Diverging Banking Sector: New Facts and Macro Implications*

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Abstract

We document the emergence of two distinct types of banks over the past decade: high-rate banks, which set deposit rates to match market rates, hold shorter-term assets, and earn a spread through higher credit risk in personal and business loans; and low-rate banks, which offer low, stable deposit rates, hold longer-term assets, like MBS, and lend less to firms. This divergence shifts deposits toward high-rate banks during monetary tightening, reducing the banking sector's maturity transformation capacity and concentrating credit risk among high-rate banks. Technological advancements appear to drive this trend: high-rate banks operate primarily online and attract rate-sensitive, less-sticky depositors.

Keywords: banking, monetary policy, interest rate risk, credit risk

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1 Introduction

Heterogeneity in deposit rates across banks has increased substantially over the past 15 years. For example, JP Morgan Chase, US Bank, Wells Fargo and Bank of America pay virtually zero interest on savings accounts, while Goldman Sachs, Citi, Ally, and Capital One offer nearly 450 basis points as of June 2024, shown in Table 1. This heterogeneity in deposit rates is a new feature—in 2006, when market interest rates were similar to today's levels, the spread between the 75th and 25th percentiles of deposit rates among the top 25 banks was around 70 bps. Today, that spread has widened to over 350 basis points. The bimodal distribution of deposit rates highlights the existence of two distinct types of banks: high-rate banks, which offer deposit rates close to market rates, and low-rate banks, which maintain low, market-insensitive deposit rates.

These two types of banks have diverged not only in the deposit rates they offer but also in their distinct business models. To show this, we focus on large systemically important banks—the 25 largest banks as classified by the Federal Reserve's H.8 report—and categorize those ranked in the top tercile by deposit rates as high-rate banks.[1] High-rate banks operate with far fewer physical branches and engage far less in maturity transformation—they hold fewer long-term real estate loans and hold shorter maturity securities that match the duration of their deposits. However, these banks earn a larger lending spread by taking on greater credit risk, primarily through personal and commercial and industrial (C&I) lending. As high-rate banks have gained prominence over the past 10 to 15 years, we have observed a significant shift in the behavior of low-rate banks. Specifically, we show that low-rate banks now offer deposit rates that are lower and significantly less responsive to changes in interest rates than in the past. Additionally, they have markedly reallocated their assets, reducing lending to businesses and personal lending in favor of holding safer, long-duration securities.

Recognizing the emergence of these two types of banks is important for understanding the transmission of monetary policy, the banking sector's capacity for maturity transformation, and its ability to continue providing liquidity and credit to the economy. Monetary policy affects the distribution of deposits between these banks: when rates rise, the rate gap between high-

[1] We primarily concentrate on the largest 25 banks for several key reasons. First, we follow the Federal Reserve's definition of large banks, as outlined here, with one key modification: we focus on the bank holding company, which ultimately sets the deposit rate (see Ben-David, Palvia and Spatt (2017)). Notably, our findings remain robust even when we perform the analysis at the individual bank level. Second, these banks make up 70% of aggregate bank assets due to a highly skewed size distribution (see Appendix Figure B.1), and thus the influence of the largest banks is disproportionately significant in shaping macroeconomic implications. Third, small banks are regulated very differently than large banks. Fourth, as shown by d'Avernas et al. (2023), small banks and large banks have different business models throughout the sample, while we show large banks behave very similar before 2009. We show our results are robust when extending the analysis to include the top 100 banks, which account for 85% of total bank assets.

and low-rate banks widens, prompting deposits to shift towards high-rate banks. These high-rate banks disproportionately channel the inflow of deposits to riskier lending, such as personal and C&I loans. Thus, tighter monetary policy does not necessarily reduce credit supply to the real economy. Additionally, these banks tend to hold shorter-maturity assets—on average three years shorter than low-rate banks—which reduces the extent of maturity transformation performed by the banking sector. Should deposits continue to shift toward high-rate banks, especially in a prolonged high-interest-rate environment, the banking sector's ability to absorb interest rate risk may weaken considerably, while credit risk could become increasingly concentrated within high-rate banks. This shift could affect the overall risk profile and stability of the banking system.

What explains the emergence of these two types of banks? Our findings are consistent with the technology mechanism proposed and causally identified by Jiang, Yu and Zhang (2022). They argue that digital disruption allows banks to operate without physical branches, driving divergent strategies in branch operations and deposit rate setting.[2] Consistently, we observe that, since 2009, high-rate banks, have experienced a 75% greater reduction in the number of branches compared to low-rate banks, accompanied by a 64% decline in branch-to-deposit ratio. This trend coincides with the rapid growth of e-banking services, marked by a surge in Google searches for mobile banking apps, starting in 2009. Additionally, high-rate banks invest more in IT and often locate their fewer branches in demographically younger counties, indicating a younger customer base.

With lower operational costs and less dependency on location-based competition, high-rate banks offer deposit rates that more closely mirror market interest rates. However, because their rates fluctuate significantly with market changes, these banks maintain significantly shorter duration assets. Despite earning a modest deposit spread, high-rate banks take on substantial credit risk to maintain a high net interest margin. Over the past decade, the average credit spread of high-rate banks, defined as the difference between loan rates and maturity-matched Treasury yields, has been approximately 80 basis points higher than that of low-rate banks. Additionally, charge-offs on loans and leases for high-rate banks have been three times those of low-rate banks during the same period.

While the growing heterogeneity in the banking sector is partly driven by the rise of high-rate banks, a significant portion also reflects the changing behavior of low-rate banks. For instance, low-rate banks previously had a CD rate sensitivity of around 0.68, meaning they passed along 68 basis points for every 100 basis point increase in the Federal Funds rate. This sensitivity has now dropped

[2] Specifically, Jiang, Yu and Zhang (2022) show that the rollover of 3G network infrastructure results in the divergence of deposit rate strategies among banks. The study finds that, following the 3G expansion, banks with reduced reliance on branches close branches and target tech-savvy customers, while banks maintaining a strong branch network pivot towards serving branch-captive consumers. Consequently, the former group offers higher deposit rates to attract tech-savvy consumers, while the latter group offers lower rates, extracting rents from branch-captive consumers.

to approximately 0.15, with low-rate banks passing only 15 basis points to depositors during recent rate-hiking cycles. As a result, their deposits behave more like fixed-rate liabilities, leading these banks to hold *longer*-duration and safer securities than before. One possible explanation for this shift is that as some banks transition to online operations, low-rate banks that maintain physical branches tend to retain depositors who value in-person banking services, resulting in a stickier depositor base. This allows them to charge higher markups in the form of even lower deposit rates that are insensitive to fluctuations in market interest rates. Alternatively, as low-rate banks in our sample offer both online services and physical branches, they may incur higher marginal costs, which compels them to offer lower deposit rates. However, when examining non-interest expenses, we do not find evidence of higher costs.

The diverging patterns we document could be driven both by existing banks changing their business model as well as changes in the composition of the top 25 banks. Our findings indicate that both composition changes and within-bank strategy adjustments have significantly contributed to the emerging divergent patterns. Furthermore, while our study centers on the top 25 banks, our findings can be generalized to the top 100 banks. In addition, we show robustness of our results to using only realized deposit rates (interest expense), as well as using deposit rates from RateWatch. Our main measure classifies high- and low-rate banks based on the entire sample period, and is, thus, persistent and avoids issues of switching. However, our main findings are robust to categorizing high- and low-rate banks on a quarterly basis, thereby allowing banks to switch types more frequently.

While our evidence suggests that e-banking services are the primary driver of the banking sector's divergence, we address concerns about the potential influence of the 2008 Financial Crisis. To explore alternative explanations, we focus on regulatory changes and liquidity injections from the Federal Reserve. Our findings indicate that these factors are insufficient to explain the observed divergence.

To rationalize our findings, we provide a simple model in the style of Salop (1979) and Allen and Gale (2004). We examine the strategies of two banks competing for deposits while offering loans with differing risk profiles. Depositors prefer in-person services and value proximity to branches. In equilibrium, the two banks locate at opposite ends on a circle and offer identical deposit rates lower than the market rate, thereby earning rents from depositors' valuation of branch accessibility. We then introduce "e-banking," a service independent of physical location that enhances depositor utility through convenience. In response to this new technology, both banks integrate e-banking into their service offerings. However, when operating branches is relatively costly, a divergent banking sector emerges; one bank transitions entirely to an e-banking model, raising its deposit rates to attract a broader depositor base but earning lower rents per depositor. In contrast, the other bank maintains its branches to cater to depositors who prioritize location, thus securing higher rents per depositor through lower deposit rates. This generates a deposit rate spread between the two banks, as in the data, driving deposit flows toward the e-bank. Turning to the asset side, the branch-retaining bank opts for a less risky loan portfolio, aiming to safeguard the rents earned from its depositors. In contrast, the e-bank, which gathers lower rents from its depositors, pursues riskier loans to achieve higher yields. This divergence mirrors empirical trends in branch operations, deposit rates, and lending strategies.

The emergence of a diverging banking sector carries several macroeconomic implications. First, it affects how monetary policy is transmitted through the banking sector. Traditionally, as Drechsler, Savov and Schnabl (2017) highlights, rising interest rates lead to deposit outflows from banks to money market funds, resulting in an overall contraction in bank lending. However, our analysis reveals a more nuanced dynamic within a bifurcated banking sector. During periods of monetary tightening, we find that deposit outflows disproportionately impact low-rate banks. In response, low-rate banks primarily divest their long-term but relatively safe holdings, such as mortgage-backed securities (MBSs). Quantitatively, a 1 percentage point increase in the Federal Funds rate induces low-rate banks to reduce their MBS share by 0.6%. In contrast, high-rate banks with larger portfolios of personal and C&I loans expand lending. Specifically, a 1 percentage point hike in the Federal Funds rate leads to a 0.5% and 0.3% increase in the shares of personal and C&I loans, respectively, among high-rate banks. This happens because high-rate banks provide attractive deposit rates when interest rates rise, potentially drawing in more deposits and allowing them to expand their focused lending activities. We also demonstrate that these results are not primarily driven by increased loan demand from households and businesses, as the lending spreads for these loans remain relatively stable even as their quantities grow. Collectively, these results reveal that while tighter monetary policy leads low-rate banks to reduce their securities holdings, it paradoxically prompts high-rate banks to expand their credit offerings to households and businesses.

This perspective also sheds light on why, despite the sharp interest rate increases by the Federal Reserve since 2022, a substantial credit crunch has not materialized. These increases were accompanied with annual deposit outflows surpassing 8%, the highest since 1973. Despite these outflows, credit availability has remained stable. This stability arises from rate hikes disproportionately affecting low-rate banks, leading to reductions in their holdings of Treasuries and agency MBSs. In contrast, high-rate banks experienced minimal deposit outflows, enabling them to maintain lending to households and businesses with little disruption. Therefore, monetary policy is expected to have a stronger impact on the mortgage market, while exerting a comparatively milder effect on personal and business loans moving forward.

Second, as deposits shift from low-rate to high-rate banks, it alters the overall capacity of the banking sector to engage in maturity transformation and to provide loans to households and businesses. A back-of-the-envelope calculation indicates that with a 10% shift of deposits from low-rate to high-rate banks, the banking sector as a whole tends to originate loans and securities with maturities that are approximately 5% shorter and assumes about 8% higher credit risk. This redistribution not only affects the risk profile and hence the stability of the banking sector but also its fundamental ability to meet the maturity transformation needs of the economy.

Understanding this shift is especially relevant today as more banks choose to operate without physical branches, engaging in intense competition over deposit rates. This is largely driven by the preferences of younger customers, who are more sensitive to interest rates and place less importance on in-person banking services (Jiang, Yu and Zhang, 2022). As the banking sector increasingly adopts this model, the capacity for maturity transformation—a critical function in the financial system—could be substantially reduced.

Third, our paper has implications for risk in the banking system. Our findings indicate that banks with diverging strategies exhibit distinct risk profiles: low-rate banks are more vulnerable to interest rate risk, while high-rate banks are more exposed to credit risk. Although both types of risk can precipitate bank runs, they materialize under different economic conditions.

Related Literature Our paper contributes to several strands of the literature. First, our paper contributes to our understanding of monetary policy transmission through the banking sector. The literature highlights several channels through which monetary policy passes through banks: the bank lending channel (e.g., Bernanke and Blinder, 1988; Kashyap and Stein, 1994), bank capital channel (e.g., Bolton and Freixas, 2000; Van den Heuvel et al., 2002), and deposit market power channel (e.g., Drechsler, Savov and Schnabl, 2017). Traditional studies on monetary policy transmission often treat the banking sector as homogenous, focusing on aggregate deposit quantities. This perspective suggests that rising interest rates lead to a net outflow of deposits and hence reduced bank lending. Our findings reveal a more nuanced dynamic within the banking sector. Beyond aggregate measures, we examine the heterogeneous impact of interest rate changes on deposit flows across two distinct bank types: low-rate and high-rate banks. These banks diverge not only in their liability management but also in their asset portfolios. When market rates rise, deposits tend to migrate from low-rate banks to high-rate banks, supporting lending to personal and C&I loans, which high-rate banks increasingly originate. This is related to Supera (2021) which finds that tighter monetary policy increases the supply of time deposits that fund business loans. In contrast, we find that lending to real estate loans and MBSs declines due to deposit outflows from low-rate banks. These diverging patterns suggest that, due to a pronounced response in low-rate banks' deposit flows to policy rate changes, monetary policy has a stronger effect on real estate markets but a reduced impact on personal and commercial lending today. This highlights the limitations of aggregate deposit flow analysis and emphasizes the need to account for intra-bank heterogeneity in assessing banks' capacity for maturity transformation, liquidity provision, and credit supply.

While recent research has highlighted the distinct behavior of FinTech banks in response to monetary policy, existing research presents contrasting views. Koont, Santos and Zingales (2023) suggest digital banks, identified by having mobile applications with more than 300 reviews, experience deposit outflows despite competitive rates due to "flighty" clientele.[3] In contrast, Erel et al. (2023) examine a sample of purely online banks and find that these banks offer higher rates and attract more deposits when interest rates rise. Our findings align more closely with those of Erel et al. (2023), though our focus is on a sample of very large banks, thereby complementing and extending their insights. We also observe significant changes among low-rate banks, which have begun to offer less sensitive deposit rates and hold safer, longer-term securities. The substantial migration of deposits away from low-rate and systematically important banks during rate hikes highlights potential fragility in the banking sector, as discussed in recent studies by Haddad, Hartman-Glaser and Muir (2023) and Drechsler et al. (2023).

We broadly examine the impact of digital disruption within the banking sector. Prior research, such as Buchak et al. (2018), has shown how regulatory arbitrage has fueled the rapid expansion of shadow banks. In contrast, we focus on how technology is transforming traditional banks themselves. Jiang, Yu and Zhang (2022) illustrate how digital disruption drives branch closures, leading to divergent strategies in branch operations and deposit rate setting. While some banks continue to leverage physical branches to charge higher rates on deposits and loans, others operate remotely, offering lower-cost services. This shift has substantial implications for financial inclusion. Similarly, Haendler (2022) find that small community banks are slow to adopt mobile banking, resulting in losses of deposits and small business lending. Meanwhile, Koont (2023) demonstrate that mid-sized banks see faster growth and attract more uninsured deposits following mobile banking adoption. Our paper complements these studies by presenting new evidence on the diversity of asset and liability management practices across banks and discussing the broader implications for monetary policy effectiveness, maturity transformation, and credit supply to households and businesses.

Our paper contributes to our understanding of heterogeneity within the banking sector.

[3] Our analysis focuses on the largest 25 banks, all of which provide online and mobile banking services. By Koont, Santos and Zingales (2023)'s classification of digital banks, all top 25 banks, with their popular mobile apps, would qualify as digital.

While existing literature has extensively examined the distribution of deposit rates within banks (e.g., Radecki, 1998; Heitfield, 1999; Biehl, 2002; Heitfield and Prager, 2004; Park and Pennacchi, 2008; Granja and Paixao, 2021), less attention has been paid to the distribution of deposit rates across banks. Recent research by Iyer, Kundu and Paltalidis (2023) explores the heterogeneity in deposit rates across banks within a region, suggesting that greater variation in deposit rates reflects a gradual buildup of liquidity shortages. Expanding on this view, our study finds that the banking sector has exhibited increased heterogeneity in deposit rates. This finding complements the work of d'Avernas et al. (2023), which highlights variation in deposit pricing behavior between large and small banks. Beyond deposit rate heterogeneity, banks also differ significantly in deposit and asset productivity (Egan, Lewellen and Sunderam 2022), uninsured deposit share, and consequently, bank-run likelihood (Egan, Hortaçsu and Matvos, 2017). For example, recent research by Benmelech, Yang and Zator (2023) demonstrates that banks with low branch density attract more uninsured depositors, leading to a higher risk of bank runs during the 2022 banking crisis. In contrast to these studies which focus on specific aspects of bank heterogeneity, our study provides a comprehensive perspective on the dynamics of banks' business models over recent decades, connecting both the liability and asset sides of banks' balance sheet.

Lastly, we provide a new perspective on the banking sector. Hanson et al. (2024) show that banks are increasingly resembling bond funds that invest in long-term securities. Our findings indicate that this trend is predominantly observed among low-rate banks. Furthermore, it is important to emphasize that high-rate banks should not be confused with money market funds, which also tend to experience inflows when interest rates rise (Xiao, 2020). In fact, it is the high-rate banks that engage in lending activities. In summary, our findings suggest that high-rate banks conduct traditional banking practices—they take deposits and lend to risky businesses, while low-rate banks function more like long-term bond funds.

2 Motivating Fact: Divergence in Deposit Rates

We start by highlighting a notable trend in banking over the past two decades: the growing dispersion of deposit rates. Before 2009, deposit rates among large banks were relatively uniform, as indicated by a low standard deviation. However, the subsequent period has experienced a significant transformation. Today, deposit rates exhibit a bimodal distribution, characterized by two distinct peaks and an economically large spread between them.

Figure 1 illustrates the dispersion of bank deposit rates for the 25 largest banks in 2006Q3, 2019Q1, and 2023Q4, the peak of three recent rate cycles. We use two measures of deposit rates:

the 12-month certificate of deposit rate ("CD rate")—the most widely offered deposit product from the RateWatch database—and the interest expense rate on deposits ("DepRate"), calculated using data from the Call Report. In 2006Q3, deposit rates exhibited a unimodal distribution, with similar mean and median values, and low standard deviation.[4] However, the subsequent rate cycles in 2019Q1 and 2023Q4 reveal a shift towards bimodality, with divergent mean and median values. The divergence is quantitatively very large: from 2006Q3 to 2023Q4, the standard deviation of the CD rate more than tripled from 0.53 to 2.02.

While the distributions reveal a noticeable disparity in deposit rates across banks, a potential concern is whether the variability in rates signifies a systematic shift or is influenced by a few small banks offering exceptionally high-rates. We examine the allocation of bank assets corresponding to various measures of CD rates relative to the sample average: below 0.75 times the average, between 0.75 and 1.25 times the average, and above 1.25 times the average. Figure 2 illustrates a significant shift in the distribution of banks' asset shares. Prior to 2009, more than 70% of bank assets were associated with rates close to the sample average. However, by the fourth quarter of 2023, this landscape had changed dramatically: assets linked to banks offering rates between 0.75 and 1.25 times the average dropped to just 4%, while 74% of assets were tied to rates below 0.75 times the average, and 22% were linked to rates above 1.25 times the average, as classified in panel (a) according to CD rates. A similar trend emerges from the DepRate classification in panel (b).[5] Furthermore, the divergent patterns in deposit rates are evident across the entire banking spectrum over an extensive sample period, as shown in Appendix Figures B.2 and B.3.

In fact, this divergence in deposit rates is accompanied by significant differences in banks' business models, particularly regarding branch operations, lending behavior, and asset allocation. Section 3 describes the data and methodology of this analysis. Section 4 documents the widening divergence of business models among banks over the years. Section 5 then investigates the impact of this growing disparity on two key aspects: the transmission of monetary policy and the risk-taking capacity of the banking sector as a whole. To strengthen these findings, Section 6 delves into potential alternative explanations and conducts robustness checks on our findings. Finally, in Section 7, we introduce a simple theoretical framework to illuminate the economic forces driving this bank divergence phenomenon.

