand parameters and marginal costs. We then solve for the Nash equilibrium rates and compare them to the observed post-merger rates for Truist. The exercise corresponds to the limiting case of a full divestiture remedy in which all of Truist's overlapping-county branches are reassigned to their pre-merger owners, and provides the policy-relevant benchmark for evaluating the merger's competitive effect. The Money Market $10,000 baseline produces the cleanest demand estimate, so we use it as the main simulation benchmark and omit the CD diagnostics from the main text.

Formally, at each post-merger year t we hold the demand parameters fixed at their pre-merger estimates, reassign Truist's branches to their BB&T or SunTrust legacy entities, and re-solve:

$$r_{jmt}^{\text{no-merger}} = l_{jt} - mc_{jmt} - \frac{s_{jmt}^{\text{no-merger}}}{\partial s_{jmt}^{\text{no-merger}} / \partial r_{jmt}}, \tag{3.14}$$

for all banks j simultaneously. The difference $r_{jmt}^{\text{observed}} - r_{jmt}^{\text{no-merger}}$ isolates the competition effect of the merger on deposit rates in each market.

Demand parameters (α, β) are estimated on the pre-merger 2013–2019 sample under the single-IV specification reported in Table 3.1 and held fixed across the post-merger years; the counterfactual is reported at the 2019 baseline as the headline (Table 3.4) with each post-merger year $t \in \{2020, 2021, 2022, 2023\}$ available as a forward robustness in Appendix C.[1]

Table 3.3 reports the implied rate change for the merged Truist at the 2019 baseline and at each post-merger year. Column Δr_{merged} is the difference $r_{\text{merged}} - r_{\text{separate}}$ at that year's market state, with the un-merger counterfactual re-solved each year using observed Truist rates and shares to recover marginal costs. Negative values indicate the merger lowered Truist's deposit rate relative to the separate-ownership counterfactual (anti-competitive); positive values indicate the merger raised rates.

Time pattern of the implied rate effect. The headline 2019 column estimates the merger's implied effect using the actual pre-merger market state in the last year before consummation; this is our preferred number because the demand parameters are estimated on data that ends just before the panel year being simulated, so the fixed-$\hat{\alpha}$ assumption is least demanding. At this baseline the merger lowered Truist's deposit rate by approximately 25 basis points relative to the un-merger counterfactual, an anti-competitive effect consistent with the reduced-form sign in the difference-

[1] The simulation is implemented using the `mergersim` package of Björnerstedt and Verboven (2016). Implementation details, including the recovery of marginal costs from observed prices and the attribution of post-merger Truist branches to BB&T and SunTrust legacy entities, are described in Appendix C.

Table 3.3: No-merger counterfactual rate change by year, Money Market \$10,000 (headline demand specification, column 1 of Table 3.1)

	2019 (headline)	2020	2021	2022	2023
Δr_{merged} (bp)	$-$**25.5**	-8.7	$+4.8$	$+5.3$	$+9.5$
N obs	50,242	$\sim$33,000	$\sim$33,000	$\sim$33,000	$\sim$33,000
Converged	1	1	1	1	1

Notes: Static (column 1) and forward (columns 2–5) counterfactuals at one year each. The 2019 column re-solves the un-merger at the actual 2019 baseline panel and is the headline structural number used in the paper text and Table 3.4. The 2020–2023 columns use the 2019-Summary-of-Deposits legacy attribution to artificially split Truist into BB&T and SunTrust legacy entities and re-solve at each post-merger year, holding pre-merger demand parameters fixed at the 2013–2019 estimates ($\hat{\alpha} = 5.93$ pp, SE $= 1.74$, $t = 3.41$, Kleibergen–Paap $F = 22.9$). The forward years should be read as exploratory: depositor preferences over rate vary with the level of the federal funds rate, which spiked in 2022–2023, so $\hat{\alpha}$ held fixed at the pre-merger value is a strong assumption out of sample. Negative Δr_{merged} means the merger lowered Truist's rate (anti-competitive); positive means the merger raised it. Data sources: RateWatch, Summary of Deposits, Call Reports.

in-differences. The forward columns (2020–2023) ask what the merger's effect would be if the pre-merger demand parameters described post-merger depositor behavior. The implied effect is anti-competitive in 2020 (-8.7 bp) and reverses sign by 2021 ($+4.8$ to $+9.5$ bp). We read the time pattern as suggesting that the local market-power channel that drives the 2019 result attenuates over the post-merger years, consistent with rival entry, consolidation among smaller competitors, and the post-2020 deposit-pricing environment in which the federal funds rate rose sharply and depositor sensitivity to rates may have shifted. The forward sims should therefore be read as exploratory: $\hat{\alpha}$ held fixed at the pre-merger value is a strong assumption out of sample, particularly for 2022–2023 when policy rates jumped from near zero to over five percent.

Demand-side robustness. Appendix Table 3.4 reports the same counterfactual under alternative pre-merger demand windows, varying the start year from 2013 to 2016 with the end year held at 2019. The estimated demand parameter $\hat{\alpha}$ rises as the window narrows toward the merger consummation, but the implied counterfactual rate change is small and negative across all windows, consistent with elastic depositor demand attenuating the price effect of the ownership change.

Welfare and surplus. We report deposit-weighted welfare envelopes that multiply the model-implied rate change by observed bank deposits in each overlap county-bank cell. For Truist, the envelope producer-surplus gain is $+\sum_{j \in \text{Truist}} D_j \cdot \Delta p_j$, where $\Delta p_j = p_j^{\text{merged}} - p_j^{\text{separate}}$ is the

Table 3.4: Implied surplus changes under the no-merger counterfactual: Money Market \$10,000, 2019 baseline, demand window 2013–2019

	Headline log rival county footprint	Robustness log rival total branches
$\hat{\alpha}$ (pp)	5.93	3.92
$t(\hat{\alpha})$	3.41	2.98
KP-F	22.9	27.1
Δr_{merged} (bp)	-25.5	-37.9
Δ Producer surplus, Truist (\$M / yr)	$+306$	$+455$
Δ Consumer surplus, overlap (\$M / yr)	-556	-826
Net welfare (\$M / yr)	-250	-371

Notes: Implied changes in consumer and producer surplus from the merger relative to the un-merger counterfactual, evaluated at the 2019 baseline. Magnitudes in millions of dollars per year, summed across overlapping counties (the panel is annual, June-anchored TTM). Demand is estimated on the pre-merger 2013–2019 sample. The headline column uses a single just-identified instrument, log rival county footprint (the leave-one-out log of the number of counties served by rival banks in the same market); the robustness column substitutes log rival total branches. Both specifications satisfy standard demand-estimation criteria ($\hat{\alpha} > 0$, $|t(\hat{\alpha})| \geq 1.96$, $\hat{\beta}_z > 0$, KP-F$\geq$ 10, just-identified so Hansen J is vacuous). Welfare envelopes use the deposit-weighted formula $\sum_j D_j \cdot \Delta p_j$ with Δp in decimal-fraction units, which is the unit-invariant mechanical consequence of the simulated rate change. Implementation details are in Appendix C.

simulated change in the price variable (rate enters as $0.10 - r/100$, so positive Δp corresponds to a rate markdown). The envelope consumer-surplus change is the symmetric quantity over all banks. Magnitudes are in millions of dollars per year, summed across overlapping counties.

Interpretation. The structural counterfactual implies that the merger lowered Truist's deposit rate in overlap counties by approximately 25 basis points relative to a continued-separate-ownership counterfactual, transferring approximately \$306 million per year to Truist as producer surplus while costing depositors approximately \$556 million per year. Net welfare loss is approximately \$250 million per year. The structural rate effect is an order of magnitude larger than the difference-in-differences estimate of approximately 1–2 basis points (the headline annual specification) or 7–9 basis points at peak in the quarterly event study. The two are consistent: the difference-in-differences identifies the differential effect on overlap relative to non-overlap counties, netting out general industry trends, while the structural counterfactual recovers the Truist-specific markdown in overlap counties directly. We treat the structural number as the policy-relevant magnitude and the difference-in-differences as a conservative lower bound that complements it. We report alternative pre-merger windows and the BLP-full benchmark in Appendix C.

3.6 Conclusion

This paper studies the competitive effects of the 2019 BB&T–SunTrust merger in U.S. retail banking. The partial geographic overlap between the two banks generates clean variation that separates the local competition effect of increased concentration from the scale effect of becoming a larger institution. We bring together a reduced-form difference-in-differences design and a structural deposit-demand-and-pricing model to quantify the merger's pricing and stability consequences.

The reduced-form analysis shows that, in counties where both BB&T and SunTrust operated before the merger, rival banks widened their deposit spreads by approximately two basis points on the headline annual specification and by roughly seven to nine basis points at peak in the quarterly event study, both relative to rivals in counties served by only one of the two predecessors. The effect is statistically significant in the unweighted county-and-year fixed-effect specification and persists through the end of our sample period. The branch-level robustness using only RateWatch data shows that the merger's effect is particularly large in counties without competing top-four U.S. banks, where deposit spreads rose by approximately fifteen basis points. These magnitudes are at the lower end of the retail-banking merger-retrospective literature and consistent with both bank-wide pricing rules at large institutions and elastic depositor demand for liquid deposit products.

The structural counterfactual reassigns Truist's branches to their 2019 BB&T or SunTrust legacy ownership, holding pre-merger demand parameters fixed at the values estimated on the 2013–2019 sample under the single-IV specification (log rival county footprint as the excluded instrument). The implied rate effect is anti-competitive in sign and economically meaningful: at the 2019 baseline the merger lowered Truist's deposit rate by approximately 25 basis points relative to the un-merger counterfactual. The implied change in consumer surplus across overlap counties is a loss of approximately $556 million per year, and the implied producer-surplus gain to Truist is approximately $306 million per year. The consumer loss exceeds the producer gain because rival banks in overlap counties also lower rates in equilibrium, so depositors at non-Truist banks are also affected. The structural rate effect is an order of magnitude larger than the difference-in-differences estimate; the gap is consistent with the DiD netting out general industry trends that the structural model captures directly.

The bank-level stability event study shows that the merged Truist experienced a short-run drop in its log Z-score around the merger consummation, contemporaneous with the COVID-19 pandemic, followed by a recovery to its pre-merger trend by mid-2021. We treat this evidence as a useful descriptive complement rather than a clean causal estimate, and we report robustness across alternative treatment definitions in Appendix B.

The results indicate that a major regional bank merger of this scale produced modest but detectable anti-competitive effects on deposit pricing and a temporary, mostly mechanical disruption to balance-sheet stability that recovered within two years. From a policy standpoint, the heterogeneity of effects across competitive environments, with larger spreads in markets without top-four bank competition, suggests that antitrust review of bank mergers should weight overlapping counties' outside competitive options more heavily than aggregate concentration measures alone.

Appendix

A Additional Descriptive Statistics

This appendix provides supplementary descriptive evidence on the U.S. banking industry that complements the regression-sample summary in the main text.

Universe of U.S. Commercial Banks (Full SoD Snapshot)

For reference, Table 3.5 reports the full universe of U.S. commercial banks from the FDIC Summary of Deposits, broken down by AUM tier (Panel A), state footprint (Panel B), and county footprint among single-state banks (Panel C). The regression-sample restriction to banks observed in the RateWatch panel for the Money Market $10,000 product (Table 3.1) drops the firm count from 4,649 to 1,854 but preserves the broad tier structure.