[4] In 2006Q3, the average Federal Fund rate was 525 basis points. Among the top 25 banks, the average CD rate was 397 basis points, with a corresponding median of 394 basis points; and the average DepRate was 301 basis points, with a corresponding median of 299 basis points.

[5] The asset share of banks offering deposit rates between 0.75 and 1.25 times the market average declined from 82% in the pre-2008 period to 42% by the end of the sample period.

3 Data and Methodology

In this section, we describe the data and methodology used in our analysis. Our sample spans from 2001Q1 through 2023Q4, encompassing three rate-hiking cycles: 2004Q3-2007Q4, 2015Q4-2019Q4, and 2022Q1-2023Q4.[6]

3.1 Data

Bank data. Our analysis utilizes quarterly balance sheet data of FDIC-insured banks from the FDIC's Statistics on Depository Institutions (SDI) and Call Reports, spanning 2001Q1 to 2023Q4. We aggregate this data to the bank holding company (BHC) level using RSSDHCR as the identifier, or RSSDID for standalone banks. This approach differs from directly sourcing BHC Y-9 reports, which include non-banking subsidiaries. In constructing growth variables, we account for mergers and acquisitions (M&As), using data from the Federal Financial Institutions Examination Council's (FFIEC) National Information Center. This ensures our growth calculations are not distorted by consolidation activities. For a comprehensive exposition of our data construction process and variable definitions, readers are directed to Appendix A.

Deposit rates. We source weekly surveyed deposit rate data from the RateWatch database, provided by S&P Global, covering the period from 2001Q1 through 2023Q4.[7] The data cover various deposit products, including certificate deposits with different maturities, saving accounts, and money market accounts. Our primary focus is the deposit rates of 12-month certificate deposit accounts with a minimum of $10,000 ("CD rate"). The CD rate exhibits the highest correlation with DepRate, which reflects the average cost of deposits for banks, computed from the call reports.[8] Additionally, we supplement the CD rate with the rate of saving accounts ("SAV rate"), which constitute the largest category of deposits among time, demand, and saving deposits. To ensure accurate data and reduce potential biases from misreporting, we calculate the CD and SAV rates at the BHC level in a two-step process. First, we calculate the average rate for each branch. This step helps mitigate the influence of potential outliers or branch-specific reporting discrepancies. Then, we aggregate this data to the BHC-quarter level by averaging the branch-level rates within each BHC. This approach

[6] We define each cycle as starting in the first quarter when the Federal Funds rate begins to rise and ending two quarters after the cycle's peak.

[7] While this data is collected weekly, it's important to note that banks contribute this information voluntarily, resulting in only about 50% of banks providing data.

[8] Panel B of Table B.2 reports a robust correlation of 0.91 between the CD rate and DepRate. Other deposit products exhibit slightly weaker correlations with DepRate: the correlation between DepRate and MM rate (for $25,000 money market deposit accounts) is 0.82, while the correlation between DepRate and SAV rate is 0.65.

provides a more robust and representative picture of rate setting activity across the BHC.[9]

Branch data. We obtain branch-level bank deposit information from the FDIC. The FDIC administers an annual survey that encompasses all FDIC-insured institutions. The survey, known as the *Summary of Deposits* (SOD), compiles data on a branch's deposits and the corresponding parent bank information as of each June 30th.

Demographics data. To understand the demographic characteristics of bank customers, we use the US Census county-level data to calculate the average customer age of a bank by weighting the average county age of a bank by the number of branches in each county. We also use household survey data from the FDIC Survey of Consumer Use of Banking and Financial Services to examine the characteristics of households that use bank tellers versus e-banking.

3.2 Methodology

We identify and analyze the emergence of two distinct categories within systemically important banks, exploring their impact on macroeconomic dynamics. We categorize banks based on deposit rates into high and low-rate types and then examine how related factors such as branch operations, asset allocation, loan portfolio risk profiles, and monetary policy transmission have evolved for each group.

It is important to note that our use of deposit rates for classification does not imply causality with other operational decisions, all of which we recognize as endogenous choices made by banks. Indeed, in the stylized model presented in Section 7, deposit rates are endogenous to risk-taking. Nevertheless, deposit rates are a useful metric for classifying banks primarily due to their frequent updates and reliable empirical measurement, making them a timely and observable criterion for distinguishing between different banking models. In Section 6.1.1, we explore various potential drivers of this divergence and find that the proliferation of e-banking likely serves as the primary catalyst.

In our main analysis, we focus on the largest 25 Bank Holding Companies (BHCs) based on quarterly total assets, following the Federal Reserve's definition of large banks, as detailed here.[10]

[9] Appendix Table B.1 indicates that deposit rates are primarily determined at the BHC level. BHC fixed effects alone explain as much of the variation in deposit rates as bank-level fixed effects.

[10] To ensure a stable and consistent sample, we identify top 25 banks based on their quarterly ranking, requiring a bank to remain in the top 25 for four consecutive quarters before inclusion. This approach addresses the issue of fluctuations where banks may temporarily reach the top 25 but then drop out. This year-long criterion ensures we focus on banks with sustained systemic significance.

These BHCs are classified into high-rate and low-rate types, with the classification methodology detailed in the following section. We then aggregate and analyze time-series patterns of various characteristics for each bank type. To assess the significance of observed differences, we employ the following specification:

$$Y_{i,q} = \delta_q + \alpha \cdot \mathbb{1}(\text{High-rate}_i) + \beta \cdot \mathbb{1}(\text{High-rate}_i) \times \text{Post}_q + \text{Controls}_{i,q-1} + \varepsilon_{i,q}. \tag{1}$$

where i and q indicate the bank and quarter-year, respectively, $\mathbb{1}_{\text{High-rate}_i}$ denotes whether bank i is a high-rate bank, and Post_t denotes the post-2009 period. We include two control variables—return on assets and the Tier 1 and 2 capital ratios from the previous quarter. Observations are weighted by the asset size from the previous quarter, ensuring the estimated effects accurately reflect the aggregate impact across the designated bank types. We use Driscoll-Kraay standard errors, clustering at the quarterly frequency to account for heteroskedasticity, cross-sectional dependence, and we use a lag length of 4 quarters to account for autocorrelation.

Since we are examining diverging patterns, both α and β are important for interpretation. The α coefficient represents the difference in $Y_{i,q}$ between high- and low-rate banks prior to 2009, while β measures the divergence relative to the pre-2009 period. Divergence is confirmed if α is insignificant and β is significant, or if both coefficients are significant with the same sign. Conversely, if both coefficients are significant but with opposite signs, it indicates divergence before 2009 and convergence thereafter.[11]

We choose 2009 as our cutoff year, as Figure 2 reveals a clear divergence in bank types based on deposit rates starting from that year. This period also coincides with the advent of e-banking services, which we argue likely contributed to the observed divergence. In Section 6.3, we thoroughly examine the robustness of our cutoff choices, and expand the analysis to include a broader set of banks and extend the sample period.

3.3 Classification of High- and Low-rate Banks

We aim to establish a consistent classification for each bank throughout the sample period to avoid biases due to time-varying misclassifications, which are more likely to occur before 2009 due to the smaller dispersion in deposit rates, as shown in Figure 1.[12] This process involves three steps.

[11] Note that β alone does not specify which bank type primarily drives this divergence, as both categories are likely to adapt their strategies over time. Time-series plots provide a visual representation of the distinct adjustments each type of bank has implemented.

[12] Misclassifications can significantly bias our estimated β. For instance, if bank A is consistently a high-rate bank and bank B a low-rate bank, yet bank A is misclassified as low-rate pre-2009 and correctly as high-rate post-2009, then β from the regression would reflect this misclassification rather than true strategic evolution between A and B.

First, we rely on both the CD and DepRate rates to mitigate the noise and limitations inherent in each individual measure. DepRate offers a direct and comprehensive measure of the deposit rates paid by banks, but it may adjust slowly. Conversely, the CD rate provides more immediate insight into banks' pricing strategies but is limited to a specific product category and may suffer from missing data due to potential self-reporting issues. To incorporate information from both rates, we use a weighted rank method. We first rank banks based on each rate, then standardize these ranks based on the number of banks, ensuring that the standardized ranks fall within the same range (0 to 1). We then average these standardized ranks. When the CD data is available, we equally weight both standardized ranks. Otherwise, we rely solely on the standardized DepRate ranking.[13]

To ensure consistent categorization, we employ five-year rolling averages to smooth the combined ranking. Based on this ranking, we designate banks in the top tercile as high-rate and the remainder as low-rate to account for the skewed distribution of banks by rate offerings, as illustrated in Figure 1. Following this, 60% (31 out of 51) of banks are consistently categorized into one type, and 35% remain in the same category for over 90% of the sample period, indicating a high degree of classification persistence.

Finally, we assign banks with time-varying classifications to their dominant type, detailed in Appendix Table B.3. Consistent with Table 1, high-rate banks include Citi and Ally Bank, while low-rate banks feature Bank of America and JP Morgan.

The marked divergence in rate-setting behavior between high-rate and low-rate banks raises an important question: What factors influence a bank's decision to be a high-rate or low-rate type? In Appendix Table B.4, we investigate what characteristics prior to 2009 predict their classification. Our findings suggest that banks with a lower ratio of branches to deposits and relatively smaller asset sizes were more likely to be high-rate banks.

4 Diverging Banking Sector

The diverging pattern in the banking sector is evident even through summary statistics, as presented in Panel A of Table 2. This table summarizes key characteristics of high-rate and low-rate banks across two distinct periods: 2001-2007 and 2017-2023.

During 2001-2007, high-rate banks generally had fewer branches and shorter asset maturities

[13] For illustration, consider the case with three banks: A, B, and C where A offers the highest rate and C offers the lowest rate. B does not report their CD rate. Consequently, based on DepRate alone, their standardized ranking would be is 1/3 (A), 2/3 (B), and 3/3 (C). Based on the CD rate (available for A and C only), the standardized ranking is 1/3 (A) and 2/3 (C), respectively. We take an average of the two rankings and produce an average ranking of 1/3 (A), 2/3 (B), and 5/6 (C). Finally, we rerank them based on the averages: 1 (A), 2 (B), 3 (C).

compared to low-rate banks, with no significant differences in asset size, insured deposit share, branch-deposit ratio, net interest margin (NIM), or charge-off rates. However, post-2017, significant differences have emerged across all metrics except size: high-rate banks exhibit significantly lower branch-deposit ratios, fewer branches, shorter maturities, higher NIM rates and charge-off rates. Notably, the divergence is primarily driven by shifts by low-rate banks. For example, the NIM rate of high-rate banks remained stable at around 300 basis points, while that of low-rate banks decreased from 280 to 230 basis points, with similar patterns observed in other statistics.

Next, we examine this divergence and discuss their implications.

4.1 Diverging Deposit Rates

We validate our classification over time by analyzing the rate behavior of high- and low-rate banks in Figure 3. Figure 3a presents the time series average of deposit rates for each of the two groups. We find that the high- and low-rate banks exhibited remarkably similar deposit rates through the monetary policy cycle before 2009, featuring a relatively consistent and narrow-rate differential between the two groups. However, a dramatic shift occurs starting with the second rate hiking episode of our sample period from 2015. During this period, high-rate banks actively raise rates in response to rising interest rates, while low-rate banks remain largely stagnant. This leads to a considerable disparity between the two groups, as shown in Figure 3b. Furthermore, Figure 3c illustrates this shift for a select subset of individual banks. Notably, under the new banking regime, JP Morgan Chase, US Bancorp, and Bank of America set CD rates close to 0 even when the Federal Funds rate exceeded 500 basis points. Prior to 2009, these banks adjusted CD rates similarly to other high-rate banks, such as Citi and Goldman Sachs.

4.2 Diverging Branches

The divergence pattern is also evident in banks' branching strategies. High-rate banks have increasingly reduced their reliance on physical branches, whereas low-rate banks have maintained an extensive branch presence in recent decades.

Figure 4 displays the cumulative branch growth of high- and low-rate banks, revealing two significant trends.[14] Initially, both types of banks expanded their branch networks until 2009. However, since then, both categories have reduced their branch numbers, with high-rate banks experiencing a much more pronounced reduction—exceeding 60% from 2011 to 2023. This

[14] Branch growth is calculated based on the same set of banks each quarter to ensure that changes are not influenced by shifts in bank composition.

indicates that while branches were crucial for banking operations before 2009, high-rate banks have significantly decreased their reliance on branches for conducting business.

To address concerns that branch closures by high-rate banks might be driven by deposit withdrawals, we further analyze the logged ratio of branches to the real value of deposits (deposits normalized by the consumer price index). A higher branch-to-deposit ratio reflects a strong physical branch presence, indicating more branches relative to deposit levels. Conversely, a lower ratio suggests a decreased reliance on physical branches. Figure 4b illustrates that while the branch-to-deposit ratio has decreased for both high-rate and low-rate banks, the decline is markedly steeper among high-rate banks. This trend underscores high-rate banks' significant move away from traditional branch-based banking, potentially indicating a shift towards digital banking solutions.[15]

Moreover, the two types of banks cater to distinct demographics. As illustrated in Figure 4c, high-rate banks increasingly focus on areas with customers that are approximately two years younger than those served by low-rate banks. We further analyze the target clientele of branch-based banks and mobile banks in Appendix Figure B.5 using the FDIC Survey of Consumer Use of Banking and Financial Services. Our findings reveal that physical branches tend to attract a clientele that is older, less educated, and has a lower income compared to mobile banking users.[16]

To determine the statistical significance of the observed divergences, we apply regression analysis based on Equation (1), with detailed results presented in Table 3. The findings confirm earlier trends: post-2009, high-rate banks exhibit a significantly greater reduction in branch numbers (75%), branch-to-deposit ratios (64%), and an additional 0.5-year decline in average customer age compared to low-rate banks post-2009.[17] These magnitudes remain robust even after incorporating quarter fixed effects to adjust for aggregate shocks, as shown in the even-numbered columns of the table.

These observations are consistent with the findings of Jiang, Yu and Zhang (2022): low-rate banks are branch-reliant banks, prioritizing the maintenance of branch networks, while high-rate banks are less branch-reliant, increasingly focusing on providing primarily e-banking services. For instance, high-rate banks like Ally and Goldman Sachs have a limited number of branches, whereas major low-rate banks such as JP Morgan, Bank of America, and Wells Fargo maintain a relatively

[15] Appendix Figure B.4 demonstrates that the dispersion of the branch-to-deposits ratio has significantly increased across three rate cycles. This pattern is consistent with the dispersion in deposit rates shown in Figure 1.

[16] Between 2012 and 2018, the average age of households using physical branches increased by 2.77 years (4.92%), while the average age of households using mobile banks increased by 1.46 years (3.65%). The average income of households using physical branches also increased by \$5.29K (11.63%), compared to \$9.96K (17.23%) for households using e-banking over the same time period. In terms of education, 50% of households using physical branches have a college degree, compared to over 75% of households using e-banking.

[17] We compute these magnitudes in columns (1) and (3) using: $e^{-\beta} - 1$.

stable number of branches.

Despite a modest reduction in their branch networks, it may seem counterintuitive that low-rate banks have paradoxically increased the implicit costs for their depositors, evidenced by significantly lower deposit rates compared to the pre-2009 period. We highlight two potential explanations. One possibility is that the operational costs for low-rate banks have risen, partly due to their provision of both traditional in-person banking services and e-banking services. Another plausible explanation is that low-rate banks may charge higher markups in their deposit businesses. This could stem from several factors, including a more concentrated branch network due to closures by high-rate banks, or the increased branch-reliance of their customer base as less branch-reliant customers migrate toward banks offering more appealing interest rates. To assess the dominant explanation, we analyze the non-interest expense as a ratio of assets between the two types of banks, shown in Appendix Figure B.6. Our findings indicate a slight decline in the non-interest expense rate for low-rate banks over the sample period, contradicting the marginal cost-based hypothesis. Later, we provide additional evidence that aligns with the markup explanation.

4.3 Divergence on Asset Composition

Next, we examine the divergence on the asset side of the banks' balance sheets. The key insight from our analysis is that banks adjust their asset mix to better align with their liability structures—for instance, low-rate banks, which have near "fixed-rate" liabilities, are better positioned to hold long-duration fixed-rate assets.

4.3.1 Net Interest Margin

We begin by examining banks' net interest margins. Figure 5a reveals that high-rate banks maintain a significantly higher net interest margin compared to low-rate banks post-2009, despite offering higher deposit rates. As net interest margin represents the difference between interest earned and interest paid, this finding suggests that high-rate banks achieve higher yields on their assets. Figure 5b supports this, showing that while both bank types had similar interest income rates before 2009, high-rate banks attained significantly higher income rates afterward, indicating a shift in their portfolios toward higher-yielding assets.[18]

[18] The time-series pattern for interest expense rate is shown in Appendix Figure B.6. The divergence pattern is less pronounced than the gap in Figure 3. This is because interest expense encompasses not only payments on various deposit products but also wholesale funding costs and interest on bonds or other debt securities, offering a comprehensive view of a bank's overall funding costs. Additionally, since interest accrues over time with payments spread out, changes in interest expenses tend to be more gradual than shifts in CD rates, resulting in a less distinct divergence in patterns.

4.3.2 Asset Reallocation

Banks can pursue higher yields through two primary strategies: assuming more credit risk or investing in longer-maturity assets to capture a term premium. To understand their strategies, we examine the portfolio holdings of high-rate and low-rate banks. Loans are categorized into four segments: personal loans, C&I loans, real estate loans, and other loans. Securities are divided into two categories: MBSs and other securities.[19]

Figure 6 presents an overview of the asset composition of the two types of banks, revealing distinct patterns in their investment strategies. Low-rate banks have increased their allocation to long-term investments, such as treasuries, MBSs, and real estate, from 44% to 55% during the sample period, while decreasing their exposure to personal and C&I loans from 36% to 25%. In contrast, high-rate banks have reduced their holdings in long-term investments from 49% to 40%, while their personal and C&I lending increased from 33% to approximately 39% by 2023.

Table 4 provides a detailed examination of asset allocation shifts. Since 2009, high-rate banks have significantly expanded their portfolios, increasing personal loans by 6.4 percentage points and C&I loans by 2.7 percentage points, while simultaneously reducing their MBS holdings by 2.5 percentage points, in contrast to low-rate banks. This represents a notable shift from the pre-2009 period, when differences in personal loans were 4.1 percentage points, MBS holdings were -8.8 percentage points, and disparities in C&I loans were minimal. The most dramatic shift is in real estate loans, where high-rate banks transitioned from holding 6.4 percentage points *more* to 6.1 percentage points *less* than low-rate banks.

The final two rows of Table 4 show the charge-off rates and maturity for each asset category. The charge-off rate, which indicates the percentage of loans or credit accounts considered uncollectible and written off as losses, serves as a key measure of a bank's credit quality. Personal and C&I loans generally involve higher credit risk than other loan types and securities. Therefore, the increase in these loans by high-rate banks suggests a shift towards greater credit risk. Conversely, real estate loans and MBSs have much longer maturities.[20] Hence, by reducing their holdings of real estate loans and MBSs, high-rate banks lower their exposure to interest rate risk.

These changes offer prima-facie evidence of a growing divergence in asset management strategies between high-rate and low-rate banks. Specifically, high-rate banks take on more credit

[19] As shown in Figure 6, treasury securities comprised less than 1% of the portfolio before 2009. We group them with other securities, which include U.S. government, agency, and sponsored agency obligations, as well as securities issued by states and political subdivisions, among others. Other loans include loans to financial firms, loans to finance agricultural production and farmers, loans to foreign governments and official institutions etc.

[20] Call reports only capture maturities for specific loan categories: (1) closed-end loans secured by first liens on 1-4 family residential properties in domestic offices and (2) rest of loans and leases. We approximate the maturity of personal, C&I, and other loans using the average maturity reported for the broader "rest of loans and leases" category.

risk through lending to firms and households. In contrast, low-rate banks hold longer-term assets, engaging more in maturity transformation. The next two sections provide a deeper examination of these two aspects of risk.

4.3.3 Credit Risk

As discussed above, credit risk is mainly associated with loan portfolios, given that securities like Treasuries and MBSs generally carry government backing. By increasing their emphasis on personal and C&I loans, high-rate banks face heightened exposure to credit risk.