Table 3.5: Background statistics for U.S. banks (full SoD universe, June 2023)

Panel A. Bank size by assets under management (AUM)				
Bank AUM	Number of Firms	Number of Branches	Deposits Held (billions)	Deposit Share
$1+ T	4	13,911	$6,050	35.1%
$250 B – $1 T	10	9,303	$3,236	18.8%
$100 B – $250 B	19	8,049	$2,446	14.2%
$10 B – $100 B	125	13,060	$2,656	15.4%
$1 B – $10 B	842	18,014	$1,910	11.1%
≤ $1 B	3,655	15,459	$953	5.5%
Total	**4,649**	**77,474**	**17,169**	**100%**
Panel B. Bank size by state footprint				
Branch Footprint	Number of Firms	Number of Branches	Deposits Held (billions)	Deposit Share
25+ states	5	18,024	$6,269	36.5%
10-24 states	23	14,498	$3,103	18.1%
2-9 states	703	22,713	$4,127	24.0%
1 state	3,918	22,239	$3,671	21.4%
Panel C. County footprint of banks operating in one state				
Branch Footprint	Number of Firms	Number of Branches	Deposits Held (billions)	Deposit Share
10+ counties	88	3,357	$339	9.2%
2-9 counties	2,140	15,284	$1,442	39.3%
1 county	1,690	3,598	$1,890	51.5%

Notes: Data as of June 30, 2023. Deposit share is computed as a fraction of total U.S. commercial bank deposits in Panels A and B and relative to single-state banks only in Panel C. Branch footprint is defined by the number of states in which a bank operates at least one branch in Panel B and the number of counties in which a bank operates at least one branch in Panel C. Panel C is restricted to banks operating in a single state. Data source: Summary of Deposits (FDIC).

Table 3.1: Treatment and control groups for reduced-form analysis

Specification	Treated counties	Control counties	Focus of comparison
Both vs. One *(preferred)*	Had both BB&T and SunTrust	Had one bank only	Concentration
One vs. None	Had one bank only	Had neither bank	Scale
Any vs. None	Had at least one bank	Had neither bank	Geographic footprint
Both vs. None	Had both BB&T and SunTrust	Had neither bank	Broad treated vs. untreated

Notes: Treatment status is based on 2019 Summary of Deposits data. "Both" counties had branches of both BB&T and SunTrust before the merger. "One" counties had either BB&T or SunTrust, which became part of Truist, but their local number of competitors did not change. "None" counties had no pre-merger presence of either bank.

B Reduced-Form Robustness and Auxiliary Specifications

This section reports auxiliary specifications referenced in the main text. Table 3.1 summarizes the four treatment–control comparisons used across these specifications.

This appendix collects robustness exercises for the reduced-form deposit-spread results: alternative treatment contrasts, the bank-county fixed-effects specification, the CD product, the branch-level RateWatch panel, and alternative treatment definitions for the bank-level stability event study.

Reduced-Form Deposit-Spread Results, Alternative Contrasts and Products

Table 3.6 reports the corresponding branch-level difference-in-differences estimates for the auxiliary contrasts. The branch-level specification uses the raw RateWatch panel without aggregation to the bank-county-year cell and includes only month and county fixed effects (no bank or market controls), so the table exposes the competitive contrast more directly than the controlled market-panel regressions in the main text. The three auxiliary contrasts isolate different margins of the merger: One vs. None compares counties served by exactly one of the two predecessors to counties served by neither, isolating the bank-wide scale effect of merging into a larger institution; Any vs. None compares counties served by either predecessor to counties served by neither, capturing the joint effect of geographic footprint; Both vs. None compares overlapping counties to counties served by neither predecessor, combining local competition and scale margins. Across these contrasts the point estimates have the same sign as the headline Both vs. One specification but consistently smaller magnitudes and standard errors that overlap zero, confirming that the within-Truist contrast in the main text is the more informative comparison.

Annual Market-Panel DiD with Bank-County Fixed Effects

Table 3.2 repeats the headline specification with bank-county and year fixed effects in place of the headline's county and year fixed effects, isolating only within-bank-county time variation. Two features of the deposit market compress this within-bank-county variation. First, both BB&T/SunTrust and most large rivals operating in the same counties (Bank of America, JPMorgan Chase, Wells Fargo, Citi) post a single rate across many counties under zone-based pricing, so the same bank's spread in an overlapping county and a single-Truist county tends to move together over time. Second, the within-bank-county time series is short: the 2016–2022 window provides only seven years, of which 2020 is dropped as a transition year, leaving a two-year post-merger

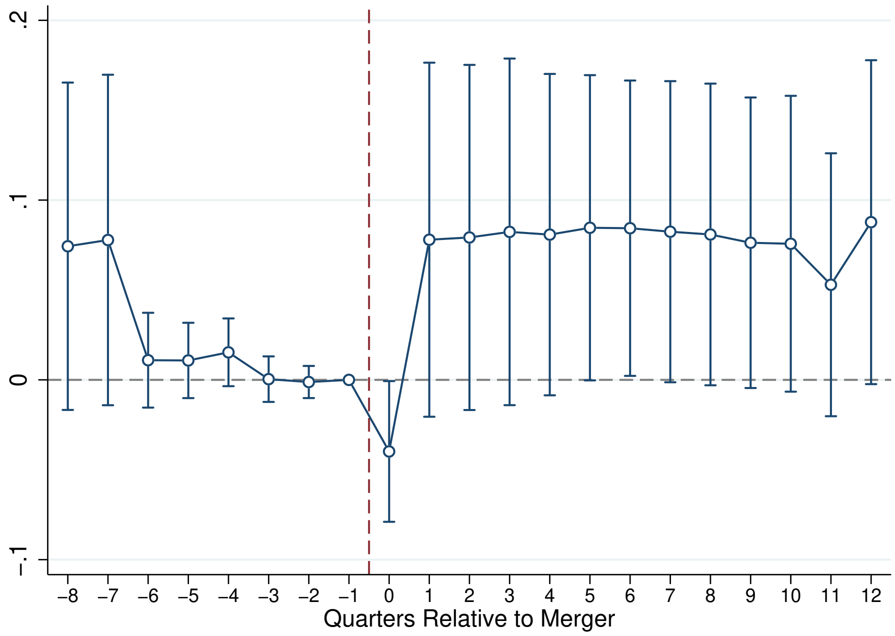


Figure 3.1: Quarterly event study: deposit spread, Both vs. One, Money Market $10,000

Notes: Quarterly event-study coefficients from equation (3.3) on the bank–county–quarter market panel for the Money Market $10,000 product. Sample is rivals of BB&T and SunTrust in counties classified as Both vs. One on the basis of pre-merger Truist-pair presence. Treatment is the interaction between the bank-county's pre-merger Truist-pair classification and event-time relative to merger consummation in 2019Q4. The omitted reference is event-time -1 (2019Q3); the implementation uses the placement of the omitted dummy at the end of the regression to let the collinearity-drop algorithm select the reference, producing a zero anchor at quarter -1. The vertical dashed line marks merger consummation. The specification absorbs bank–county and quarter fixed effects with the bank and market controls used in the annual specification. Standard errors are clustered at the bank–county level. Ninety-five-percent confidence intervals are shown. Data sources: RateWatch, Summary of Deposits, Federal Reserve Economic Data, FFIEC Call Reports.

window (2021 and 2022). Table 3.3 extends the comparison to the twelve-month $2,500 CD product, where the merger effect is large enough to remain significant under bank-county fixed effects.