To verify this, we examine the overall returns of loan portfolios. Figure 7a shows a notable divergence in loan rates: while both bank types reported similar rates before 2009, a distinct divergence emerges post-2009. By the end of the sample period, high-rate banks charge borrowers approximately 910 basis points, compared to 630 basis points charged by low-rate banks. Column 1 of Panel A in Table 5 further supports this divergence through regression analysis.

To isolate the credit risk premium, we subtract the equivalent maturity Treasury yield from the loan rate. Figure 7b illustrates the evolution of credit spreads for the two types of banks over time. Similar to loan rates, a significant divergence in credit spreads emerges post-2009, with high-rate banks showing an excess of 260 basis points by the sample period's end. Column 2 of Panel A in Table 5 confirms this, indicating a 78 basis point increase in credit spreads for high-rate banks compared to low-rate banks after 2009, which is 24% higher than the sample average credit spread of 324 basis points. This suggests high-rate banks engage in riskier lending to generate higher spreads.

Higher credit spreads come at a cost. Post 2009, high-rate banks experience significantly higher charge-off rates compared to low-rate banks, as illustrated in Figure 7c. By the end of the sample period, high-rate banks report a charge-off rate more than three times that of low-rate banks. This divergence is further confirmed in column 3 of Panel A in Table 5.

Banks can manage credit risk not only by adjusting their portfolio allocation but also within each loan category. Panel B of Table 5 breaks down the post-2009 charge-off rates across different loan types. Except for the "other loans" category, there are no significant diverging patterns in charge-off rates among loan categories. This indicates that changes in portfolio allocation are the primary means by which banks shift their credit risk.

The heightened credit risk assumed by high-rate banks suggests that wholesale funding providers might perceive them as riskier borrowers. This perception can manifest in both higher costs and potentially lower utilization of wholesale funding for these banks. Indeed, as illustrated in Appendix Figure B.7, high-rate banks pay significantly higher wholesale funding rates and utilize a smaller proportion of wholesale funding compared to low-rate banks post-2009. These findings further support the market's perception of higher risk for high-rate banks.

In summary, high-rate banks have assumed more credit risk compared to low-rate banks in recent years, by holding a higher proportion of riskier personal and C&I loans.

4.3.4 Maturity Transformation

While low-rate banks take on less credit risk than their high-rate counterparts, they tend to engage more in maturity transformation by increasing their investments in real estate loans and MBSs, as shown in Figure 6.

Figure 8a clearly illustrates a divergence in asset maturity between the two types of banks. Before 2009, low-rate banks had an average maturity of about 6 years, which was 50% longer than the 4-year maturity for high-rate banks. Post-2009, low-rate banks' asset maturity extended to nearly 8 years, while high-rate banks' maturity remained around 4-5 years. Consequently, by the end of 2023, low-rate banks' assets had roughly double the maturity of high-rate banks. Similarly, Figure 8b shows that high-rate banks consistently maintained a higher share of short-term assets, ranging from 50% to 60%, while low-rate banks experienced a decline in their short-term asset share from 55% to 40% by 2023. The divergence in asset maturity is further confirmed in Panel A of Table 6. The analysis indicates that post-2009, high-rate banks had assets with 0.5 years shorter maturity (around 8% lower than the sample average) and held 4.4% more short-term assets (around 9% higher than the sample average) compared to low-rate banks.

Panel B of Table 6 investigates changes in the maturity of various asset categories. The only significant finding is that high-rate banks shorten the maturity of their treasury holdings. However, given that treasuries make up a relatively small portion of banks' balance sheets, this implies that asset allocation, much like credit risk, is the primary mechanism for banks to adjust their maturity and exposure to interest rate risk.

Collectively, our findings suggest contrasting asset allocation choices between low-rate and high-rate banks. Low-rate banks opt for safe, long-term investments, while high-rate banks shift towards riskier, shorter-term investments. This choice of asset mix aligns with the banks' liability structures. Consistent with Drechsler, Savov and Schnabl (2021), we find that both types of banks engage in maturity matching on both sides of their balance sheets. Deposits at low-rate banks resemble fixed-rate debt, as their deposit rates do not fluctuate with market interest rates. Therefore, they hold fixed-rate securities, such as long-maturity Treasuries and MBSs, to align maturities. In contrast, high-rate banks, operating with a narrower margin from depositors, manage interest rate risk on their liability side, by favoring investments with shorter maturities to hedge against interest rate risk. Furthermore, the different liability structures also lead to distinct risk-taking motives. Low-rate banks, benefiting from a large spread from depositors, opt for safer assets to minimize the risk of losing the spread earned from depositors. Conversely, high-rate banks seek higher yields by taking on more credit risk. In Section 7, we develop a simple model to further illustrate this underlying mechanism.

5 Macroeconomic Effects

The diverging patterns observed among these large banks carry significant macroeconomic implications. This section examines the effects on the transmission of monetary policy through the banking sector (Section 5.1) and the broader outcomes for the aggregate banking sector (Section 5.2).

5.1 Transmission of Monetary Policy

Given that the two types of banks exhibit distinct deposit rate-setting behavior in response to monetary policy shifts, the patterns of deposit inflows and outflows can vary considerably, which, in turn, impacts lending and asset allocation. This section explores these dynamics. Additionally, monetary policy changes can serve as exogenous shocks to the banking system, offering further evidence of how banks adjust their asset allocation in response to these shocks.

5.1.1 Rate Sensitivity to Federal Funds rate Changes

We begin by analyzing the response of deposit rates from high-rate and low-rate banks to the Federal Funds rate changes across three rate-hiking periods. Figure 9 illustrates the deposit rate sensitivity for CD rates, savings deposit rates, and DepRate across these periods, calculated as the ratio of the total change in deposit rates to adjustments in the Federal Funds rate. In the first rate-hiking cycle from 2004Q3 to 2007Q4, both types of banks exhibited similar sensitivities to changes in the Federal Funds rate. However, a distinct pattern has emerged in subsequent cycles, despite a stable average sensitivity overall. Low-rate banks have exhibited a near-zero response to rate hikes, while high-rate banks have significantly raised their deposit rates, demonstrating a strongly positive sensitivity.

We test these relationships through the following regression:

$$\begin{aligned}\Delta Y_{i,y} &= \Delta \text{Fed Funds}_y \times \mathbb{1}(\text{High-rate}_i) \times \text{Post}_q + \Delta \text{Fed Funds}_y \times \mathbb{1}(\text{High-rate}_i) \\ &\quad + \Delta \text{Fed Funds}_y \times \text{Post}_q + \times \mathbb{1}(\text{High-rate}_i) \times \text{Post}_q + \Delta \text{Fed Funds}_y + \mathbb{1}(\text{High-rate}_i) \\ &\quad + \Delta \text{Fed Funds}_y \times \mathbb{1}(\text{High-rate}_i) \times \text{Crisis} + Controls_{i,q-1} + \varepsilon_{i,q}, \end{aligned} \tag{2}$$

where ΔFed Funds$_y$ and $\Delta \text{Y}_{i,y}$ denote the one-year changes in the Federal Funds Target Rate and various deposit rates, respectively. We control for the extreme market conditions of the 2008 Financial Crisis by incorporating a dummy variable for the year 2008.

The first three columns of Table 7 confirm a distinct divergence in deposit rate sensitivity between high-rate and low-rate banks after 2009. Taking CD rates as an example, post 2009, high-rate banks show an average deposit rate sensitivity of 0.56, starkly contrasting with the 0.15 of low-rate banks.[21] This marks a significant change from pre-2009, where the sensitivity for both types of banks were similar: 0.68 for low-rate banks and 0.71 for high-rate banks. The divergence stems mainly from low-rate banks reducing their sensitivity, while high-rate banks slightly increase theirs. Similar patterns are observed for savings and interest expense rate sensitivities.

The heightened interest-rate sensitivity of high-rate banks does not necessarily translate to an increase in interest rate risk. As illustrated in column 4 of Table 7, these banks experience higher interest income rates during periods of rising rates post-2009, effectively offsetting the negative impacts on their net interest margin (NIM). Indeed, the sensitivity of the NIM, detailed in column 5, is comparable between high- and low-rate banks, with figures at 0.12 and 0.16 respectively.[22] This is consistent with findings in Section 4.3 that high-rate banks predominantly invest in short-term, floating-rate assets, effectively mitigating their interest rate risk. For robustness, we include quarter fixed effects in Appendix Table B.5 to control for common macroeconomic factors, yielding consistent results.

5.1.2 Deposits Reallocation During Monetary Policy Cycles

The divergence in deposit rate sensitivities among high-rate and low-rate banks significantly affects how deposits are redistributed during monetary policy cycles.

Figure 10 contrasts the deposit growth of high-rate and low-rate banks across three rate-hiking cycles. To ensure accuracy, we adjust the deposit growth to account for mergers and acquisitions

[21] The calculation of the average CD rate sensitivity for high-rate banks is derived from the sum 0.373 + 0.038 - 0.527 + 0.676, whereas for low-rate banks, it is calculated from 0.676 - 0.527.

[22] The average NIM sensitivity for high-rate banks is calculated from the sum 0.136 - 0.173 + 0.160 - 0.001, while for low-rate banks, it's 0.160 - 0.0001.

(M&A) activities, isolating organic growth trends from consolidation effects.[23] During the first cycle from 2004Q3 to 2007Q4, both bank types exhibited similar growth rates. However, a significant divergence has emerged in the subsequent cycles, with high-rate banks demonstrating notably higher deposit growth. Notably, from 2022Q1 to 2023Q4, deposits in high-rate banks remained stable, while low-rate banks experienced a 10% outflow.[24]

We further quantify the magnitude of deposit reallocation using Equation (2). The first two columns of Table 8 corroborate that after 2009, high-rate banks attract more deposits during periods of interest rate hikes. Specifically, a 100 basis point increase in the Federal Funds rate is associated with a 1.64 percentage points increase in annual deposit growth for high-rate banks relative to their low-rate counterparts, after 2009.[25] This is a significant shift from the pre-2009 trend, where interest rate hikes were associated with deposit *outflows* from high-rate banks, albeit the effect was statistically insignificant. This trend emphasizes the significant impact of monetary policy on deposit allocation between high-rate and low-rate banks.

5.1.3 Monetary Policy Transmission to Lending

Given the divergence in asset holdings between the two types of banks post-2009, the reallocation of deposits has implications for the transmission of monetary policy across various asset categories.

We explore the growth trajectories of personal loans, C&I loans, real estate loans, and MBSs relative to monetary policy cycles, analyzing how annual changes in asset category shares correlate with Federal Funds rate fluctuations. Notably, we focus on changes in asset share rather than volume growth. This approach is motivated by the observation that high-rate banks typically experience enhanced deposit growth following interest rate hikes, which would naturally lead to increased growth across their asset classes. By examining relative shares, we can determine whether these banks disproportionately allocate their increased capital base to specific asset categories that enhance balance sheet alignment.[26]

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[23] M&As between banks significantly impact the deposit growth of acquiring institutions. For instance, following Wells Fargo's acquisition of Wachovia on October 3, 2008, deposits surged from \$375 billion to \$807 billion, with \$444 billion attributable to Wachovia. Thus, analyzing deposit growth without accounting for M&As can be misleading. To address this, we adjust the deposit growth calculation for quarter (t) using the formula: $\log \frac{(\text{Deposits}_t - \text{Acquired Deposits}t)}{\text{Deposits}t-1}$. More details can be found in Appendix A.

[24] It is noteworthy that while both SVB and First Republic are classified as low-rate banks, the significant deposit outflows observed among low-rate banks were not solely attributable to these banks' failures. Neither SVB nor First Republic was included in the top 25 bank sample at the onset of the bank run.

[25] The difference in annual deposit growth between high-rate and low-rate banks after 2009 is computed as 2.426 - 0.787 = 1.64%.

[26] To illustrate the concept, consider two banks, H and L, each initially investing in an amount X of C&I loans and Y of MBSs, financed through deposits. Let us assume that δ deposits flow from Bank L to Bank H. If Bank L divests from MBSs and Bank H uses the additional deposits to invest in C&I loans—a strategy that aligns with

The results, detailed in Table 8, point to distinct asset allocation strategies between high-rate and low-rate banks in response to interest rate fluctuations. High-rate banks predominantly direct incoming deposits toward personal and C&I loans, during periods of monetary tightening. Specifically, in the post-2009 era, a 1 percentage point increase in the Federal Funds rate is associated with a 0.53 percentage points increase in the share of personal loans (column 3) and a 0.36 percentage points increase in the share of C&I loans (column 5) for high-rate banks.[27] Conversely, low-rate banks show a notable reduction in their MBS holdings in response to deposit outflows during interest rate hikes. Specifically, a 1 percentage point increase in the Federal Funds rate leads to a 0.56 percentage points decrease in the MBS share for low-rate banks, as shown in column 9.[28] The results remain robust after controlling for quarter fixed effects, as indicated in the even-numbered columns.

Our findings introduce a nuanced understanding of the impact of monetary policy on bank lending. The traditional view posits that an increase in the Federal Funds rate generally leads to a contraction in aggregate bank credit. However, our results reveal a more complex dynamic: rising interest rates also induce a reallocation of deposits from low-rate to high-rate banks, reshaping the landscape of credit provision. Specifically, while an uptick in the Federal Funds rate prompts low-rate banks to shrink their securities portfolios, it leads to an expansion of credit for high-rate banks, particularly to households and small businesses.

Finally, a potential concern is whether the increased lending activity results from heightened demand from households or firms, rather than the expansion of loan supply by high-rate banks boosted by substantial deposit inflows. Appendix Table B.6 mitigates this concern by demonstrating that changes in the lending rate across asset categories remain similar between banks and over time, indicating that the diverging lending patterns are unlikely to be driven by loan demand. While not definitive, this evidence supports the interpretation that elevated Federal Funds rates encourage high-rate banks to expand their credit provision to personal and C&I loans, while low-rate banks significantly reduce their MBS holdings.

Overall, our findings reveal a stark contrast in how high-rate and low-rate banks react to shifts in monetary policy, with significant implications for credit allocation and the broader economy. In

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balance sheet matching—the share of C&I loans in Bank H increases because $\frac{X+\delta}{X+Y+\delta} > \frac{X}{X+Y}$. Concurrently, the share of MBSs in Bank L's portfolio decreases as $\frac{Y-\delta}{X+Y-\delta} < \frac{Y}{X+Y}$. Conversely, if Bank L sells off C&I loans and Bank H invests in MBSs, the share of C&I loans in Bank H would decrease, while the share of MBSs in Bank L would increase. If both banks allocate inflows and outflows proportionally to their existing shares, then the shares would remain unchanged. Therefore, changes in these shares can reveal how banks manage their deposit inflows and outflows differently, highlighting their strategic allocation responses to shifts in deposits.

[27] The magnitude for high-rate banks post-2009 is derived by aggregating four coefficients involving the term ΔFFar_y. For example, the effect size of personal loans is calculated as 1.046 - 0.825 + 0.313 - 0.003 = 0.531.

[28] This decrease is calculated as -0.563 = -0.128 - 0.435.

the subsequent section, we will delve deeper into the implications of these differences.

5.2 Aggregate Implications

Explaining the Absence of a Large Credit Crunch for Recent Rate Hikes The current rate-hiking cycle began with a sharp increase in interest rates, starting from roughly 0 basis points in early 2022 to around 530 basis points by the end of 2023. Concurrently, aggregate deposit growth declined substantially as shown in Panel A of Figure 11.[29] The annual decline in aggregate deposit growth of 8% is the largest percentage decline in deposits since the H8 data series began in 1973 (according to the FRED database) and was accompanied by disruptions in the banking sector, including the failure of several high-profile banks. According to the deposits channel of monetary policy, such a dramatic decrease in deposits would usually indicate a large credit crunch, leading to a significant contraction in credit availability (Drechsler, Savov and Schnabl, 2017). However, as we have shown, this aggregate deposit outflow masks substantial heterogeneity across banks, with the majority of the outflows concentrated in low-rate banks (recall Figure 10c). Further, we have shown that high- and low-rate banks exhibit distinct lending behavior and asset profiles. In particular, low-rate banks focus substantially on MBSs, and real estate lending relative to high-rate banks. Panel B of Figure 11 shows that the aggregate outflow of deposits, which again is significantly concentrated in low-rate banks, coincides almost perfectly with a large drop in holdings of Treasuries and agency MBSs. In contrast to low-rate banks, high-rate banks prioritize personal lending. Hence, the growth rate of personal loans is negatively correlated with aggregate deposit growth, as shown in Panel C of Figure 11.[30]

These findings highlight the importance of considering heterogeneity across banks to understand the aggregate effects of monetary policy and to identify potential areas where credit contraction may occur. Given that monetary policy disproportionately impacts low-rate banks, asset categories they primarily focus on, such as MBSs and real estate loans, are likely to contract more than those targeted by high-rate banks, such as personal and C&I loans.[31] Thus, our analy-

[29] We use total deposits DPSACBM027SBOG minus large time deposits LTDACBM027NBOG.

[30] We use the series USGSEC for Treasury and agency securities, and the series CONSUMER for personal loans.

[31] An alternative explanation for the observed dynamics could be that as the economy recovers, the demand for loans increases, prompting banks to extend more consumer and C&I loans. To support this expansion, banks may liquidate a significant portion of their treasury and agency securities holdings. However, this strategy is economically viable only if the yield from loans exceeds that from treasuries or agency securities to a greater extent than in the period prior to the increase in the Federal Funds rate. According to the Fred Economic database, the average spread between the rate on new 60-month auto loans (RIFLPBCIANM60NM) and the 5-year treasury yield (DGS5) stood at 426 basis points during 2020-2021 but fell to 308 basis points during 2022-2023. This decrease implies that the marginal benefit of liquidating agency securities for lending has diminished. Consequently, this explanation may not adequately account for the behavior observed in the banking sector.

sis demonstrates the importance of considering deposit distribution across bank types for a more nuanced understanding of the deposit and lending channels of monetary policy transmission.

Aggregate Banking Sector Capacity for Maturity Transformation and Risk-Taking Given the distinct portfolio composition of high-rate and low-rate banks, the banking sector's ability to undertake maturity transformation and originate higher-risk loans is significantly influenced by the distribution of deposits between these banks. If deposits continue to flow towards high-rate banks—whether due to prolonged periods of tight monetary policy or tech-savvy depositors favoring these banks—the sector as a whole is less likely to engage in maturity transformation and increasingly assume greater credit risk. According to our estimates, if 10% of deposits shift from low-rate to high-rate banks, the banking sector as a whole invests in assets with approximately 5% shorter maturities and assumes 8% higher credit risk.[32] This shift could increase credit risk concentration within the banking sector while limiting its ability to provide long-term financing for infrastructure and mortgages.

Implications for Regulators Our findings indicate that diverging banks face distinct risk profiles: low-rate banks are more susceptible to interest rate risk, while high-rate banks are more susceptible to credit risk. Although both risk types have the potential to precipitate bank runs, their underlying dynamics and economic contexts differ substantially. As shown by Jiang et al. (2023), interest rate risk becomes particularly salient during periods of monetary tightening, which typically coincide with robust economic conditions. Conversely, credit risk tends to rise during economic downturns, often prompting monetary easing through reductions in the Federal Funds rate. This difference in risk exposure suggests a more complex interplay between monetary policy, economic cycles, and bank stability.

6 Mechanisms and Robustness

Our analysis has identified three key trends within the banking sector: increasing disparities in deposit rates, divergent branching strategies, and specialized asset portfolios. This section is dedicated to exploring the mechanisms behind these divergences and confirming the robustness of

[32] As of the fourth quarter of 2023, the weighted average maturities for high- and low-rate banks were 4.48 and 7.34 years, respectively. If high-rate banks experience an additional 10% inflow of deposits from low-rate banks, the average maturity of assets held in the banking sector would decrease by around 0.29 years, representing a reduction of 5%, benchmarked to the average maturity of 5.93 years. Similarly, the credit spreads for high- and low-rate banks are 401 and 137 basis points, respectively, as of the fourth quarter of 2023. With a similar 10% inflow of deposits from low to high-rate banks, the average credit spread would increase by 26 basis points, representing a 8% increase from the average of 324 basis points.

our findings.

6.1 Mechanisms

In this section, we first investigate the e-banking mechanism by studying the direct impact of technology on the observed divergences within the banking sector, ruling out alternative explanations. We then decompose the divergence into two sources: changes in the composition of banks or strategic shifts within banks over time. Finally, we conduct additional robustness checks.

6.1.1 e-Banking and the Divergence

We begin by examining public interest in online and mobile banking. Prior to 2009, Google search intensity for terms like ”mobile banking” and ”online banking” remained relatively low and stable (Appendix Figure B.8a). However, a significant surge in search volume occurred around 2009, especially for mobile banking searches, indicating a growing interest in e-banking. For instance, mobile banking searches climbed from an index of 17 in 2009 to 75 (out of 100) in 2022.[33] This trend aligns with the emergence and growing popularity of mobile banking apps from major banks (e.g., Citi, JP Morgan Chase), as shown in Appendix Figure B.8b. Google search trends for these apps began in 2008 and have grown steadily since. Additionally, the widespread adoption of 3G technology, essential for mobile banking activity, coincides with the surge in mobile banking interest.[34] These trends collectively indicate that e-banking began to gain significant popularity around 2009.

To corroborate technology's contribution to the observed divergence, we conduct a series of tests. In column 1 of Table 10, we demonstrate that high-rate banks increase their IT expenditure, including data processing and telecommunications expenses, by 1.5 percentage points more than low-rate banks post-2009, indicating a differential investment in technological infrastructure. We further refine our main analysis by replacing the binary "Post" variable with continuous measures of technological adoption: Google search intensity for mobile banking and the 3G coverage ratio. To facilitate comparison with our baseline results, we normalize both measures to a 0-1 scale, consistent with the "Post" variable. Panel A of Table 9 presents the results of retesting our main findings using these continuous measures. All key results maintain statistical significance, with the economic magnitudes exceeding those of the baseline model, particularly in specifications utilizing

[33] Survey evidence from the Pew Research Center shows that 18% of internet users banked online in 2000, compared to 56% in 2010, after which the percentage stabilized.

[34] We employ the same measure of 3G internet coverage as used in Jiang, Yu and Zhang (2022), capturing the proportion of the US population covered by 3G networks.

the mobile banking Google search intensity. These findings robustly support the mechanism that technological development is a significant driver of the observed divergence in banking strategies.

6.1.2 Alternative Explanations

The pivotal year of 2009 raises questions about whether the diverging patterns in the banking sector are a result of the stringent regulations implemented after the financial crisis or differences in deposit compositions. This section explores alternative explanations for these trends, including regulatory changes, the impact of liquidity injections post-crisis, and differences in the distribution of insured versus uninsured deposits, as well as distributions in savings and CD account holdings between high-rate and low-rate banks.

Regulatory Changes Following the 2007-2008 financial crisis, Basel III and the Dodd-Frank Act introduced stricter capital requirements and robust liquidity provisions to enhance banking sector resilience, particularly among large banks. For example, banking institutions are required to maintain a minimum Total Capital Ratio (sum of Tier 1 and Tier 2 capital) of 8% of risk-weighted assets for all banks, with an additional 1% to 3.5% surcharge for Global Systemically Important Banks (G-SIBs). The Dodd-Frank Act initially applied Enhanced Prudential Standards (EPS) to all BHCs with assets above $50 billion. Despite all top 25 banks in our sample exceeding the $50 billion mark, only eight of them are G-SIBs. This regulatory disparity might influence the divergent business models within the banking sector. We test this hypothesis by examining differences in Tier 1/2 ratios between the two bank types before and after 2009 in column 2 of Table 10. The absence of significant differences suggests that these regulatory changes post-financial crisis are not the primary driver of the sector's divergence.[35]

Liquidity Injection from the Federal Reserve After the 2008 financial crisis, the Federal Reserve launched several quantitative easing (QE) programs aimed at boosting liquidity in the banking system, primarily through purchasing U.S. government-backed securities. Before 2009, low-rate banks maintained a slightly higher proportion of MBSs and Treasuries as depicted in Figure 6. Diamond, Jiang and Ma (2023) argue that the influx of reserves could crowd out lending due to balance sheet constraints, potentially explaining part of the observed divergence in lending between two types of banks. To explore this hypothesis, we analyze reserve shares, which are significantly influenced by QE operations (see, e.g., Acharya et al. (2023)). The results, presented

[35] Appendix Figure B.9 plots how the Tier 1 and Tier 2 ratios evolve over time for the two types of banks. Right after the financial crisis, there was a increase in the Tier 1 ratio, which was mainly driven by the $33 billion equity injection to Citibank. At the same time, Citibank redeemed $24.2 billion of subordinated notes, which lowered the Tier 2 ratio, see 10-K file.

in column 3 of Table 10 and Appendix Figure B.10, show no significant divergence in reserve shares over time between the bank types. This absence of disparity suggests that the divergences observed within the banking sector likely do not stem from differential impacts of QE on the reserve balances of high- and low-rate banks.

Distribution of Insured and Uninsured Deposits Chang, Cheng and Hong (2023) demonstrate that banks with advanced screening technologies attract more uninsured deposits and tend to issue riskier loans. This dynamic could partially explain the observed divergences in risk-taking behavior and deposit flows, especially if high-rate banks have enhanced their screening technology over time. If this hypothesis holds, we would expect to see a divergence in the share of uninsured deposits between high- and low-rate banks. We investigate this hypothesis in column 4 of Table 10, which shows that although high-rate banks have a higher share of uninsured deposits compared to low-rate banks post-2009, this is primarily because high-rate banks had much lower uninsured deposit shares before 2009. Appendix Figure B.11 supports this, showing minimal differences in uninsured deposit shares between the two bank types after 2009. Additionally, our findings on diverging charge-off rates suggest that even advanced screening technology at high-rate banks cannot completely mitigate the credit risks they are exposed to. Therefore, the divergence in screening technology and difference in uninsured deposit share do not fully explain the divergences documented in our study.

Distribution of Savings and CD Deposits Supera (2021) argue that banks finance business loans using time deposits, which tend to increase with the Federal Funds rates. If high-rate banks rely more on time deposits, while low-rate banks depend on more liquid deposits such as savings and demand deposits, the divergence in asset composition patterns might be attributed to differences in time deposit shares rather than fundamentally distinct business models across banks.

We examine this hypothesis in column 5 of Table 10 and Appendix Figure B.12. Our findings reveal that high-rate banks have a higher share of time deposits compared to low-rate banks post-2009. We further explore whether this increased share of time deposits can explain the growth of C&I loans in our sample. Building on the analysis of Figure 1 from Supera (2021), we extend the sample through 2023Q4 in Appendix Figure B.13. The updated figure shows that the pre-2009 correlation between C&I lending and time deposit share disappears after 2009, suggesting that the dynamics of C&I loans are not primarily driven by the proportion of time deposits versus other liquid deposits in recent decades.

To further assess whether the high shares of time deposits influence changes in C&I loans, we modify our regression models to include a new three-way interaction, replacing the high-rate bank indicator with the share of time deposits to total assets from the previous quarter. Results from

Appendix Table B.7 suggest that, although time deposits might explain changes in personal loans before 2009 (see column 2), their influence diminishes post-2009, as indicated by the negative coefficients of the three-way interaction. Furthermore, following Table 13 in Supera (2021), we incorporate growth in time, savings, and demand deposits as controls in our specification of Appendix Table B.8. This analysis shows that only the growth in savings deposits is correlated with increases in personal and C&I loans, challenging the hypothesis that banks primarily use time deposits to finance business loans after 2009. Importantly, our findings remain robust across both tables, highlighting the need to consider the diverse strategies of banks to fully understand the dynamics of investment behavior within the banking sector.

6.2 Decomposing the Divergence: Composition vs. Within Bank Changes

While our findings point to a robust link between the proliferation of e-banking services and the divergence within the banking sector, it remains unclear whether the observed changes are driven by changes in the composition of banks within the top 25 or by strategic shifts within these banks over time. This section addresses this question.

We decompose the observed divergence in the banking sector into two sources: changes in the composition of banks or strategic shifts within individual banks over time.

Impact of New Bank Holding Companies The financial crisis period led to the emergence of newly classified banks. Prominent examples include Goldman Sachs' transition to BHC status in September 2008 and Ally Financial's subsequent acceptance by the Federal Reserve three months later, leading to their inclusion in our sample. To assess the influence of these new entrants on our findings, we exclude all banks that entered our sample post-2001. This excludes Ally Financial, Goldman Sachs, Regions Financial, Bank of New York Mellon, and First Republic Bank. We then rerun our main analysis on this adjusted dataset. Row 1 in Panel B of Table 9 presents the results of this robustness check. The persistence of our main findings in this restricted sample indicates that the observed divergence is not primarily driven by these new entrants.

Composition of Systemically Important Banks Throughout our sample period, 51 BHCs entered the top 25, signaling considerable compositional changes. To see how this influences our results, we exclude banks that entered the top 25 post-2009 and focus on those within the top 25 before 2009, extending their data throughout the analysis period.[36] The results, shown in row 2 of Panel B in Table 9, show qualitatively similar results in all 8 columns. Quantitatively all results are

[36] Banks entering the top 25 post-2009 tend to be smaller, offer higher deposit rates, and operate fewer branches than their predecessors. However, their asset-side metrics like net interest margin, maturity, and charge-off rates remain consistent with earlier top banks. Detailed summary statistics are provided in Table B.9.

similar except the reduction in the branch-deposit ratio from -1.02 to -0.19, suggesting that much of the branch divergence is attributable to compositional changes post-2009.

To further validate the findings, we conduct a series of simulations in which we randomly select 25 banks from the top 100 each quarter, re-estimate our baseline findings, and repeat this process 10,000 times. If the observed diverging patterns were solely attributable to composition effects, we would expect random compositions to significantly alter the economic magnitudes. However, consistent results across simulations, as shown in row 3 of Panel B, demonstrate that the changing composition of the top 25 banks is not the sole driver of the observed divergences.

Overall, these results suggest that compositional changes of the top 25 banks play a modest role in our findings.

Strategic Shifts at the Bank Level To examine time-varying strategic shifts at the bank level, we incorporate BHC fixed effects in our analysis, as reported in row 4 of Panel B in Table 9. The divergence in branch-deposit ratios remains statistically significant (column 1), albeit with a substantially reduced magnitude. This finding aligns with the results in row 2, suggesting that banks with lower branch dependency have become a larger proportion of systemically important institutions in the banking sector. Results pertaining to credit spread (column 2) and monetary policy transmission (columns 6-8) remain robust, with economic magnitudes comparable to the baseline model. The coefficient on maturity is reduced by approximately half, diminishing its statistical significance. A more pronounced difference emerges in the asset composition results (columns 4 and 5). After controlling for bank fixed effects, we find that high-rate banks do not exhibit a significant increase in personal and C&I loan shares, nor a significant reduction in real estate loans and MBSs post-2009.

To resolve the discrepancy between the fixed effects results and our baseline findings, we compare level regression with fixed effects in column 4 to a regression analyzing changes in lending in column 8 of Table 9. The significant positive coefficient in column 8 indicates that high-rate banks experience greater growth in personal and C&I loan shares during periods of interest rate increases, even after controlling for bank-specific time-invariant factors. This result suggests that the divergence between columns 4 and 8 may be attributed to heterogeneous loan growth patterns across varying interest rate environments, particularly given the prolonged zero-rate period in our post-2009 sample. Empirical evidence corroborates this hypothesis. During the zero-rate regime (2009-2016), high-rate banks exhibited an average annual personal and C&I loan growth of -0.82%, compared to -0.05% for low-rate banks. This substantial negative growth for high-rate banks during the extended zero-rate environment likely obscures their loan growth during later rate hike cycles. These findings demonstrate the importance of considering the prevailing interest rate environment when analyzing bank lending behavior, particularly in the context of divergent banking strategies.

Overall, our results demonstrate that both the changing composition of systemically important banks and within-bank strategic adjustments contribute to the observed diverging patterns in the banking sector. Notably, the macroeconomic implications of this wide divergence are significant, regardless of whether the primary drivers are compositional changes or strategic adjustments.

6.3 Robustness

This section presents a series of tests to confirm the robustness of our main findings.

Choice of Cutoff Year Considering the gradual nature of technological innovation, we conduct two robustness checks to ensure our findings do not solely depend on the 2009 cutoff year. Firstly, we shift the cutoff to 2010, detailed in row 1 of Panel C in Table 9, and secondly, we exclude the years 2009-2011, as outlined in row 2, to minimize potential confounding effects from the Financial Crisis. In both cases, our findings remain consistent.

Alternative Specifications To confirm the robustness of our results under various weighting schemes, we apply equal weights in row 3 and observe that our findings remain consistent.

Alternative Classification Methods We also address concerns regarding our bank classification methodology in Rows 4 to 7 of Panel C. Our primary analysis employs both CD rates and deposit rates, leveraging their complementary strengths. However, we recognize potential limitations with CD rates due to their product-specific nature and limited applicability across banks. To validate the robustness of our findings, additional analyses using only the DepRate in row 4 of Table 9 confirm our baseline results. The extensive data series available for DepRate also enables us to expand our analysis across an extended sample period starting from 1994 (row 5), include the top 100 bank BHCs in row 6, and include all BHCs in row 7. These tests enhance the generalizability and relevance of our findings, consistently demonstrating the bifurcation within the banking sector.

In summary, the robustness checks presented in Table 9 confirm that the divergence in the banking sector is a widespread and systematic phenomenon.

7 Endogenous Emergence of a Diverging Banking Sector: A Simple Framework

In this section, we offer a simple framework to rationalize the divergence observed in the banking sector. Our static model is based on the frameworks established by Salop (1979), Allen and Gale

(2004). A key aspect of our model is the integration of endogenous adoption of e-banking by banks, facilitated by technological advancements, as studied in Jiang, Yu and Zhang (2022). We have intentionally simplified the model to include only essential components, which allows for a focused analysis of the economic dynamics involved.

7.1 Without e-Banking Services

The economy has two banks, labeled A and B, which compete for depositors and extend loans to risky projects. We assume that before the advent of e-banking services, the existence of physical branches were essential in attracting depositors.

Depositors Depositors are uniformly distributed around the circle, whose circumference is normalized to be one. Let $s \in [0, 1)$ be the location of a depositor. Every depositor has one dollar and faces a decision regarding the choice of bank for their deposit. The depositors' utility is influenced by two primary factors: the deposit rates offered by the banks and the proximity of the bank to their location:

$$U_i(j) = r_j + \eta(1/2 - d_{i,j})\mathbb{1}(\text{Branch}_j) \quad \forall j \in \{A, B\},$$

where r_j is the deposit rate offered by bank j, $d_{i,j}$ represents the distance from depositor i to bank j, and η presents utility derived from branch services. Depositor i chooses bank A if $U_i(A) > U_i(B)$.

Banks Banks A and B choose to situate their branches on a circular layout. To streamline our analysis, we restrict each bank to establishing just one branch, with cost per branch (κ), which includes costs like office rental fees, payable upfront.[37] By operating a local branch, banks set the deposit rate r_j to attract depositors and also decide on the risk level associated with their loan portfolios, represented by a return L_j. Banks can generate value from both deposit-taking and extending loans.

Following Allen and Gale (2004), we model the return on a risky loan portfolio using a two-point distribution: it yields a return of $L_j = f + l_j$ with probability $p(l_j)$, and a default return of zero with a probability $1 - p(l_j)$. Here, f signifies the Federal Funds rate, while l_j represents the risk premium. For simplicity, we assume $p(l_j) = \alpha - l_j$ for $l_j \in [0, \alpha]$, so that riskier lending has a higher default probability.

[37] To simplify the analysis, we assume an upfront marginal cost per branch. If this cost were assumed to be paid ex-post, it would link to the banks' survival probabilities, thereby complicating the analysis in asymmetric scenarios with the presence of e-banking. However, our results would still remain robust under certain parameter regimes. Furthermore, we believe the upfront cost assumption accurately reflects the fixed costs associated with branch maintenance per period.

Banks' maximize the following profit function:

$$\max_{l_j, r_j} \; p(l_j)(f + l_j - r_j)D_j - \kappa \mathbb{1}(\text{Branch}_j), \tag{3}$$

where D_j is the amount of depositors choosing bank j. Banks encounter two trade-offs. First, offering a higher deposit rate attracts more deposits from competitors, but results in a reduced deposit spread. Second, while taking more risk yields a greater risk premium, it also increases the bank's exposure to the risk of default.[38]

Results Given the symmetry of the two banks, they position their branches equidistantly around a circle. The unique solution is characterized as follows, with the proof detailed in Appendix C:

$$r_A = r_B = r^* = f + \alpha - \eta, \quad l_A = l_B = l^* = \alpha - \frac{\eta}{2}.$$

Depositors' preference for the geographical proximity of bank branches enables banks to impose a markup of $\frac{\eta}{2}$ on their deposit services. Importantly, equilibrium risk raking l^* inversely correlates with η. Banks take less risk as the deposit markup charged increases. The rationale behind this is that the markup earned on the banks' liabilities side is an almost guaranteed return. When such a return is high, banks are less inclined to pursue risky projects that expose them to default risk.

It is crucial to contrast our risk-taking mechanism from the perspective on outstanding debt as argued by Jensen and Meckling (1976). The key distinction lies in the role of bank deposits in our scenario, which generate value for banks. When this value creation is significant, it limits banks' incentives to take risks, thus moderating potential risk-taking. Conversely, when the value creation from liabilities is minimal, the effects described by Jensen and Meckling (1976) come into play, encouraging banks to take risks to expropriate wealth from depositors.

The markup also helps cover the costs associated with operating branches, resulting in the equilibrium profits for Bank A and Bank B being equal to

$$Prof_A = Prof_B = \frac{\eta^2}{8} - \kappa.$$

We assume $\frac{\eta^2}{8} - \kappa \geq 0$ to ensure that the equilibrium scenario involves both banks operating branches.

In summary, before the emergence of e-banking, banks are homogeneous, providing similar deposit rates below the Federal Funds rate and exhibiting similar levels of risk-taking.

[38] We assume that deposits are insured by the FDIC, thereby providing depositors with a consistent incentive to deposit their capital.

7.2 With e-Banking Services

The advent of e-banking services revolutionized banking by allowing banks to cater to depositors without being limited by geographical boundaries. Following Jiang, Yu and Zhang (2022), we assume depositors gain utility, represented as γ, from the convenience of e-banking services:[39]

$$V_i(j) = r_j + \eta(1/2 - d_{i,j})\mathbb{1}(\text{Branch}_j) + \gamma\mathbb{1}(\text{e-Banking}_j) \quad \forall j \in \{A, B\}.$$

As banking services are not solely reliant on physical branches, banks are presented with three strategic choices: maintaining existing branches, adopting e-banking services only, or combining both. The banks' objective function is revised to reflect this modification:

$$\max_{l_j, r_j, b_j, e_j} p(l_j)\Big(f + l_j - r_j\Big)D_j - \kappa\mathbb{1}(b_j) \tag{4}$$

where b_j = Branch if bank j decides to keep branches open, and e_j = e-Banking if bank j offers e-banking services. Under this set-up, we solve the banks' optimal strategies, as outlined in Theorem 7.1 and proof in Appendix C.

Theorem 7.1 *After e-banking service is available, two potential market structures can emerge:*

- *When the cost of branch (κ) is relatively large, a diverging banking sector emerges. {A: Branch + e-Banking, B: e-Banking only} and its symmetric case are Nash equilibria. In this case, $r_B - r_A = \frac{\eta}{5}$ and $l_B - l_A = \frac{\eta}{10}$.*
- *When the cost of branch (κ) is relatively small, no diverging pattern emerges. Both banks offer a combination of branch services and e-banking services.*

The results above show that when operating branches is relatively costly, a diverging banking sector endogenously emerges in the e-banking era. One type of banks offer *both branch and e-banking services*, whereas the other type offers *e-banking* exclusively. The specialized business models affect how banks manage their liabilities and assets. Local branches provide a competitive advantage in attracting customers concerned about geographical proximity, allowing banks with branches to offer lower deposit rates. This ensures a substantial rent for these banks, prompting them to minimize default risk by selecting loan portfolios that are comparatively safer, albeit yielding lower returns. Conversely, e-banking-only banks need to provide higher deposit rates to attract depositors, leading to a narrow deposit spread. Consequently, they opt for a riskier loan portfolio that promises higher returns to maximize profits.