Robustness Across Products: CD 12-Month $2,500

Table 3.3 repeats the two-column specification on the twelve-month CD $2,500 product. Columns (1) and (2) report the headline county and year fixed-effects specification; columns (3) and (4) report the bank-county and year fixed-effects specification. The point estimates are larger than for the headline Money Market $10,000 product (about seven basis points under county and year fixed effects, and four basis points under the strict bank-county fixed effects), and the merger effect remains statistically significant in both specifications. The result confirms that the merger's effect on deposit spreads is robust to the choice of product and to the strict within-bank-county identification.

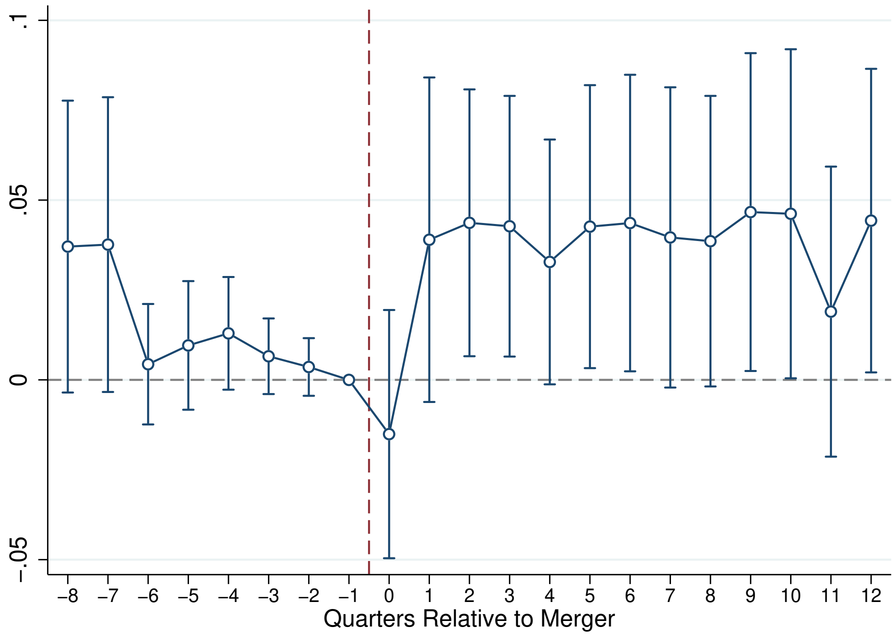


Figure 3.2: Quarterly event study: deposit spread, Both vs. One, Money Market $2,500

Notes: Same specification as Figure 3.1, applied to the Money Market $2,500 product. Sample, fixed effects, controls, treatment definition, and clustering structure are unchanged. The smaller post-merger magnitudes relative to the $10,000 product are consistent with greater depositor rate sensitivity at the lower-balance tier. Data sources: RateWatch, Summary of Deposits, Federal Reserve Economic Data, FFIEC Call Reports.

Table 3.2: Both-vs-One annual market-panel DiD, Money Market $10,000 (bank-county and year fixed effects)

	(1) FE only	(2) + controls
Treat × Post	0.008 (0.007)	0.012 (0.007)
Bank-county FE	✓	✓
Year FE	✓	✓
Bank + Market Controls	–	✓
Observations	6,786	6,786

Notes: Annual market-panel DiD for the Both vs. One contrast on the Money Market $10,000 product, with bank-county and year fixed effects in place of the headline's county and year fixed effects. Sample, dependent variable, treatment definition, controls, and clustering match Table 3.2; the smaller observation count (6,786 vs. 6,817) reflects 31 singleton bank-county cells dropped by `reghdfe` when the bank-county fixed effect is added. The bank-county fixed effect isolates within-bank-county time variation. Standard errors clustered at the bank-county level.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Branch-Level Robustness Using RateWatch Only

As a robustness check we estimate the difference-in-differences specification at the branch–month level using the raw RateWatch panel without aggregating to the bank-county-year market panel and without the bank or market controls used in the main specification. The dependent variable is

Table 3.3: Both-vs-One annual market-panel DiD, CD 12-month $2,500 (county-year vs. bank-county fixed effects)

	County and year FE		Bank-county and year FE	
	(1) FE only	(2) + controls	(3) FE only	(4) + controls
Treat × Post	0.020	0.068***	0.024	0.041**
	(0.024)	(0.023)	(0.020)	(0.018)
County FE	✓	✓	–	–
Bank-county FE	–	–	✓	✓
Year FE	✓	✓	✓	✓
Bank + Market Controls	–	✓	–	✓
Observations	5,593	5,593	5,558	5,558

Notes: Annual market-panel difference-in-differences estimates for the Both vs. One contrast on the twelve-month $2,500 CD product. Sample, dependent variable, and treatment definition match Table 3.2: bank–county–year cells for 2016–2022, restricted to rivals of BB&T and SunTrust; deposit spread (federal funds rate minus deposit rate, in percentage points) as the outcome; Treat equal to one in overlapping counties; Post equal to one for years 2021 onward, with 2020 dropped. Columns (1) and (2) use the headline county-and-year fixed-effects specification (no bank fixed effects), so the treatment effect is identified from both cross-bank variation within counties and within-bank-county time variation. Columns (3) and (4) replace the county fixed effect with a bank-county pair fixed effect, isolating only within-bank-county time variation. Bank and market controls (added in columns 2 and 4) match those in Table 3.2. Standard errors are clustered at the bank-county level. Sample size differs slightly between the two FE structures because singleton bank-county pairs are dropped in the bank-county fixed-effect estimation. Data sources: RateWatch, Summary of Deposits, Federal Reserve Economic Data, FFIEC Call Reports.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.4: Difference-in-differences results, branch level (RateWatch data only)