[39] For example, Lu, Song and Zeng (2024) demonstrates that depositors value fast-payment technology and tend to transfer their deposits from slower banks to faster banks.

Robustness of Model Our results remain robust when we model banks' lending opportunities following the framework proposed by Boyd and De Nicolo (2005), where banks set lending rates and borrowers (entrepreneurs) determine the riskiness of their projects. In this framework, high-rate banks set higher lending rates to cover their deposit expenses. In response, borrowers optimally choose riskier projects. Moreover, our results are robust when we model the quality of branch service, η, as a decision variable for each bank. Here, a higher η incurs higher costs but results in better branch quality, which attracts more depositors.

Model Limitations Although our static model does not predict maturity transformation, insights from Drechsler, Savov and Schnabl (2021) suggest that banks with branches likely invest in longer-maturity assets to hedge the stable franchise value of their branches. In contrast, e-banking-focused banks typically hold shorter-maturity assets. Additionally, our model overlooks the dynamic market structure in the banking sector. Jiang, Yu and Zhang (2022) illustrate how digital disruption has ushered in a wave of new e-banking-centric banks, intensifying competition within that segment. Concurrently, incumbent banks with branches might gain market power as competitors reduce their physical presence. This dynamic could further accentuate the disparities in deposit rates and risk-taking between branch-centric banks and e-banking-focused banks.

8 Conclusion

We document a significant bifurcation in the U.S. banking sector over the past two decades, characterized by the emergence of two distinct types of banks: high-rate banks, which align their deposit rates closely with market interest rates, and low-rate banks, whose rates are less responsive to market fluctuations. While overall deposit rate sensitivity remains stable, a clear bimodal distribution in deposit rates has emerged. High-rate banks typically have fewer physical branches and hold more short-term loans, earning their margins primarily through higher credit risk. Conversely, low-rate banks often engage in extensive maturity transformation, holding longer-term but safer assets.

This divergence has implications for monetary policy transmission and financial stability. During monetary tightening, deposits shift from low- to high-rate banks and results in a reallocation of assets: low-rate banks disproportionately divest from MBSs, while high-rate banks expand their personal and business lending. This dynamic adds to the conventional understanding of the effects of monetary policy on bank lending and emphasizes the need for a more nuanced approach to analyzing deposit and lending channels of monetary policy. Furthermore, the ongoing redistribution of deposits alters the banking sector's capacity for maturity transformation and credit provision.

Lastly, the concentration of interest rate risk in low-rate banks and credit risk in high-rate institutions may necessitate a reevaluation of bank risk assessment methodologies and regulatory frameworks to address the evolving risk landscape.

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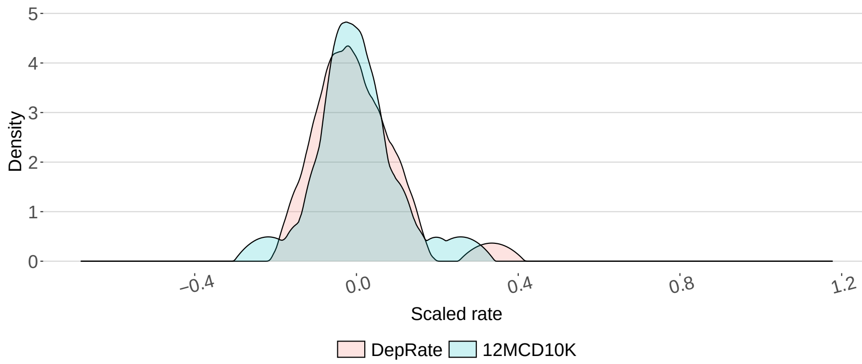
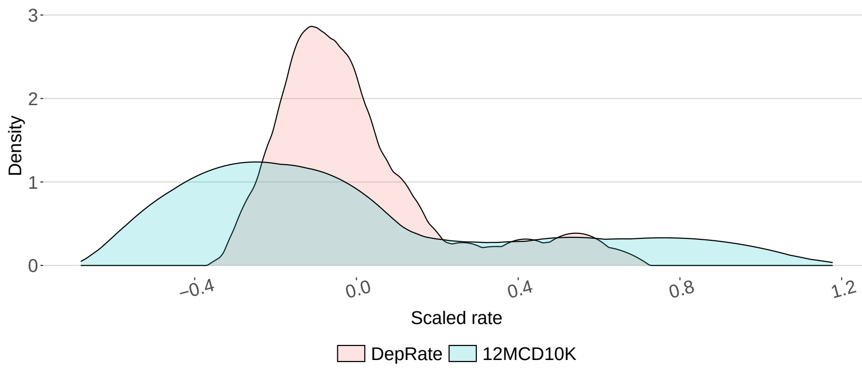
Figure 1: Dispersion of Deposit Rates for Top 25 Banks

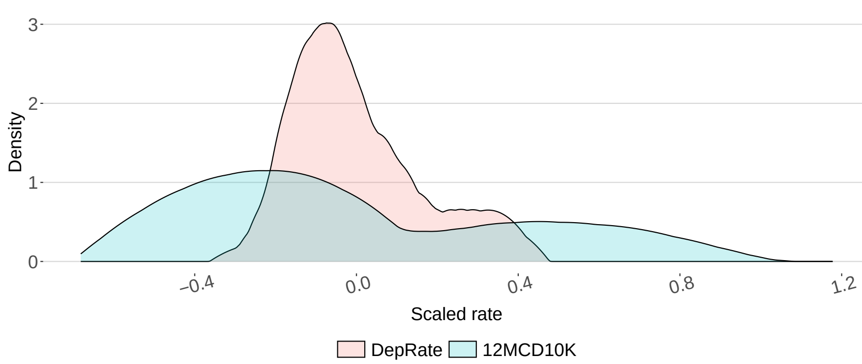
(a) 2006Q3



(b) 2019Q1



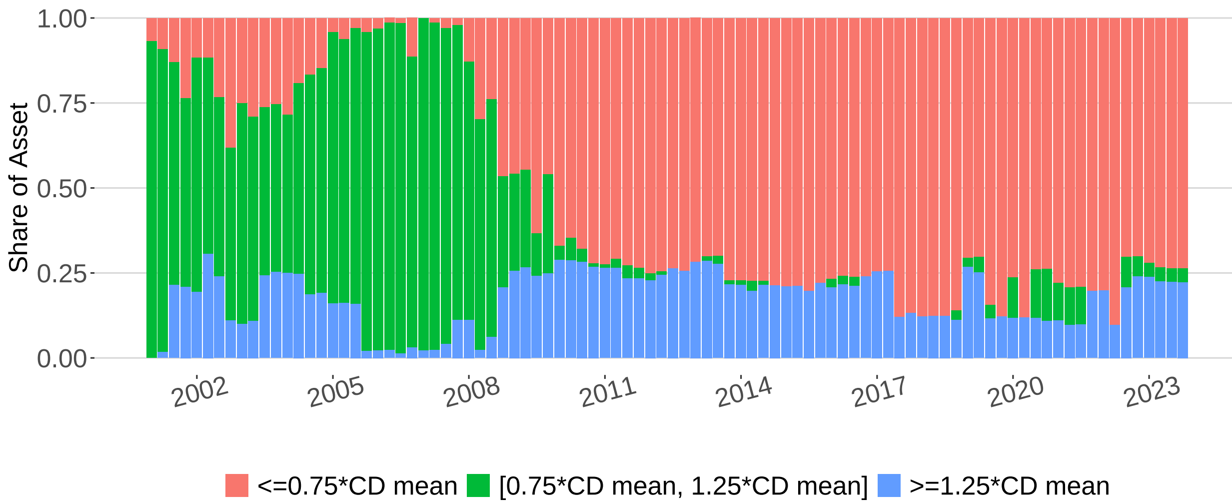
(c) 2023Q4



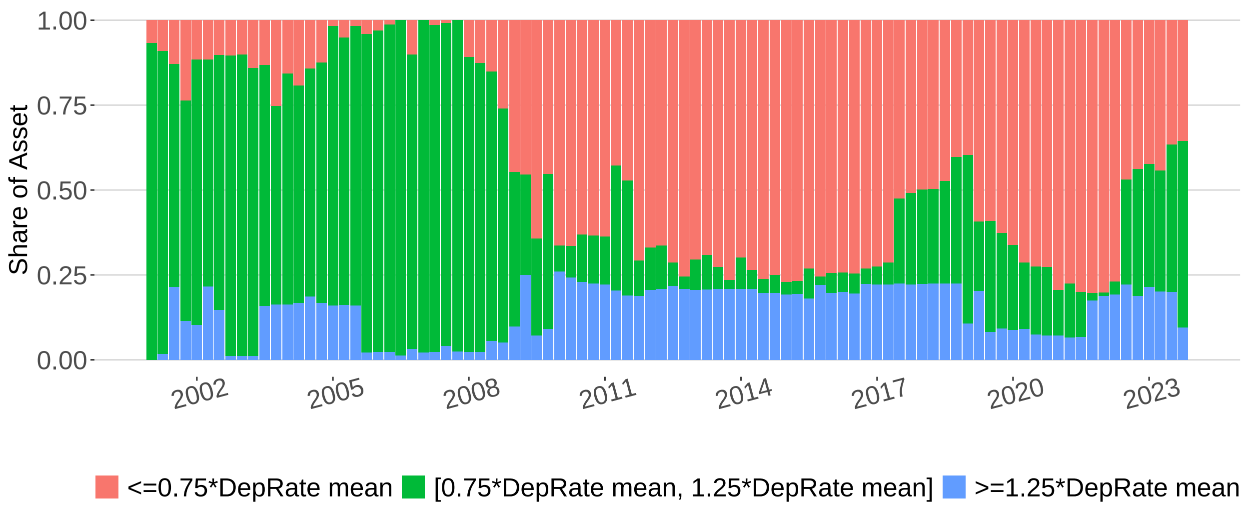
Notes: This figure depicts kernel density plots of the scaled and demeaned 12-month certificate of deposit rates of at least $10,000 (CD) and the scaled and demeaned deposit rates (DepRate) derived from Call Reports provided by the top 25 banks at 2006Q3, 2019Q1, and 2023Q4, representing the peak of three recent rate-hiking cycles. The scaled and demeaned CD rates (DepRate) are computed by first scaling the CD rates (DepRate) using the Market Yield on U.S. Treasury Securities at 1-Year Constant Maturity (DGS1 series in FRED), and subsequently demeaning the scaled rates. The top 25 banks are determined based on bank size each quarter.

Figure 2: Asset Distribution of Top 25 Banks

(a) Classification based on CD



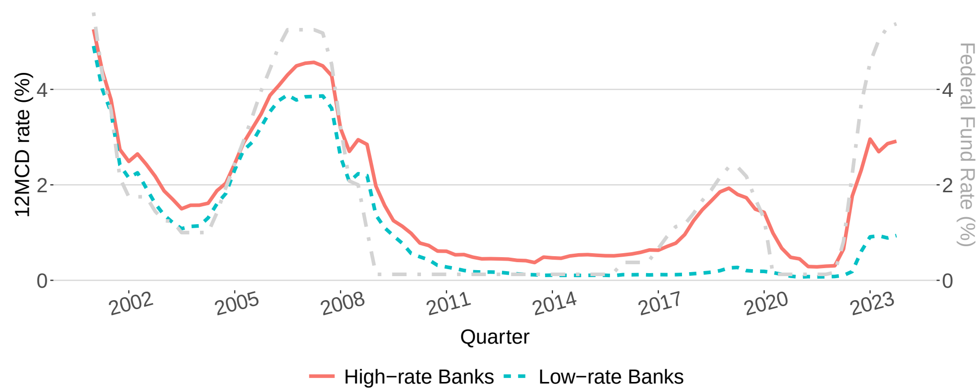
(b) Classification based on DepRate



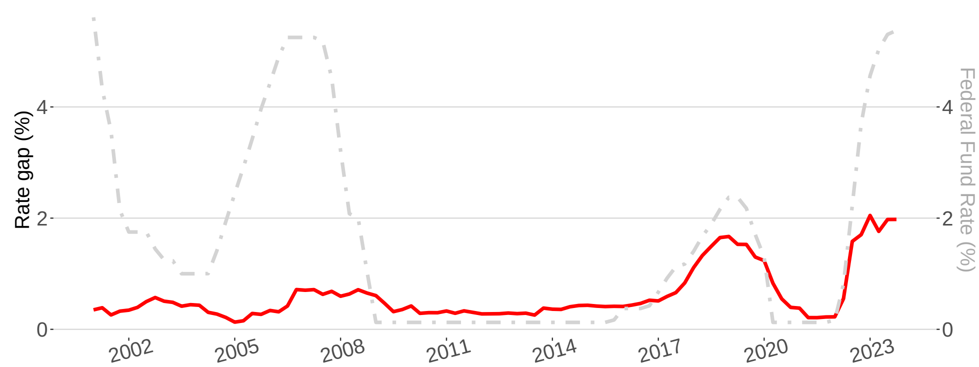
Notes: This figure illustrates the distribution of bank assets among three categories for the top 25 banks: banks with deposit rates below 0.75 times the sample average, banks with deposit rates within the range of 0.75 times to 1.25 times the sample average, and banks with deposit rates exceeding 1.25 times the sample average. Panel a and b present asset distribution classified based on 12-month certificate of deposit rates of at least $10,000 (CD) and deposit rates (DepRate) calculated from Call Reports. If the CD bank rate is unavailable, the classification is determined based on DepRate in Panel a. The top 25 banks are defined according to bank size each quarter.

Figure 3: Dispersion of Bank Deposit Rates

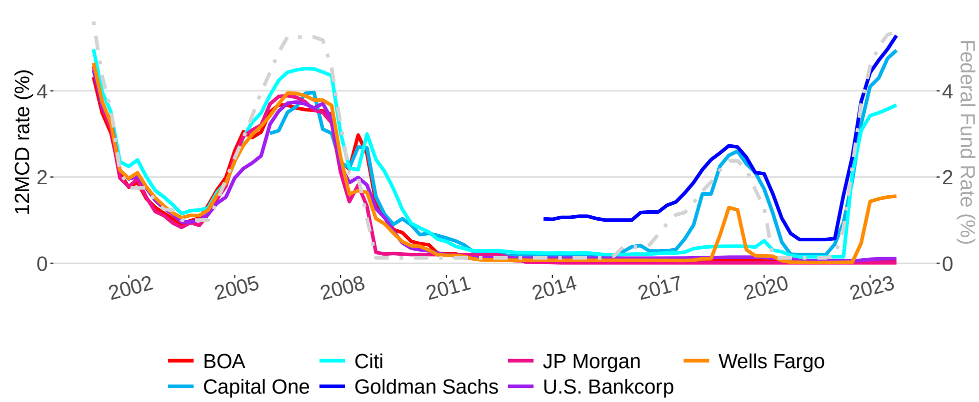
(a) CD Rate



(b) CD Rate Gap



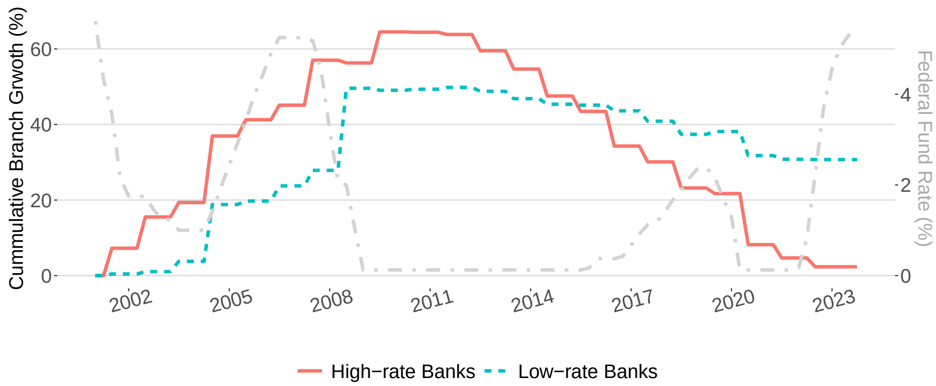
(c) CD Rate by Bank for Select Banks



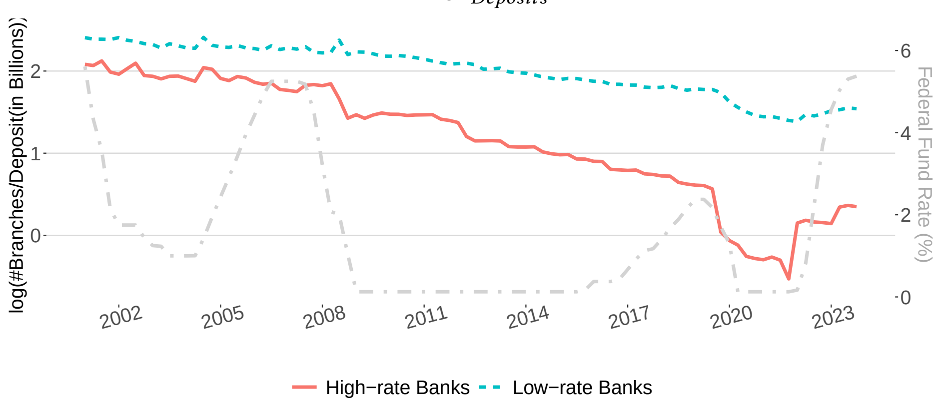
Notes: This figure depicts the dispersion in deposit rates among the top 25 banks, categorized by high and low rates from 2001Q1 to 2023Q4. Figure 3a shows a time-series of the asset-weighted average 12-month certificate deposit (CD) rates for high-rate (blue) and low-rate (red) banks. Figure 3b details the gap in CD rates between these groups, while Figure 3c illustrates the CD rates for selected banks. A bank is categorized as a *high-rate* bank if its average rank, calculated based on the CD rate and deposit rate from the Call Report, falls within the top tercile.