	(1)	(2)	(3)	(4)
Treat × Post	0.044***	0.004	0.013	0.152***
	(0.014)	(0.008)	(0.009)	(0.026)
Month FE	–	✓	✓	✓
County FE	–	✓	✓	✓
Top-4 competitor sample	–	–	✓	–
No top-4 competitor sample	–	–	–	✓
Observations	171,284	171,277	149,738	21,539

Notes: Branch-month-level DiD using only RateWatch data, no bank or market controls. Column (1) is OLS without fixed effects. Column (2) adds month and county fixed effects. Column (3) restricts the sample to counties with at least one top-4 U.S. bank (JPMorgan Chase, Bank of America, Citi, Wells Fargo) operating in the county. Column (4) restricts to counties without any top-4 U.S. bank. Standard errors are clustered at the county level. The contrast between columns (3) and (4) is the heterogeneity-by-outside-competition result discussed in Section 3.5: the merger raised spreads substantially in markets without competition from a top-4 bank, while leaving spreads largely unchanged in markets with strong outside competition.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

the deposit spread on the Money Market $10k product. Treat indicates counties with both BB&T and SunTrust prior to the merger, and Post equals one for periods after December 2019. Standard errors are clustered at the county level.

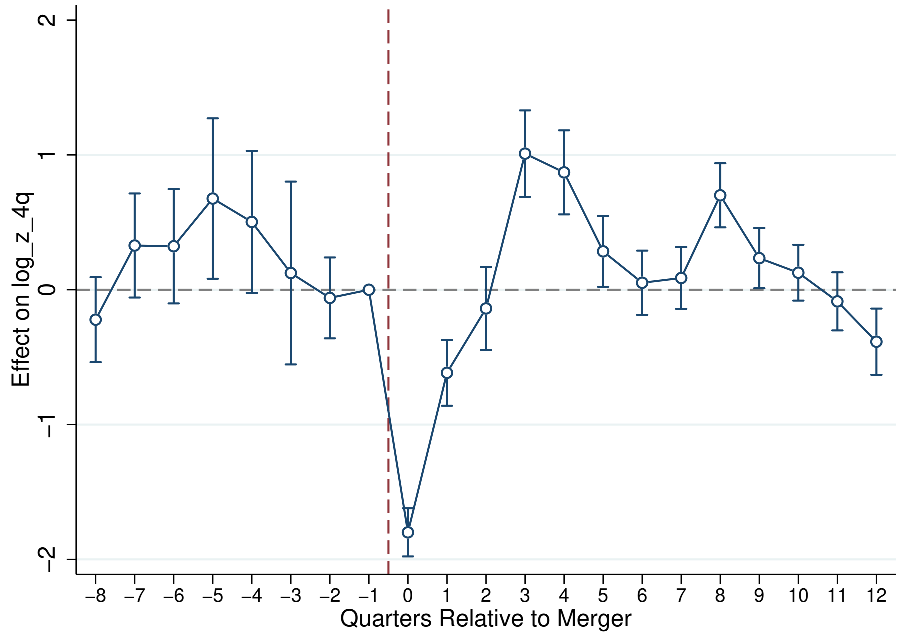


Figure 3.3: Bank-level stability event study: $\log(Z_{4q})$, combined Truist-pair treatment

Notes: Event-study coefficients from equation (3.5). Treatment is BB&T pre-merger, SunTrust pre-merger, or Truist Bank post-merger. Control group is regional banks with 2019 assets in \$10B–\$1T (n=128). Bank and quarter fixed effects, controlling for the equity-to-assets ratio. Standard errors clustered at the bank level. The vertical dashed line marks merger consummation in 2019Q4. Data source: Call Reports.

Stability Event Study, Alternative Treatment Definitions

Figure 3.3 shows the headline log *Z*-score event study using the combined Truist-pair indicator (BB&T pre, SunTrust pre, Truist post). Figure 3.4 reports the same event study with two alternative treatment definitions: BB&T-only (the legal entity that becomes Truist post-merger) and SunTrust-only (the predecessor that ceases to exist after consummation, so post-event coefficients are mechanically undefined). The post-merger pattern is similar across the first two definitions, supporting the interpretation in the main text that the short-run drop and medium-run recovery are properties of the merged institution rather than of one predecessor alone.

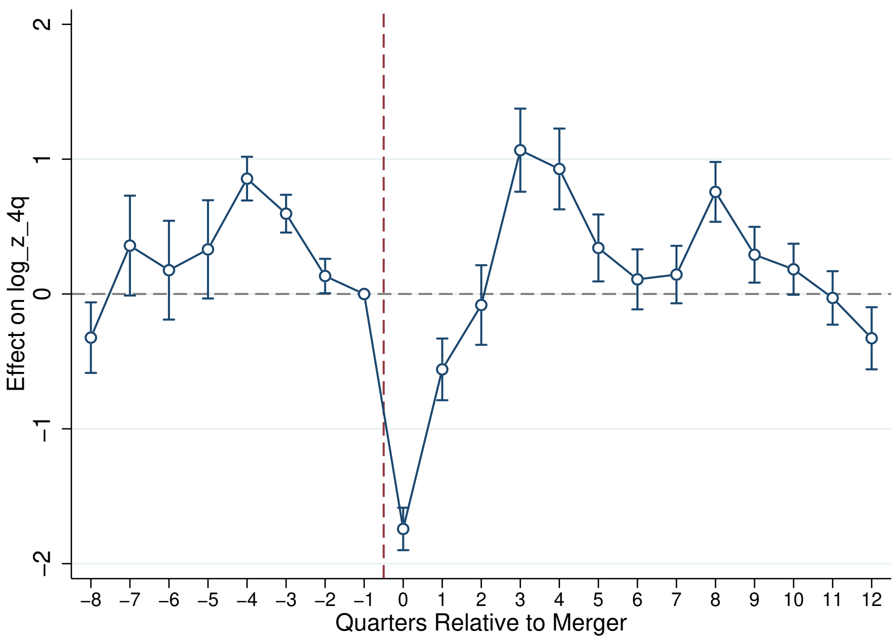


Figure 3.4: Bank-level stability event study: BB&T continuing legal entity

Notes: Event-study coefficients from equation (3.5) with the treatment indicator restricted to the BB&T charter, which is the surviving legal entity that continues as Truist Bank after the merger. Specification matches Figure 3.3 (bank and quarter fixed effects, equity-to-assets-ratio control, standard errors clustered at the bank). The control group is the regional-bank peer panel of banks with 2019 assets in the $10 billion to $1 trillion range. The omitted period is event-time −1; the vertical dashed line marks merger consummation in 2019Q4. We do not report a SunTrust-only counterpart because the SunTrust legal entity was dissolved at consummation, so post-merger coefficients for that treatment are mechanically zero. Data source: FFIEC Call Reports.

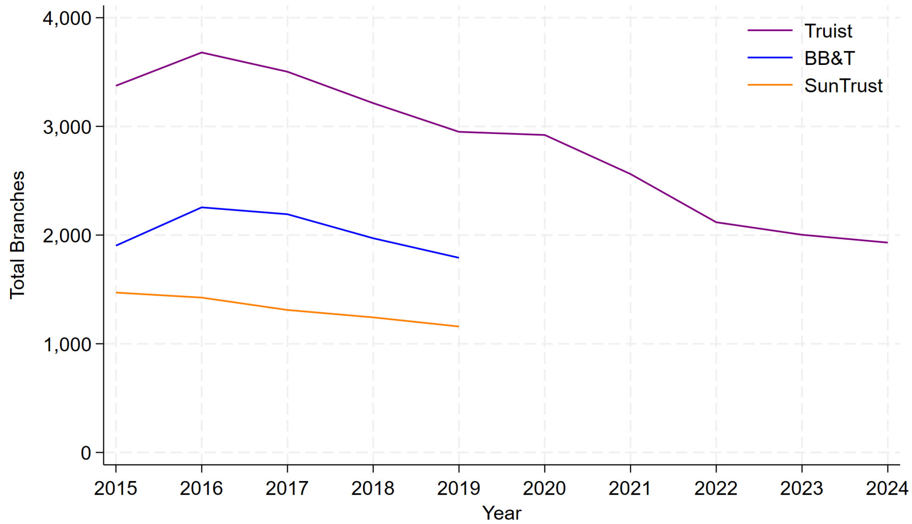


Figure 3.5: Total branches at SunTrust, BB&T, and Truist

Notes: Annual line plot of total branch counts for SunTrust, BB&T, and combined Truist (each series labeled in the legend). The BB&T and SunTrust series end at the December-2019 merger, after which the Truist series begins and declines as branches are consolidated. Data source: Summary of Deposits.

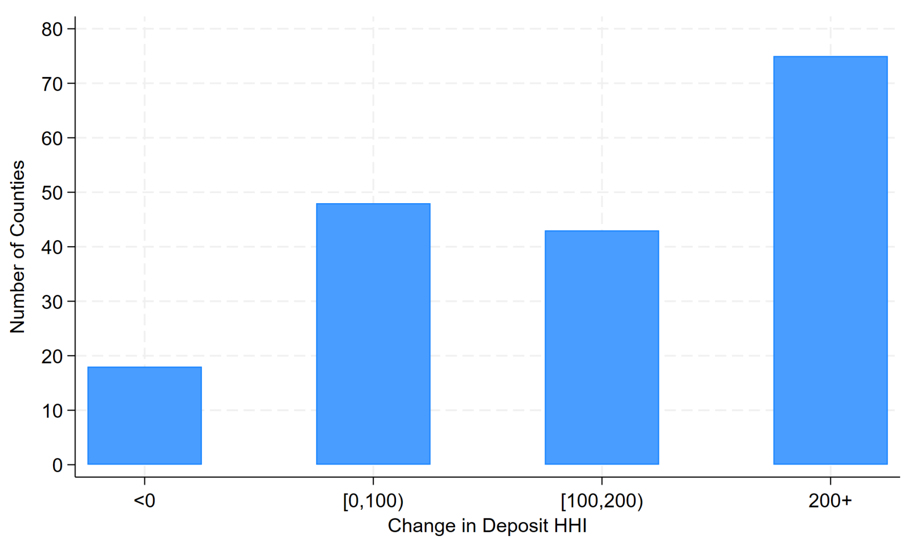


Figure 3.6: Change in deposit HHI in overlapping counties

Notes: Histogram of the change in the Herfindahl-Hirschman Index (HHI) across counties that had branches of both BB&T and SunTrust before the merger. HHI is computed using branch-level deposit shares from the Summary of Deposits (FDIC). The change compares HHI on June 30, 2020 (the year after the merger) to June 30, 2019 (just before the merger); a larger increase indicates a greater reduction in local competition. The majority of overlap counties exceed the 100-point DOJ antitrust threshold. Data source: Summary of Deposits.

Table 3.5: Summary statistics and balance tests for treatment and control groups

	Panel A. Summary Statistics			
	Both	One	Any	None
Deposit Spread	0.929	0.931	0.930	0.957
County HHI	852	1095	987	1421
County Branches	190	202	197	130
County Firms	30.5	33.5	32.2	21.2
Observations	75,053	93,352	168,405	648,865
	Panel B. Differences in Means			
	Both vs. One	One vs. None	Any vs. None	Both vs. None
Deposit Spread	0.002	0.026***	0.027***	0.028***
	(0.007)	(0.005)	(0.004)	(0.005)
County HHI	243***	326***	435***	569***
	(5.572)	(4.877)	(3.769)	(5.440)
County Branches	12.6***	-72.5***	-66.9***	-59.9***
	(1.203)	(1.071)	(0.813)	(1.154)
County Firms	3.0***	-12.3***	-11.0***	-9.3***
	(0.137)	(0.092)	(0.070)	(0.094)
Observations	168,405	742,217	817,270	723,918

Notes: This table reports summary statistics and pre-merger balance across treatment and control groups for each specification. Deposit spread is defined as the federal funds rate minus the deposit rate. County HHI is computed using branch-level deposit shares from the Summary of Deposits (FDIC). County branches and firms measure the number of bank branches and distinct banking firms operating in each county. Treatment groups are defined based on pre-merger presence of BB&T and SunTrust as described in Table 3.1. Data sources: RateWatch, Summary of Deposits. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.6: Branch-level difference-in-differences: auxiliary contrasts (Money Market $10,000)