Figure 4: Branches

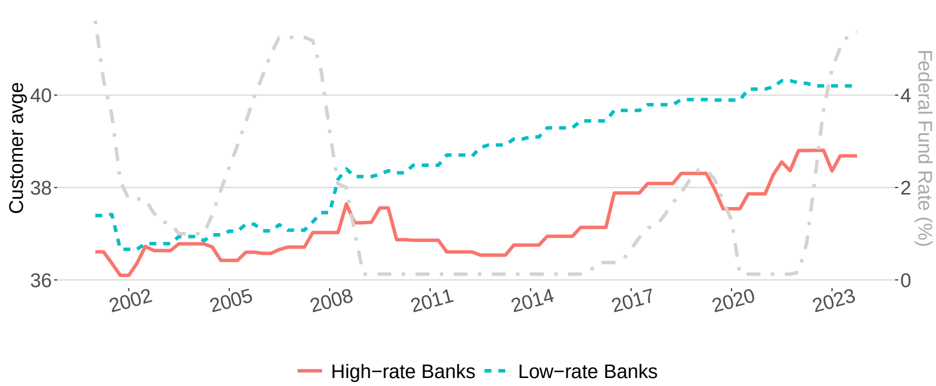
(a) Cumulative Growth of Branches



(b) log $\frac{\#Branches}{Deposits}$



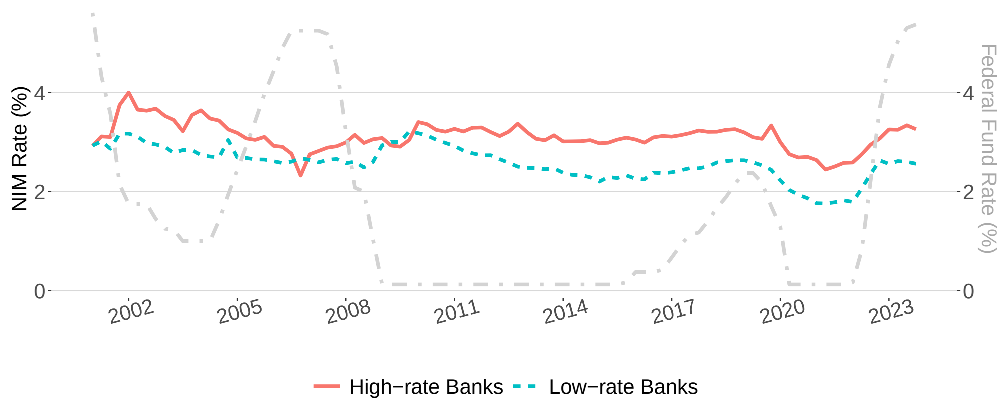
(c) Branch-weighted County Average Age



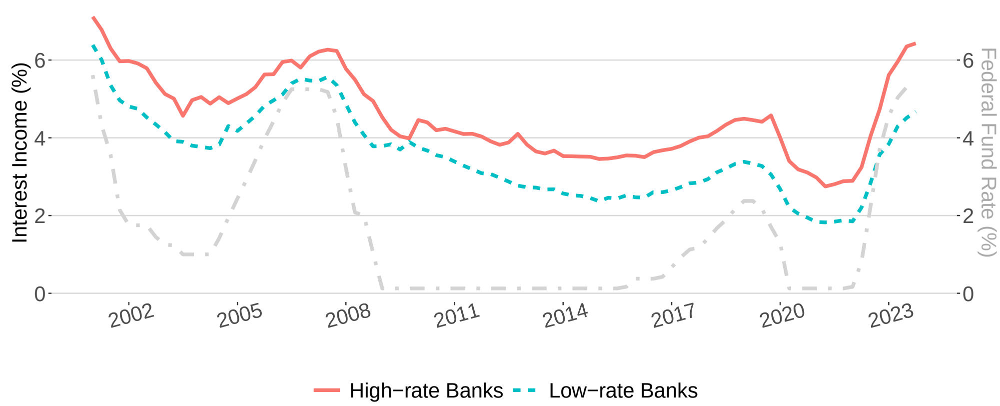
Notes: This figure compares branches operating by high- and low-rate banks among the top 25 banks from 2001Q1 through 2023Q4. Figure 4a presents the cumulative branch growth of high- and low-rate banks. Figure 4b presents the log-transformed ratio between branches and deposits (in Billions) of high- and low-rate banks, where deposits are inflation-adjusted. Figure 4c presents the branch-weighted county average age of high- and low-rate banks. The left y-axis represents the quarterly average Federal Fund Target rate (Fed Funds). A bank is categorized as a *high-rate* bank if its average rank, calculated based on the CD rate and deposit rate from the Call Report, falls within the top tercile.

Figure 5: Net Interest Margin

(a) Net Interest Margin

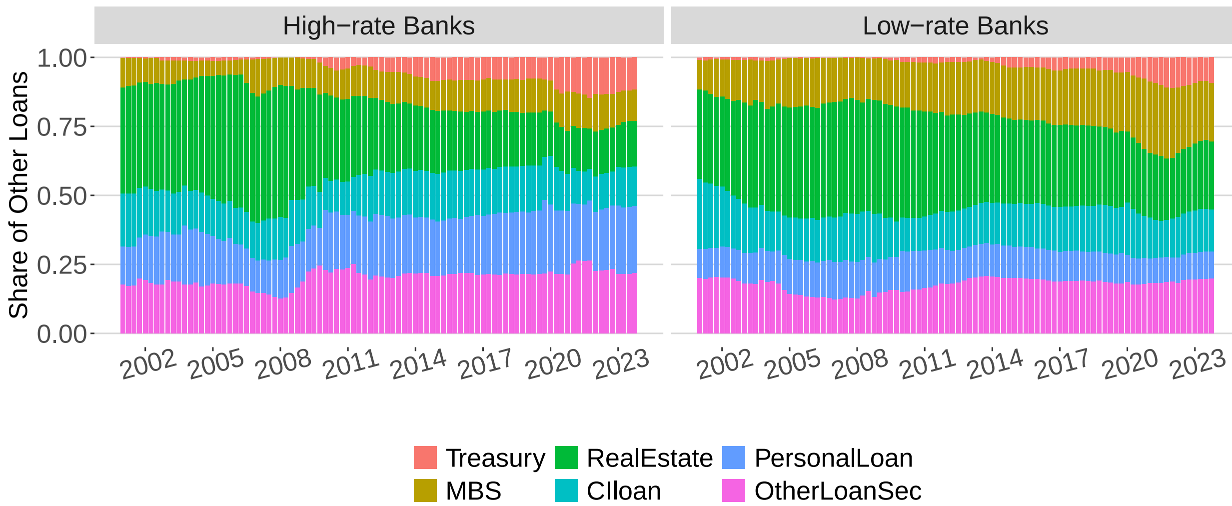


(b) Interest Income Rate



Notes: This figure compares the net interest margin and interest income rate of high- and low-rate banks among the top 25 banks from 2001Q1 through 2023Q4. Figure 5a presents the net interest margin (NIM) rate (%) for high- and low-rate banks. Figure 5b presents the interest income rate (%) of high- and low-rate banks. See Appendix Table A.1 for more details on the construction of key variables. The left y-axis represents the quarterly average Federal Fund Target rate (Fed Funds). A bank is categorized as a *high-rate* bank if its average rank each quarter, calculated based on the CD rate and deposit rate from the Call Report, falls within the top tercile.

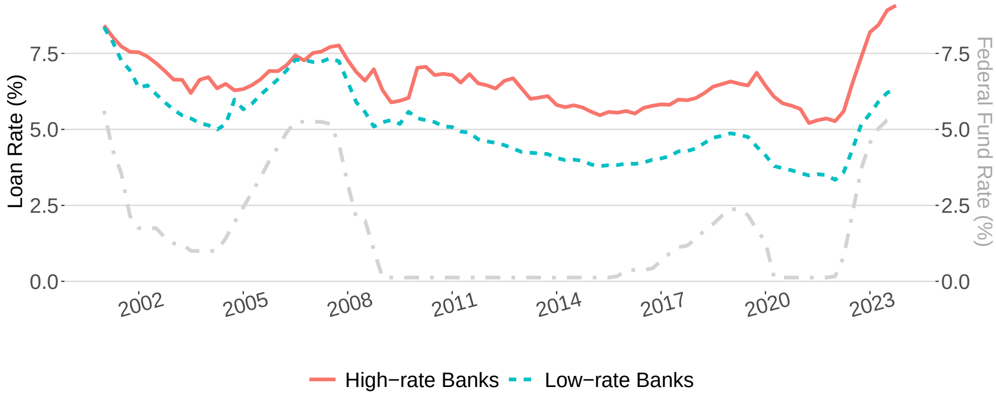
Figure 6: Portfolio Composition



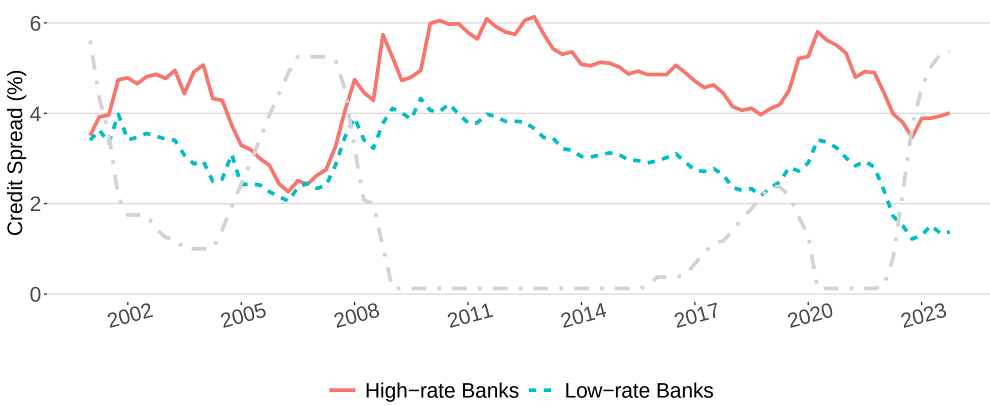
Notes: This figure compares the portfolio characteristics of high- and low-rate banks among the top 25 banks from 2001Q1 through 2023Q4. Figure examines the portfolio composition of high-rate and low-rate banks; share of treasuries, mortgage-backed securities, real estate loans, and C&I loans loans, personal loans, and the rest loans and securities. See Appendix Table A.1 for more details on the construction of key variables. A bank is categorized as a *high-rate* bank if its average rank, calculated based on the CD rate and deposit rate from the Call Report, falls within the top tercile.

Figure 7: Credit Risk

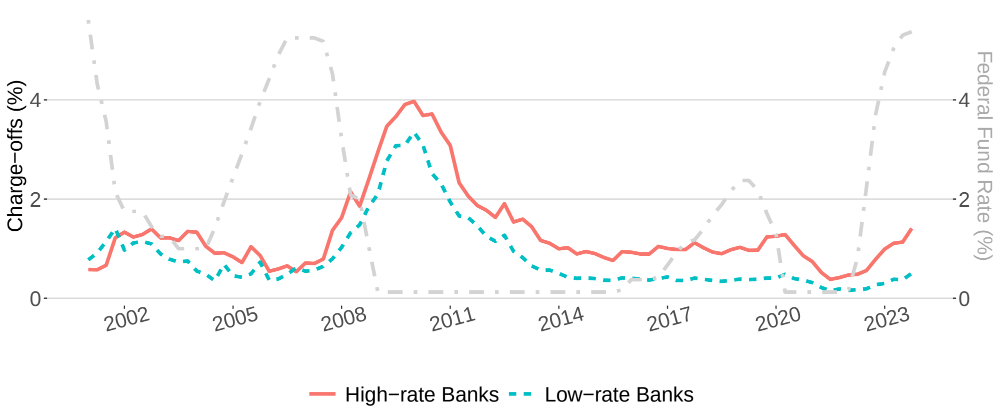
(a) Loan rate



(b) Credit spread



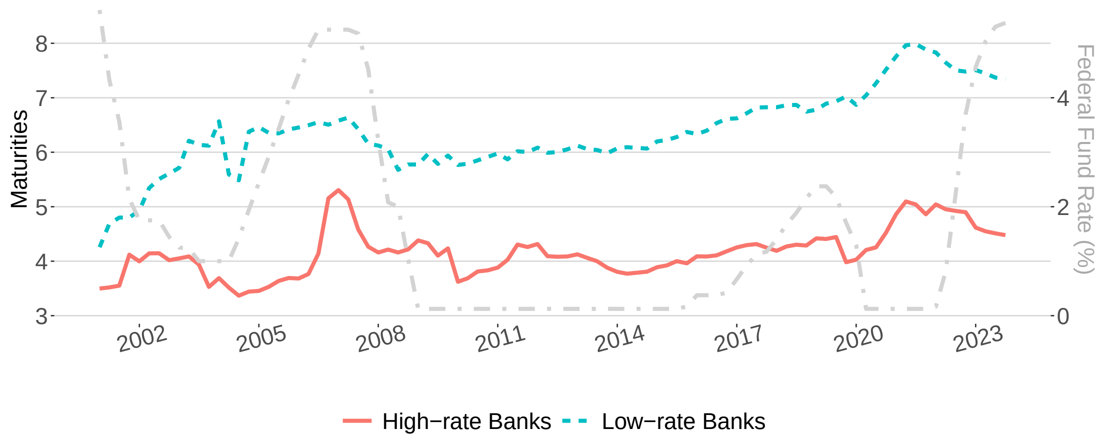
(c) Charge-offs



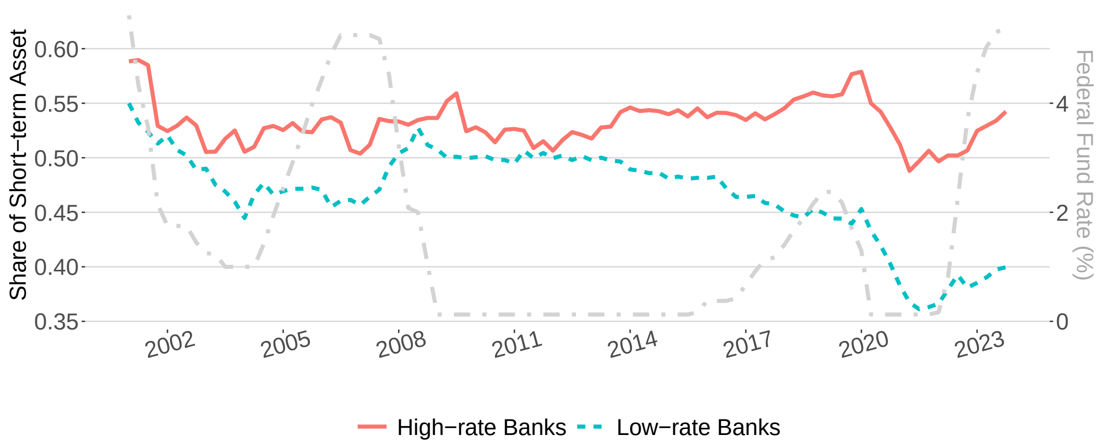
Notes: This figure compares the credit risk of high- and low-rate banks among the top 25 banks from 2001Q1 through 2023Q4. Figure 7a presents the loan rate (%) of high- and low-rate banks. Figure 7b presents the credit spread (%) of high- and low-rate banks. The credit spread is computed as the difference between the loan rate and synthetic term rate (average of term treasury yields, weighted by the share of loans with corresponding maturities). Figure 7c presents the charge-off rate (%) for high- and low-rate banks. See Appendix Table A.1 for more details on the construction of key variables. The left y-axis represents the quarterly average Federal Fund Target rate (Fed Funds). A bank is categorized as a *high-rate* bank if its average rank, calculated based on the CD rate and deposit rate from the Call Report, falls within the top tercile.

Figure 8: Maturity

(a) Maturity



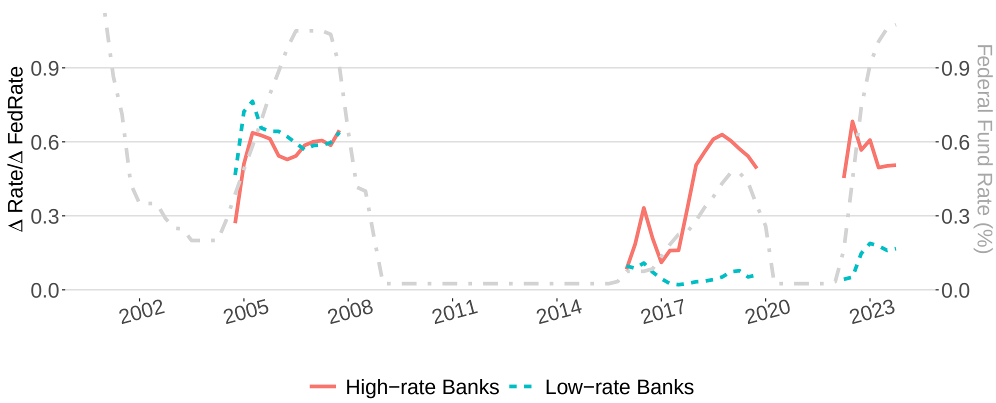
(b) Share of Short-Term Assets



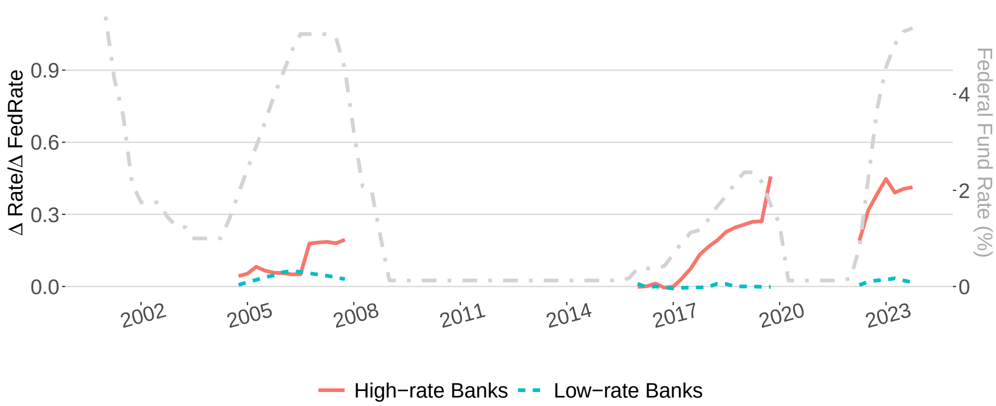
Notes: This figure compares the maturity risk of high- and low-rate banks among the top 25 banks from 2001Q1 through 2023Q4. Figure 8a presents the maturity (# of years) of high- and low-rate banks. Figure 8b presents the share of assets with less-than one-year maturity (short-term assets) for high- and low-rate banks. The left y-axis represents the quarterly average Federal Fund Target rate (Fed Funds). A bank is categorized as a *high-rate* bank if its average rank, calculated based on the CD rate and deposit rate from the Call Report, falls within the top tercile.

Figure 9: Deposit Rate Sensitivity

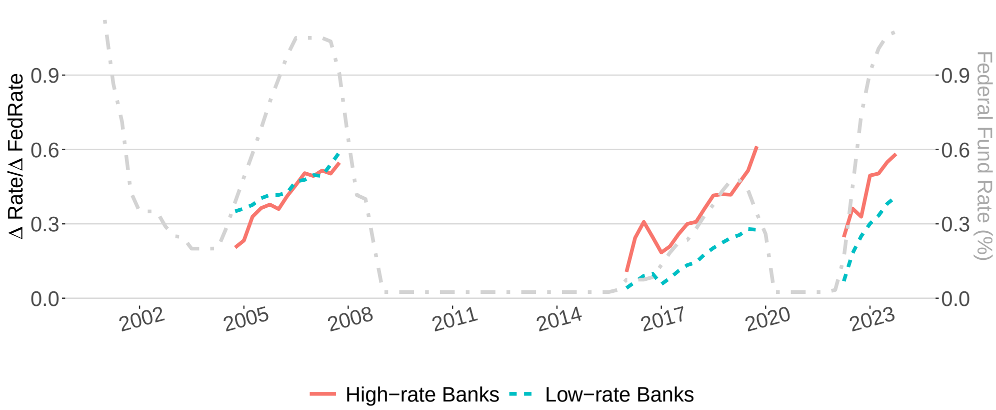
(a) CD



(b) SAV



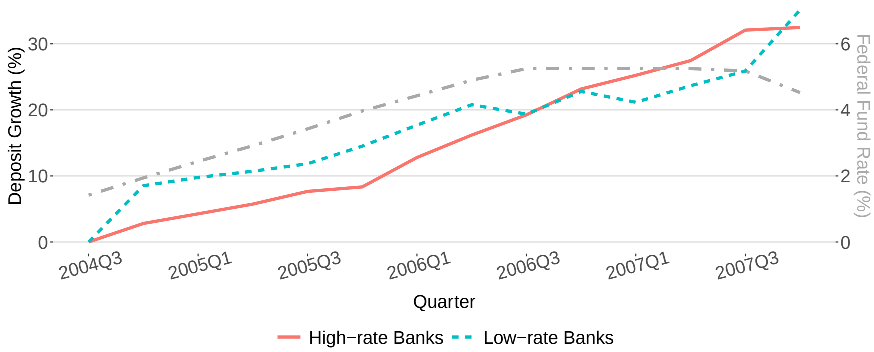
(c) DepRate



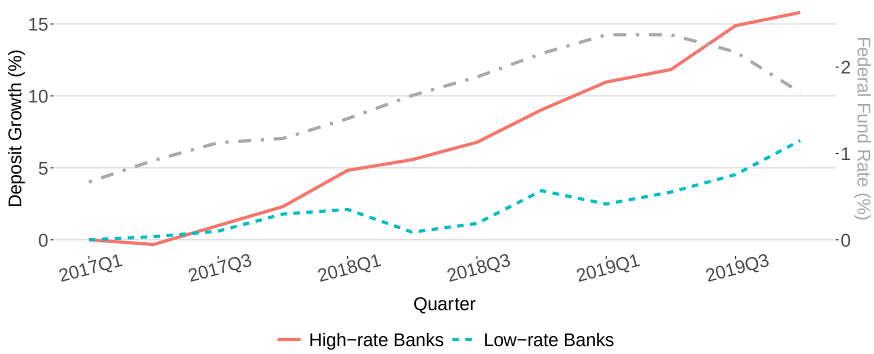
Notes: This figure compares the average deposit rate sensitivity of high- and low-rate banks among the top 25 banks over the three recent rate hiking cycles: 2004Q3 through 2007Q4, 2015Q4 through 2019Q4, and 2022Q1 through 2023Q4. Deposit rate sensitivity is defined as the ratio of the cumulative change in deposit rates from the first quarter of each rate-hiking cycle to the corresponding change in the Federal Funds Target rate. We analyze three types of deposit rates: the CD rate in Panel A, the savings rate in Panel B, and the deposit rate from the Call Report (DepRate) in Panel C. We extend the sample for DepRate back to 1994 due to data availability. The left y-axis represents the quarterly average Federal Fund Target rate (Fed Funds). A bank is categorized as a *high-rate* bank if its average rank, calculated based on the CD rate and deposit rate from the Call Report, falls within the top tercile.