	(1)	(2)	(3)	(4)
	Panel A. One vs. None			
Treat × Post	-0.065***	-0.008	-0.027***	0.078***
	(0.010)	(0.005)	(0.006)	(0.010)
Observations	761,250	761,227	445,534	315,693
	Panel B. Any vs. None			
Treat × Post	-0.046***	-0.006	-0.021***	0.103***
	(0.008)	(0.004)	(0.005)	(0.009)
Observations	837,575	837,549	518,448	319,101
	Panel C. Both vs. None			
Treat × Post	-0.021**	-0.003	-0.014**	0.227***
	(0.011)	(0.006)	(0.007)	(0.023)
Observations	742,616	742,594	441,624	300,970
Month FE	–	✓	✓	✓
County FE	–	✓	✓	✓
Top-4 competitor sample	–	–	✓	–
No top-4 competitor sample	–	–	–	✓

Notes: Branch-level difference-in-differences estimates on the raw RateWatch panel (no aggregation to the bank-county-year cell) for the Money Market $10,000 product. Sample period 2016–2022, with 2020 dropped as a transition year. Three panels report alternative treatment-control comparisons: One vs. None compares counties served by exactly one of BB&T or SunTrust before the merger to counties served by neither, isolating the bank-wide scale effect; Any vs. None compares counties served by either predecessor to counties served by neither, capturing geographic-footprint exposure; Both vs. None compares overlapping counties to counties served by neither predecessor, combining local-competition and scale margins. Dependent variable is the deposit spread (federal funds rate minus the deposit rate, in percentage points). Column (1) is the OLS specification with no fixed effects; column (2) adds month and county fixed effects; columns (3) and (4) split the sample by the presence of a top-four U.S. bank (JPMorgan Chase, Bank of America, Citi, Wells Fargo) operating in the county. Standard errors are clustered at the county level and reported in parentheses. The leaner control set (only month and county fixed effects) and the larger branch-level sample size differ from the headline market-panel specification in Table 3.2. Data sources: RateWatch, Summary of Deposits.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.7: Pre-merger comparison: Truist vs. control banks

	Truist	Control	Difference	t-stat
Z-score	246.904	402.008	-155.105***	-3.30
Log(Z-score)	5.194	5.896	-0.702***	-4.19
Return on assets	0.003	0.003	0.000	0.16
Equity-to-assets ratio	0.124	0.125	-0.001	-0.13
SD(ROA), 8q	0.001	0.000	0.001***	3.46
Assets (billions)	141	206	-65***	-11.04
Observations	38	314	–	–
Banking firms	2	21	–	–

Notes: This table reports pre-merger summary statistics for Truist banks (SunTrust, BB&T, and Truist Bank) and a tighter pre-merger level-balance control group of regional banks with 2019 assets between $100 billion and $250 billion (n=21 banks), distinct from the broader $10 billion to $1 trillion event-study control panel of 128 banks used in Section 3.3. The sample is restricted to observations prior to the Truist merger (2019Q4). The difference column reports the difference in means (Truist minus Control), and the t-statistic is from a two-sample t-test. Z-scores in this balance table are constructed using an eight-quarter rolling window for the standard deviation of return on assets to smooth the pre-merger level comparison; the event-study analysis in Section 3.3 uses a four-quarter window. Data source: Call Reports.

Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.1: Demand estimates: Money Market $10,000, 2013–2019

	(1) IV (headline)	(2) IV + Cost	(3) Nested-logit IV
Money-market rate	5.927***	8.620***	8.452***
	(1.736)	(0.643)	(0.615)
Log within-nest share	–	–	0.296***
	–	–	(0.024)
Log branches in county	0.726***	0.789***	0.703***
	(0.050)	(0.038)	(0.038)
Log counties served	0.131***	0.185***	0.162***
	(0.035)	(0.014)	(0.014)
County branch share	4.252***	4.111***	2.946***
	(0.181)	(0.190)	(0.195)
Large bank indicator	0.108***	0.094***	0.183***
	(0.019)	(0.023)	(0.024)
Log Z-score (4-quarter avg.)	0.010*	0.017**	0.011*
	(0.006)	(0.007)	(0.006)
Fixed effects	county_year	county_year	county_year
Excluded IV set	ln rival county footprint	+ cost shifters	+ cost shifters
Kleibergen-Paap Wald F	22.86	34.10	33.84
Observations	59,360	59,304	59,304

Notes: Logit IV demand estimates for the Money Market $10,000 product, estimated on the bank-county-year market panel for 2013–2019 (pre-merger). Dependent variable: logit mean utility, $\delta_{jmt} = \log s_{jmt} - \log s_{0mt}$. Bank and market controls are the log of bank-j branches in county m, the log of the number of counties in which bank j operates, the within-county branch share, an indicator for banks with assets above $10 billion, and the log Z-score (4-quarter rolling) as a stability control. Column (1) is the headline IV specification using a single just-identified instrument: the leave-one-out log of the number of counties served by rival banks in the same market ("log rival county footprint"). Columns (2) and (3) add the equity-to-assets ratio, log non-interest expense over assets, and log assets per employee as cost-shifter instruments; column (3) further adds the log within-nest share as a second endogenous variable in a nested-logit specification. All specifications include county and year fixed effects. Standard errors clustered at the county-year level. The OLS benchmark and Hansen J over-identification statistic are not reported: OLS is severely downward-biased in this setting because banks adjust rates in response to local demand shocks; the Hansen J rejects in the over-identified specifications, which we attribute to mild violations of the constant-elasticity restriction across rival-sum and cost-shifter channels rather than to the headline single-IV column being unrepresentative. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C Structural Model: Implementation and Robustness

This appendix reports the full demand-estimation tables, implementation details for the no-merger counterfactual, robustness across alternative pre-merger demand windows, and a forward counterfactual for the savings product.

Demand Estimation Table

Table 3.1 reports the headline demand specification for the Money Market $10,000 product referenced throughout the structural section. The table reports three columns: an instrumental-variables specification using BLP-style rival sums as excluded instruments, the IV specification augmented with cost shifters, and a nested-logit version with county-defined nests.