Figure 10: Deposit Growth

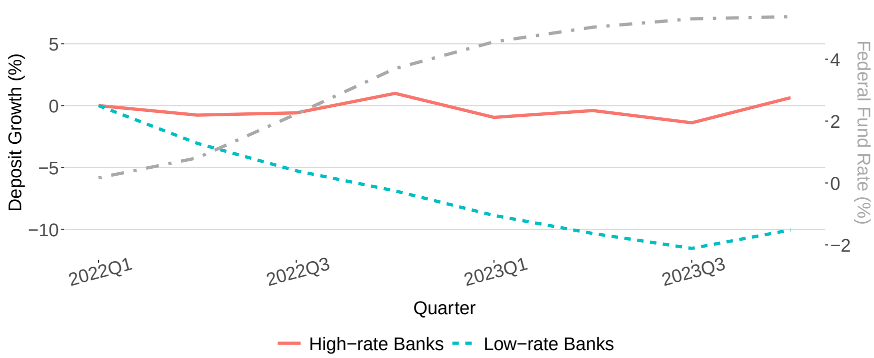
(a) 2004Q3-2007Q4



(b) 2015Q4-2019Q4



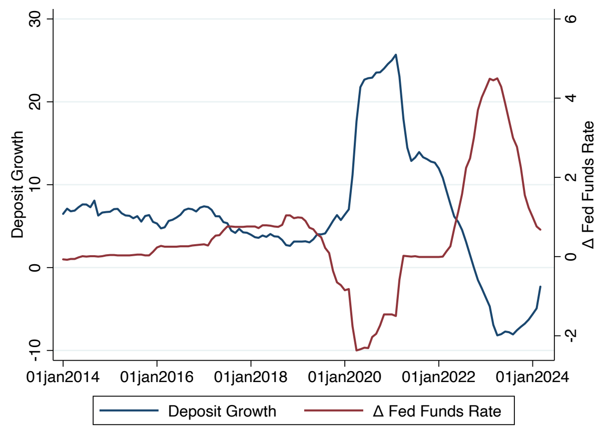
(c) 2022Q1-2023Q4



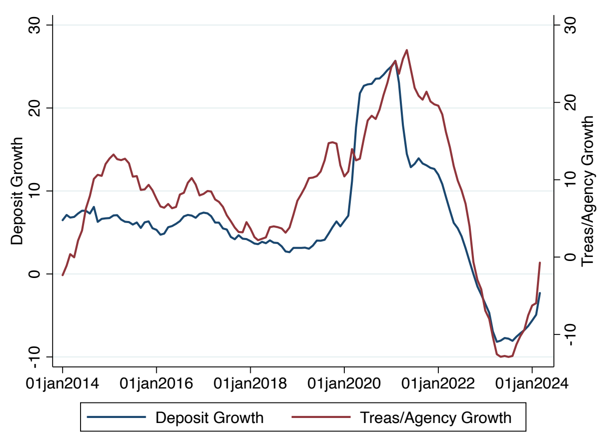
Notes: This figure compares the deposit growth of high- and low-rate banks among the top 25 banks over the three recent rate hiking cycles. Figures 10a, 10b, and 10c compare the deposit growth experienced by high-rate banks to that of low-rate banks from 2004Q3 through 2007Q4, from 2015Q4 through 2019Q4, and from 2022Q1 through 2023Q4, respectively. To facilitate comparison, the growth rates of high-rate and low-rate banks are normalized to 0% in the first quarter of each rate hiking cycle, i.e. 2004Q3, 2015Q4, and 2022Q1. The left y-axis represents the quarterly average Federal Fund Target rate (Fed Funds). A bank is categorized as a *high-rate* bank if its average rank each quarter, calculated based on the CD rate and deposit rate from the Call Report, falls within the top tercile.

Figure 11: Monetary Policy and the Aggregate Growth of Deposits, Securities, and Loans

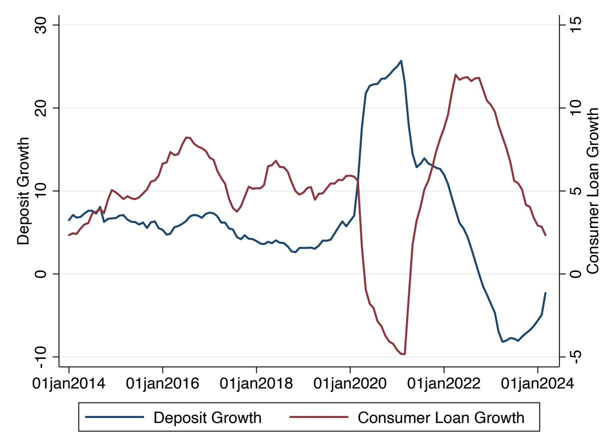
(a) Deposits and the Fed Funds



(b) Treasuries and MBSs



(c) Personal Loans



Notes: This figure explores the impact of monetary policy changes on the growth of deposits, treasuries, MBSs, and consumer loans post-2014, utilizing data from the FRED database for all commercial banks. Panel (a) displays the annual changes in the Federal Funds rate alongside the annual growth in deposits. Panel (b) shows the annual growth of deposits and the annual growth of treasuries and MBSs, while Panel (c) illustrates the annual growth of consumer loans.

Table 1: Deposit Rates on Savings Accounts

Financial institution	Savings deposit rate (APY)	Minimum opening balance
Marcus by Goldman Sachs	4.40%	$0
HSBC	4.40%	$1
Citi Bank	4.35%	$0
Capital One	4.25%	$0
Ally Bank	4.20%	$0
TD Bank	0.02%	$0
JP Morgan Chase	0.01%	$0
U.S. Bank	0.01%	$25
Wells Fargo	0.01%	$25
Bank of America	0.01%	$100

Notes: This table lists the annual percentage yield (APY) of saving accounts offered by financial institutions that are broadly available as well as some of the nation's largest banks, as of June 10, 2024. *Source:* Authors survey of banks' webpages as of June 10, 2024

Table 2: Summary Statistics

Panel A: High v.s. Low-rate Banks Comparison

	2001-2007			2017-2023		
	High	Low	Diff	High	Low	Diff
CD (%)	2.97	2.63	0.35***	1.18	0.16	1.02***
DepRate (%)	2.43	1.93	0.51***	1.10	0.52	0.58***
Assets ($B)	231.21	233.86	-2.65	459.72	592.67	-132.95
Insured Deposits Share (%)	42.79	46.11	-3.32	39.80	46.32	-6.52***
#Branches	985	2,488	-1,503**	475	3,375	-2,900***
$\log \frac{\text{\# Branches}}{\text{Deposits (\$B)}}$	1.25	1.82	-0.57	-1.38	0.64	-2.02***
NIM rate (%)	3.22	2.81	0.41	3.01	2.35	0.66***
Maturity (Years)	3.80	5.84	-2.04**	4.30	7.09	-2.79***
Charge-off Rate (%)	0.99	0.74	0.25	0.88	0.32	0.56***

Panel B: Deposit Rate

	Count	Mean	Stdev	Skewness	P5	P25	Median	P75	P95
CD (%)	1,914	1.20	1.37	1.15	0.02	0.13	0.50	2.04	4.05
DepRate (%)	2,300	1.10	1.05	1.16	0.08	0.23	0.75	1.67	3.25

Notes: Panel A compares key metrics between high-rate and low-rate banks among the top 25 banks from two periods: 2001Q1 to 2007Q4 and 2017Q1 to 2023Q4, with additional comparisons from 2008Q1 to 2016Q4 detailed in Table B.2. Metrics such as the 12-month certificate of deposit rates, deposit rates, share of insured deposits, net interest margin, quarterly deposit growth, loan and securities maturity, and loan charge-offs are analyzed. The metrics are sourced from RateWatch and Call Reports, with banks categorized into high or low-rate based on their rank in deposit rates. Observations are weighted by previous quarter asset size and standard errors for significance testing are clustered quarterly, adjusted using Driscoll-Kraay with 4-quarter lags. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively. Panel B presents the summary statistics for DepRate and CD from 2001Q1 to 2023Q4.

Table 3: Bank Branches

	log(# Branches)		$\log(\frac{\text{Branches}}{\text{Deposits}})$		Branch-weighted County Average Age	
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(High Rate)×Post	-1.373***	-1.374***	-1.010***	-1.020***	-0.502***	-0.492***
	(0.192)	(0.193)	(0.177)	(0.176)	(0.071)	(0.086)
$\mathbb{1}$(High Rate)	-0.314***	-0.289**	-0.236***	-0.236***	-0.645***	-0.606***
	(0.112)	(0.113)	(0.090)	(0.087)	(0.049)	(0.060)
Post	1.360***		0.322***		1.999***	
	(0.137)		(0.094)		(0.222)	
Controls	✓	✓	✓	✓		
Quarter FE		✓		✓		
Adjusted R^2	0.297	0.300	0.396	0.355	0.364	0.242
Observations	2,300	2,300	2,300	2,300	1,799	1,799
Mean of Dep. Variable	7.042	7.042	0.759	0.759	38.805	38.805

Notes: This table reports the estimated coefficients from the following regression specification:

$$Y_{i,q} = \delta_q + \alpha \cdot \mathbb{1}(\text{High-rate}_i) + \beta \cdot \mathbb{1}(\text{High-rate}_i) \times \text{Post}_q + Controls_{i,q-1} + \varepsilon_{i,q},$$

where i and q indicate the bank and quarter-year, respectively, $\mathbb{1}(\text{High-rate}_i)$ denotes whether bank i is a high-rate bank, $Post_t$ denotes the post-2009 period. Controls include $\text{ROA}_{i,q-1}$ and Tier $1/2_{i,q-1}$, which represent the return on assets and the Tier 1/2 capital ratio from the previous quarter, respectively. The dependent variable, $Y_{i,q}$ is the log-transformed number of branches (log(# of Branches)) in columns (1)-(2), the log-transformed ratio of branches to deposits in billions ($\log(\frac{Branches}{Deposit})$) in columns (3)-(4), and the branch-weighted county average age in columns (5)-(6), which is calculated as the county average age, which is weighted based on the number of branches in each county. A bank is categorized as a *high-rate* bank if its average rank each quarter, calculated based on the CD rate and deposit rate from the Call Report, falls within the top tercile. Each observation is weighted by its asset size from the previous quarter. Standard errors (in parentheses) are clustered at the quarter-year levels and are accounted for autocorrelation consistent errors using Driscoll-Kraay with 4-quarter lags. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

Table 4: Asset Composition Shift

	Loans				Securities	
	Personal Loans (1)	C&I loans (2)	Real Estate (3)	Other Loans (4)	MBSs (5)	Other Securities (6)
$\mathbb{1}$(High-rate)×Post	6.441***	2.733***	-12.470***	4.078***	-2.519**	1.737**
	(1.223)	(0.682)	(0.724)	(0.416)	(1.229)	(0.866)
$\mathbb{1}$(High Rate)	4.113***	-0.656	6.414***	-1.521***	-8.803***	0.452
	(1.085)	(0.506)	(0.588)	(0.349)	(1.142)	(0.775)
Quarter FE+Controls	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.231	0.144	0.160	0.035	0.256	0.183
Observations	2,300	2,300	2,300	2,300	2,300	2,300
Mean of Dep. Variable (%)	13.375	15.181	29.619	11.532	16.994	13.301
Charge-offs (%)	2.286	0.600	0.437	0.222	-	-
Maturity (years)	1.924	1.924	12.294	1.924	17.164	5.940

Notes: This table reports the estimated coefficients from the following regression specification:

$$Y_{i,q} = \delta_q + \alpha \cdot \mathbb{1}(\text{High-rate}_i) + \beta \cdot \mathbb{1}(\text{High-rate}_i) \times \text{Post}_q + Controls_{i,q-1} + \varepsilon_{i,q}$$

where i and q indicate the bank and quarter-year, respectively, $\mathbb{1}(\text{High-rate}_i)$ denotes whether bank i is a high-rate bank, $Post_t$ denotes the post-2009 period. Controls include $\text{ROA}_{i,q-1}$ and Tier $1/2_{i,q-1}$, which represent the return on assets and the Tier 1/2 capital ratio from the previous quarter, respectively. The dependent variable, $Y_{i,q}$, represents the share of different asset types in total loans and securities for each bank: personal loans (column 1), C&I loans (column 2), real estate loans (column 3), other loans (column 4), MBSs (column 5), and other securities (column 6). The data comes from the Call Reports. A bank is categorized as a *high-rate* bank if its average rank each quarter, calculated based on the CD rate and deposit rate from the Call Report, falls within the top tercile. Each observation is weighted by its asset size from the previous quarter. Standard errors (in parentheses) are clustered at the quarter-year levels and are accounted for autocorrelation consistent errors using Driscoll-Kraay with 4-quarter lags. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

Table 5: Credit Risk

Panel A: Loans and Securities

	Loan Rate	Credit Spread	Charge-offs
	(1)	(2)	(3)
$\mathbb{1}$(High-rate)×Post	0.990***	0.782***	0.246***
	(0.171)	(0.234)	(0.090)
$\mathbb{1}$(High Rate)	0.881***	1.371***	0.359***
	(0.148)	(0.224)	(0.082)
Quarter FE+Controls	✓	✓	✓
Adjusted R^2	0.389	0.403	0.165
Observations	2,300	2,233	2,300
Mean of Dep. Variable	5.254	3.243	0.852

Panel B: Charge-off Rates by Asset Class

	Real Estate Loans	C&I Loans	Personal Loans	Other Loans
	(1)	(2)	(3)	(4)
$\mathbb{1}$(High-rate)×Post	0.127	0.000	-0.084	0.079*
	(0.079)	(0.089)	(0.129)	(0.046)
$\mathbb{1}$(High Rate)	0.092	0.220***	1.038***	-0.057
	(0.065)	(0.078)	(0.112)	(0.039)
Quarter FE+Controls	✓	✓	✓	✓
Adjusted R^2	0.074	0.036	0.101	0.023
Observations	2,275	2,272	2,293	2,272
Mean of Dep. Variable	0.437	0.600	2.286	0.222

Notes: This table reports the estimated coefficients from the following regression specification:

$$Y_{i,q} = \delta_q + \alpha \cdot \mathbb{1}(\text{High-rate}_i) + \beta \cdot \mathbb{1}(\text{High-rate}_i) \times \text{Post}_q + Controls_{i,q-1} + \varepsilon_{i,q}$$

where i and q indicate the bank and quarter-year, respectively, $\mathbb{1}(\text{High-rate}_i)$ denotes whether bank i is a high-rate bank, $Post_t$ denotes the post-2009 period. Controls include $\text{ROA}_{i,q-1}$ and Tier $1/2_{i,q-1}$, which represent the return on assets and the Tier 1/2 capital ratio from the previous quarter, respectively. In panel A, the dependent variable, $Y_{i,q}$ is the loan rate in column (1), credit spread in column (2), and charge-off rate in column (3). The credit spread is computed as the difference between the loan rate and synthetic term rate (average of treasury yields, weighted by the share of loans with different maturities). Panel B analyzes the charge-off rate by asset class. The asset classes are real estate loans in column (1), other loans in column (2), mortgage-backed securities in column (3), and treasuries in column (4). All dependent variables are winsorized at the 1% and 99% levels. A bank is categorized as a *high-rate* bank if its average rank each quarter, calculated based on the CD rate and deposit rate from the Call Report, falls within the top tercile. Each observation is weighted by its asset size from the previous quarter. Standard errors (in parentheses) are clustered at the quarter-year levels and are accounted for autocorrelation consistent errors using Driscoll-Kraay with 4-quarter lags. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

Table 6: Maturity risk

Panel A: Loans and Securities

	Maturities (Years)	Short-term Share (%)
	(1)	(2)
$\mathbb{1}$(High-rate)×Post	-0.454**	4.400***
	(0.227)	(1.225)
$\mathbb{1}$(High Rate)	-1.962***	5.319***
	(0.202)	(0.640)
Quarter FE+Controls	✓	✓
Adjusted R^2	0.287	0.159
Observations	2,233	2,233
Mean of Dep. Variable	5.932	47.778

Panel B: Maturity by Asset Class

	Real Estate Loans	Other Loans	MBSs	Treasuries
	(1)	(2)	(3)	(4)
$\mathbb{1}$(High-rate)×Post	0.224	0.050	0.191	-1.871***
	(0.395)	(0.135)	(0.389)	(0.440)
$\mathbb{1}$(High Rate)	-1.161***	-0.331***	-0.040	-0.104
Quarter FE+Controls	✓	✓	✓	✓
Adjusted R^2	0.084	0.146	0.017	0.098
Observations	2,131	2,233	2,151	2,202
Mean of Dep. Variable	12.294	1.924	17.164	5.940

Notes: This table reports the estimated coefficients from the following regression specification:

$$Y_{i,q} = \delta_q + \alpha \cdot \mathbb{1}(\text{High-rate}_i) + \beta \cdot \mathbb{1}(\text{High-rate}_i) \times \text{Post}_q + Controls_{i,q-1} + \varepsilon_{i,q},$$

where i and q indicate the bank and quarter-year, respectively, $\mathbb{1}(\text{High-rate}_i)$ denotes whether bank i is a high-rate bank, $Post_t$ denotes the post-2009 period. Controls include $\text{ROA}_{i,q-1}$ and Tier $1/2_{i,q-1}$, which represent the return on assets and the Tier 1/2 capital ratio from the previous quarter, respectively. In panel A, the dependent variable, $Y_{i,q}$ is the maturity of loans and securities in column (1), and the share of loans and securities with less than one-year maturity in column (2). Panel B analyzes maturities by asset classes. The asset classes are real estate loans in column (1), other loans in column (2), mortgage-backed securities in column (3), and treasuries in column (4). The data comes from the Call Reports. A bank is categorized as a *high-rate* bank if its average rank each quarter, calculated based on the CD rate and deposit rate from the Call Report, falls within the top tercile. Each observation is weighted by its asset size from the previous quarter. Standard errors (in parentheses) are clustered at the quarter-year levels and are accounted for autocorrelation consistent errors using Driscoll-Kraay with 4-quarter lags. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

Table 7: Transmission of Monetary Policy: Deposit and Lending Rates

	Liabilities			Assets	Assets - Liability
	ΔCD	ΔSav	ΔInterest Expense	ΔInterest Income	ΔNIM
	(1)	(2)	(3)	(4)	(5)
ΔFed Funds$_y\times$ $\mathbb{1}$(High-rate) $\times$Post	0.373***	0.211***	0.127***	0.314***	0.136***
	(0.108)	(0.042)	(0.023)	(0.033)	(0.040)
ΔFed funds$_y\times$ $\mathbb{1}$(High-rate)	0.038	0.004	0.027**	-0.155***	-0.173***
	(0.028)	(0.022)	(0.011)	(0.031)	(0.032)
ΔFed funds$_y\times$Post	-0.527***	-0.127***	-0.122***	-0.035	0.160***
	(0.061)	(0.011)	(0.038)	(0.034)	(0.038)
ΔFed funds$_y$	0.676***	0.152***	0.459***	0.472***	-0.001
	(0.045)	(0.009)	(0.019)	(0.023)	(0.015)
$\mathbb{1}$(High-rate)$\times$Post	0.028	0.022	0.022	-0.014	-0.018
	(0.119)	(0.050)	(0.032)	(0.065)	(0.065)
$\mathbb{1}$(High-rate)	0.056	0.016	-0.029	0.022	0.045
	(0.075)	(0.032)	(0.023)	(0.057)	(0.056)
Post	0.027	0.190***	-0.029	0.027	0.023
	(0.108)	(0.031)	(0.057)	(0.077)	(0.059)
Controls	✓	✓	✓	✓	✓
Adjusted R^2	0.676	0.361	0.852	0.759	0.261
Observations	1,820	1,768	2,300	2,300	2,300
Mean of Dep. Variable (level)	0.850	0.217	0.915	3.616	2.658