Demand Estimation Robustness Across Windows and Specifications

Table 3.2 reports the demand estimates for the headline Money Market $10,000 product across alternative pre-merger windows (varying the start year) and across the three IV specifications (single-IV headline, IV plus cost shifters, nested-logit IV with within-nest log share). The own-rate coefficient $\hat{\alpha}$ is positive and significant in every cell, with magnitudes in the 4–9 pp range that are stable to the choice of window and specification. The Kleibergen–Paap first-stage F exceeds the Stock–Yogo 10% threshold (approximately 16) in every cell.

Table 3.2: Demand estimates: robustness across pre-merger windows and IV specifications, Money Market $10,000

	2013–2019	2014–2019	2015–2019	2016–2019
Panel A: Headline IV (single rival county footprint)				
Rate coef.	5.927***	6.006***	4.776***	3.713***
(SE)	(1.736)	(1.881)	(1.583)	(1.269)
Log branches in county	0.726***	0.721***	0.698***	0.685***
KP–F	22.86	19.19	18.27	21.22
Obs	59,360	50,229	41,288	32,696
Panel B: IV + Cost shifters				
Rate coef.	8.620***	7.130***	8.496***	8.457***
(SE)	(0.643)	(0.475)	(0.639)	(0.755)
Log branches in county	0.789***	0.746***	0.793***	0.831***
KP–F	34.10	34.77	23.33	17.70
Obs	59,304	50,180	41,244	32,661
Panel C: Nested-logit IV				
Rate coef.	8.452***	6.621***	7.940***	7.961***
(SE)	(0.615)	(0.428)	(0.580)	(0.689)
Log branches in county	0.703***	0.657***	0.699***	0.733***
KP–F	33.84	34.77	23.17	17.33
Obs	59,304	50,180	41,244	32,661

Notes: Logit IV demand estimates for the Money Market $10,000 product, varying the pre-merger demand window (start year) across columns and the IV specification across panels. Panel A is the headline single just-identified instrument (leave-one-out log of the number of counties served by rival banks in the same market). Panel B adds the equity-to-assets ratio, log non-interest expense over assets, and log assets per employee as cost-shifter instruments. Panel C adds the log within-nest share as a second endogenous variable in a nested-logit specification, with nests defined by the large-bank indicator. All specifications include county and year fixed effects and the same bank-network controls as Table 3.1. Standard errors clustered at the county-year level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Counterfactual Implementation

The counterfactual simulation is implemented with the `mergersim` package of Björnerstedt and Verboven (2016), which inverts the multinomial-logit first-order conditions to recover firm-level marginal costs from observed prices and shares and then solves the post-merger Bertrand–Nash equilibrium under the counterfactual ownership structure. We hold the demand parameters fixed at the pre-merger estimates and recover marginal costs from observed Truist prices using the merged-firm first-order conditions at each post-merger year. The no-merger equilibrium is solved by re-imposing separate BB&T and SunTrust ownership through the `newfirm()` option of `mergersim simulate`. Each post-merger Truist branch is attributed to its 2019 legacy entity (BB&T or SunTrust) using Summary of Deposits branch records: a branch is assigned to the predecessor that owned it in the June 2019 SOD release. County-year cells in which both predecessors had branches are split proportional to their 2019 deposit shares.

Forward Counterfactual by Product

Table 3.3 reports the no-merger counterfactual for the savings $2,500 product.

Table 3.3: No-merger counterfactual by year, Savings $2,500

	2020	2021	2022	2023
Δ rate, merged (pp)	0.0073	0.0072	0.0063	0.0031
Δ rate, rivals (pp)	0.0026	0.0025	0.0024	0.0009
N obs	34,155	34,155	34,155	34,155
Converged	1	1	1	1

Notes: No-merger counterfactual for the Savings $2,500 product, with one column per post-merger year. Demand parameters are estimated on the pre-merger 2013–2019 sample using the same single-IV specification as the headline Money Market $10,000 demand model and held fixed across the post-merger years. Marginal costs are recovered from observed Truist post-merger prices and shares using the merged-firm Bertrand–Nash first-order conditions at year t, and the counterfactual equilibrium is solved under separate BB&T and SunTrust ownership using the legacy attribution from 2019 Summary of Deposits branch records. Reported quantities: implied counterfactual rate change for the merged firm and for non-merging rivals (in percentage points), the simulation sample size, and a convergence indicator. Implementation details are in Appendix C. Implied rate effects on the savings product are small and slightly positive, indicating a near-zero competition effect of the merger in this product. Data sources: RateWatch, Summary of Deposits, FFIEC Call Reports.

Counterfactual Robustness Across Pre-Merger Demand Windows

Table 3.4 reports the no-merger counterfactual for the Money Market $10,000 product when the pre-merger demand sample is varied across alternative start and end years.

Table 3.4: Merger simulation results by pre-merger window, Money Market $10,000

	2013-2019	2014-2019	2015-2019	2016-2019	2016-2020	2016-2021	2016-2022	2016-2023
Δ rate, merged (pp)	-0.0088	-0.0093	-0.0122	-0.0252	-0.0232	-0.0103	-0.0113	-0.0070
Δ rate, rivals (pp)	-0.0002	-0.0002	-0.0003	-0.0007	-0.0006	-0.0003	-0.0003	-0.0002
N obs	63,163	53,428	43,982	34,850	42,974	50,789	58,417	65,912
Converged	1	1	1	1	1	1	1	1

Notes: No-merger counterfactual for the Money Market $10,000 product. Each column corresponds to a different pre-merger demand-estimation sample. Start years vary from 2013 to 2016 with the end year held at 2019, and end years vary from 2019 to 2023 with the start year held at 2016. Demand parameters are estimated on the indicated window using the headline single-IV specification of Table 3.1 and held fixed when computing the counterfactual at the 2019 baseline. Marginal costs are recovered from observed Truist post-merger prices and shares using the merged-firm Bertrand–Nash first-order conditions; the counterfactual is solved with separate BB&T and SunTrust ownership using the legacy attribution from 2019 Summary of Deposits branch records. Reported quantities: implied rate change for the merged firm and for rivals (in percentage points), the simulation sample size, and a convergence indicator. Implementation details are in Appendix C. Data sources: RateWatch, Summary of Deposits, FFIEC Call Reports.

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