Notes: This table reports the estimated coefficients from the following regression specification:

$$\begin{aligned}\Delta Y_{i,y} &= \Delta\text{Fed Funds}_y \times \mathbb{1}(\text{High-rate}_i) \times \text{Post}_q + \Delta\text{Fed Funds}_y \times \mathbb{1}(\text{High-rate}_i)\\ &+ \Delta\text{Fed Funds}_y \times \text{Post}_q + \times\mathbb{1}(\text{High-rate}_i) \times \text{Post}_q + \Delta\text{Fed Funds}_y + \mathbb{1}(\text{High-rate}_i)\\ &+ \Delta\text{Fed Funds}_y \times \mathbb{1}(\text{High-rate}_i) \times \text{Crisis} + Controls_{i,q-1} + \varepsilon_{i,q},\end{aligned}$$

where i and q indicate the bank and quarter-year, respectively, ΔFed Funds$_y$ denotes the one-year change in the Federal Funds Target Rate, $\mathbb{1}(\text{High-rate}_i)$ denotes whether bank i is a high-rate bank, Post$_q$ denotes the post-2009 period, Crisis is an indicator for year 2008. Controls include ROA$_{i,q-1}$ and Tier 1/2$_{i,q-1}$, which represent the return on assets and the Tier 1/2 capital ratio from the previous quarter, respectively. The dependent variable, $\Delta Y_{i,y}$ is the one-year change in the CD rate in column (1), the change in the saving rate in column (2), the change in interest expense in column (3), the change in net interest income in column (4), and the change in NIM in column (5). All dependent variables are winsorized at the 1% and the 99% levels. The CD and saving rates comes from RateWatch. The change in interest expense, interest income and NIM are computed from the Call Reports. See Table A.1 for more details on the construction of key variables. A bank is categorized as a *high-rate* bank if its average rank each quarter, calculated based on the CD rate and deposit rate from the Call Report, falls within the top tercile. Each observation is weighted by its asset size from the previous quarter. Standard errors (in parentheses) are clustered at the quarter-year levels and are accounted for autocorrelation consistent errors using Driscoll-Kraay with 4-quarter lags. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

Table 8: Reallocation of Deposits and Lending During Monetary Policy Cycles

	$\Delta\log(\text{Deposit}_{i,y})$		ΔPersonal Loan $\text{Share}_{i,y}$		ΔC&I Loan $\text{Share}_{i,y}$		ΔRE Loan $\text{Share}_{i,y}$		ΔMBS $\text{Share}_{i,y}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ΔFed $\text{Funds}_y\times$ $\mathbb{1}$(High-rate) $\times$Post	2.426***	2.330***	1.046***	1.050***	0.406***	0.469***	-0.438*	-0.458*	-0.561**	-0.562**
	(0.531)	(0.525)	(0.241)	(0.247)	(0.142)	(0.141)	(0.249)	(0.247)	(0.261)	(0.255)
ΔFed $\text{funds}_y\times$ $\mathbb{1}$(High-rate)	-0.787	-0.716	-0.825***	-0.823***	-0.423***	-0.454***	0.082	0.086	0.935***	0.932***
	(0.493)	(0.490)	(0.216)	(0.221)	(0.107)	(0.105)	(0.155)	(0.151)	(0.242)	(0.237)
ΔFed $\text{funds}_y\times$Post	-4.458***		0.313**		-0.411**		0.611***		-0.128	
	(0.910)		(0.122)		(0.205)		(0.221)		(0.132)	
ΔFed funds_y	0.863*		-0.003		0.784***		-0.099		-0.435***	
	(0.488)		(0.100)		(0.141)		(0.121)		(0.081)	
$\mathbb{1}$(High-rate)$\times$Post	-2.354	-2.401	1.772***	1.759***	-0.786***	-0.896***	-1.022*	-0.964*	-0.089	-0.093
	(1.487)	(1.469)	(0.427)	(0.430)	(0.254)	(0.243)	(0.548)	(0.537)	(0.906)	(0.911)
$\mathbb{1}$(High-rate)	2.376*	2.841**	-1.449***	-1.451***	0.520***	0.534***	0.989**	0.894**	-0.198	-0.170
	(1.372)	(1.341)	(0.373)	(0.374)	(0.197)	(0.186)	(0.421)	(0.411)	(0.878)	(0.887)
Post	-2.485*		-0.712***		0.731		-2.435***		0.253	
	(1.339)		(0.224)		(0.585)		(0.432)		(0.406)	
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Quarter FE		✓		✓		✓		✓		✓
Adjusted R^2	0.247	0.037	0.099	0.069	0.100	0.012	0.120	0.022	0.044	0.015
Observations	2,300	2,300	2,300	2,300	2,300	2,300	2,300	2,300	2,300	2,300
Mean of Dep. Variable (level)	5.824	5.824	13.375	13.375	15.181	15.181	29.619	29.619	16.994	16.994

Notes: This table reports the estimated coefficients from the following regression specification:

$$\begin{aligned}\Delta Y_{i,y} &= \delta_q + \Delta\text{Fed Funds}_y \times \mathbb{1}(\text{High-rate}_i) \times \text{Post}_q + \Delta\text{Fed Funds}_y \times \mathbb{1}(\text{High-rate}_i)\\ &+ \Delta\text{Fed Funds}_y \times \text{Post}_q + \times\mathbb{1}(\text{High-rate}_i) \times \text{Post}_q + \Delta\text{Fed Funds}_y + \mathbb{1}(\text{High-rate}_i)\\ &+ \Delta\text{Fed Funds}_y \times \mathbb{1}(\text{High-rate}_i) \times \text{Crisis} + Controls_{i,q-1} + \varepsilon_{i,q},\end{aligned}$$

where i and q indicate the bank and quarter-year, respectively, $\Delta\text{Fed Funds}_y$ denotes the one-year change in the Federal Funds Target Rate, $\mathbb{1}(\text{High-rate}_i)$ denotes whether bank i is a high-rate bank, Post_q denotes the post-2009 period, Crisis is an indicator for year 2008. Controls include $\text{ROA}_{i,q-1}$ and Tier $1/2_{i,q-1}$, which represent the return on assets and the Tier 1/2 capital ratio from the previous quarter, respectively. The dependent variable, $\Delta \text{Y}_{i,y}$ is the one-year growth of the total deposit, loans to individuals, C&I loans, treasury securities and MBSs of bank i, and are winsorized at the 1% and the 99% levels. A bank is categorized as a *high-rate* bank if its average rank each quarter, calculated based on the CD rate and deposit rate from the Call Report, falls within the top tercile. Each observation is weighted by its asset size from the previous quarter. Standard errors (in parentheses) are clustered at the quarter-year levels and are accounted for autocorrelation consistent errors using Driscoll-Kraay with 4-quarter lags. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

Table 9: Channel Explorations and Robustness Tests

	$\log(\frac{\text{Branches}}{Deposits})$	Credit Spread	Maturity (years)	Pers. & CI Loan Share	Real Estate & MBS Share	Δ Interest Expense	$\Delta \text{Deposit}_{i,y}$	Δ Pers. & CI Loans Share
	T3.(2)	T5.(2)	T6.(1)	T4.(1)&(2)	T4.(3)&(5)	T7.(3)	T8.(2)	T8.(4)&(6)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Baseline Results	-1.020***	0.782***	-0.454**	9.174***	-14.988***	0.124***	2.330***	1.520***
Panel A: e-Banking and Divergence								
(1) Mobile Bank Google Search	-2.086***	1.163***	-1.078***	12.697***	-23.008***	0.235***	3.837***	2.355***
(2) 3G Coverage	-1.368***	0.916***	-0.563*	10.204***	-16.760***	0.142***	2.557***	1.498***
Panel B: Decomposing the Divergence—Composition vs. Strategic Shifts								
(1) Remove New Entries	-0.621***	0.911***	-0.388*	7.726***	-14.127***	0.096***	2.181***	1.484***
(2) Keep banks entering top 25 before 2009	-0.185**	1.156***	-0.457**	8.139***	-14.568***	0.088***	1.912***	1.484***
(3) Simulation of random top 25 banks	-1.079***	0.891***	-0.665**	11.198***	-14.923***	0.111***	1.501**	0.854**
(4) Add BHC FE	-0.081**	0.509*	-0.279	-3.851*	-1.543	0.121***	1.721***	1.433***
Panel C: Robustness Tests								
Choices of Cutoff 2009								
(1) Post≥2010	-1.114***	0.812***	-0.570***	8.036***	-14.263***	0.142***	1.952***	1.226***
(2) Drop year 09-11	-1.199***	0.846***	-0.553**	9.371***	-15.516***	0.142***	2.386***	1.522***
Different Specification								
(3) Equal Weights	-1.891***	0.214	-0.768***	12.235***	-19.174***	0.117***	1.696**	1.013***
Using DepRate from Call Report to Classify Banks								
(4) Original Spec.	-0.956***	0.665***	-0.529**	9.411***	-14.145***	0.107***	2.557***	1.325***
(5) 1994-2023	-0.495***	0.688***	-0.677***	9.618***	-12.852***	0.150***	1.916***	1.186***
(6) Top 100 BHCs	-0.933***	0.568**	-0.562***	8.525***	-13.709***	0.121***	2.200***	1.304***
(7) All BHCs	-0.860***	0.609***	-0.553***	8.860***	-13.671***	0.121***	2.194***	1.292***

Notes: This table presents a comprehensive analysis of various channels and robustness checks for our main results, focusing on the key coefficients from the first columns of Table X, column Y, denoted as T.X(Y). The table's structure begins with the baseline results in the first row, providing a reference point for subsequent analyses. In Panel A, we investigate the relationship between e-Banking adoption and observed divergence patterns by replacing the "Post" variable with two alternative measures: the U.S. 3G coverage ratio and the Google search intensity for mobile banking. Panel B delves into the decomposition of the observed divergence, examining whether it primarily originates from compositional changes among systemically important banks or from strategic shifts within individual institutions. Panel C encompasses a series of robustness tests, including alterations to the 2009 cutoff year, regressions with equal weights, and reclassification of banks based on deposit rates from all reporting periods. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

Table 10: Alternative Channels

	IT Exp Rate (%) (1)	Tier 1/2 Ratio (%) (2)	Reserve Share (%) (3)	Uninsured Dep. Share (%) (4)	Time Dep. Deposits Share (%) (5)
$\mathbb{1}$(High-rate)×Post	0.015***	0.008	-0.868	9.488***	5.044***
	(0.003)	(0.202)	(0.660)	(0.871)	(1.026)
$\mathbb{1}$(High Rate)	0.004	1.146***	-0.331***	-8.515***	-2.152***
	(0.002)	(0.144)	(0.109)	(0.554)	(0.717)
Quarter FE+Controls	✓	✓	✓	✓	✓
Adjusted R^2	0.162	0.061	0.030	0.040	0.047
Observations	1,371	2,300	2,300	2,300	2,300
Mean of Dep. Variable	0.033	14.342	6.375	46.069	7.758

Notes: This table reports the estimated coefficients from the following regression specification:

$$Y_{i,q} = \delta_q + \alpha \cdot \mathbb{1}(\text{High-rate}_i) + \beta \cdot \mathbb{1}(\text{High-rate}_i) \times \text{Post}_q + Controls_{i,q-1} + \varepsilon_{i,q}$$

where i and q indicate the bank and quarter-year, respectively, $\mathbb{1}(\text{High-rate}_i)$ denotes whether bank i is a high-rate bank, $Post_t$ denotes the post-2009 period. Controls include $\text{ROA}_{i,q-1}$ and Tier $1/2_{i,q-1}$, which represent the return on assets and the Tier 1/2 capital ratio from the previous quarter, respectively. The dependent variable, $\Delta \text{Y}_{i,y}$ is IT expense ratio, Tier 1 and 2 ratio, reserve ratio, uninsured deposit share, and time deposit share. All dependent variables are winsorized at the 1% and the 99% levels. A bank is categorized as a *high-rate* bank if its average rank each quarter, calculated based on the CD rate and deposit rate from the Call Report, falls within the top tercile. Each observation is weighted by its asset size from the previous quarter. Standard errors (in parentheses) are clustered at the quarter-year levels and are accounted for autocorrelation consistent errors using Driscoll-Kraay with 4-quarter lags. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

Diverging Banking Sector: New Facts and Macro Implications
Internet Appendix

A Data Construction and Variable Definition

Our panel dataset is constructed at the bank-quarter level by combining data from two primary sources: the Survey of Depository Institutions (SDI) and Call Reports. The SDI data, which aggregates variables from multiple Call Reports, serves as our primary source. However, its coverage extends only to 2022Q2. To enhance the temporal scope of our analysis, we augment the SDI data with additional Call Report data, thereby extending our dataset through 2023Q4.

In our empirical analysis, we aggregate banks operating under the same Bank Holding Company (BHC). To account for changes in bank classification, we update our records using the latest BHC identifier, RSSDHCR. For instance, when Capital One transitioned from a domestic entity to a BHC on October 1, 2004, we retroactively applied the identifier 2277860 to all pre-transition data. This approach maintains the continuity of our time series, mitigating potential distortions in our analysis that could arise from classification changes within our sample of financial institutions.

Additionally, in constructing growth variables, including deposit growth and various loan product growth rates, we account for mergers and acquisitions (M&As). We source M&A data from the Federal Financial Institutions Examination Council's (FFIEC) National Information Center[40] and incorporate statistics on target banks from the SDI or Call Reports.

We calculate the quarterly growth of a variable Y as:

$$\text{Quarterly Growth} = \log\left(\frac{Y_t - \text{Acquired } Y_t}{Y_{t-1}}\right)$$

[40] https://www.ffiec.gov/npw/FinancialReport/DataDownload

For annual growth rates, we compute the cumulative quarterly growth after adjusting for M&As. This methodological approach ensures that our analysis is not distorted by M&A activities, thereby maintaining the integrity of our growth measurements.

Table A.1: Construction of Key Variables

Variable Name	Construction
Rates	
Deposit rate (%)	$(\text{edepdom}_q+\text{edepfor}_q)/\text{dep}_q*100*4$
Interest income rate (%)	$\text{intinc}_q/\text{asset}_q*100*4$
Interest expense rate(%)	$\text{eintexp}_q/\text{asset}_q*100*4$
NIM rate (%)	$\text{nim}_q/\text{asset}_q*100*4$
Loan rate (%)	$(\text{ilndom}_q+\text{ilnfor}_q+\text{ils}_q)/\text{lnls}_q*100*4$
Credit spread (%)	$\text{Loan rate} - \sum \text{Trea yield}_t * \frac{lnrs_t+lnot_t}{RELoan+OtherLoan}$
Noninterest income rate (%)	$\text{nonii}_q/\text{asset}_q*100*4$
Noninterest expense rate (%)	$\text{nonix}_q/\text{asset}_q*100*4$
Wholesale rate (%)	$(\text{efrepp}_q+\text{ettlotmg}_q+\text{esubnd}_q)/(\text{frepp}_q+\text{idobrmtg}_q+\text{subnd}_q)*100*4$
Asset Composition Share (%)	
Personal loan share	$\text{lncon}_q/(\text{sc}_q+\text{lnls}_q)*100$
C&I loan share	$\text{lnci}_q/(\text{sc}_q+\text{lnls}_q)*100$
Real estate loan share	$\text{lnre}_q/(\text{sc}_q+\text{lnls}_q)*100$
Other loan share	$(\text{lnls}_q-\text{lncon}_q-\text{lnci}_q-\text{lnre}_q)/(\text{sc}_q+\text{lnls}_q)*100$
MBS share	$\text{scmtgbk}_q/(\text{sc}_q+\text{lnls}_q)*100$
Other security share	$(\text{sc}_q-\text{scmtgbk}_q)/(\text{sc}_q+\text{lnls}_q)*100$
Maturities-related Variables	
MBS	$\text{scpt3les}_q+\text{scpt3t12}_q+\text{scpt1t3}_q+\text{scpt3t5}_q+\text{scpt5t15}_q+\text{scptov15}_q$
Treasury	$\text{scnm3les}_q+\text{scnm3t12}_q+\text{scnm1t3}_q+\text{scnm3t5}_q+\text{scnm5t15}_q+\text{scnmov15}_q$
RELoan	$\text{lnrs3les}_q+\text{lnrs3t12}_q+\text{lnrs1t3}_q+\text{lnrs3t5}_q+\text{lnrs5t15}_q+\text{lnrsov15}_q$
OtherLoan	$\text{lnot3les}_q+\text{lnot3t12}_q+\text{lnot1t3}_q+\text{lnot3t5}_q+\text{lnot5t15}_q+\text{lnotov15}_q$
Maturity_{MBS} (years)	$(0.125*\text{scpt3les}_q+0.625*\text{scpt3t12}_q+2*\text{scpt1t3}_q$ $+4*\text{scpt3t5}_q+10*\text{scpt5t15}_q+20*\text{scptov15}_q)/\text{MBS}$
$\text{Maturity}_{Treasury}$ (years)	$(0.125*\text{scnm3les}_q+0.625*\text{scnm3t12}_q+2*\text{scnm1t3}_q$ $+4*\text{scnm3t5}_q+10*\text{scnm5t15}_q+20*\text{scnmov15}_q)/\text{Treasury}$
Maturity_{RELoan} (years)	$(0.125*\text{lnrs3les}_q+0.625*\text{lnrs3t12}_q+2*\text{lnrs1t3}_q$ $+4*\text{lnrs3t5}_q+10*\text{lnrs5t15}_q+20*\text{lnrsov15}_q)/\text{RELoan}$
$\text{Maturity}_{OtherLoan}$ (years)	$(0.125*\text{lnot3les}_q+0.625*\text{lnot3t12}_q+2*\text{lnot1t3}_q$ $+4*\text{lnot3t5}_q+10*\text{lnot5t15}_q+20*\text{lnotov15}_q)/\text{OtherLoan}$

Maturity (years)	$\Big($0.125*(scpt3les$_q$+scnm3les$_q$+lnrs3les$_q$+lnot3les$_q$) +0.625*(scpt3t12$_q$+scnm3t12$_q$+lnrs3t12$_q$+lnot3t12$_q$) +2*(scpt1t3$_q$+scnm1t3$_q$+lnrs1t3$_q$+lnot1t3$_q$) +4*(scpt3t5$_q$+scnm3t5$_q$+lnrs3t5$_q$+lnot3t5$_q$) +10*(scpt5t15$_q$+scnm5t15$_q$+lnrs5t15$_q$+lnot5t15$_q$) +20*(scptov15$_q$+scnmov15$_q$+lnrsov15$_q$+lnotov15$_q$) $\Big)$ / (MBS+Treasury+RELoan+OtherLoan)
ShortTerm$_{MBS}$	(scpt3les$_q$+scpt3t12$_q$)/Maturity
ShortTerm$_{Treasury}$	(scnm3les$_q$+scnm3t12$_q$)/Treasury
ShortTerm$_{RELoan}$	(lnrs3les$_q$+lnrs3t12$_q$)/RELoan
ShortTerm$_{OtherLoan}$	(lnot3les$_q$+lnot3t12$_q$)/OtherLoan
Credit Risk-related Variables	
ChargeOff$_{RELoan}$	ntre$_q$/lnre$_q$*100*4
ChargeOff$_{CILoan}$	ntci$_q$/lnci$_q$*100*4
ChargeOff$_{IndLoan}$	ntcon$_q$/lncon$_q$*100*4
ChargeOff$_{Other}$	(ntlnls$_q$-ntre$_q$-ntci$_q$-ntcon$_q$)/(lnls$_q$-lnre$_q$-lnci$_q$-lncon$_{q01}$)*100*4
ChargeOff	ntlnls$_q$/lnls$_q$*100*4
Other Measures	
IT Exp rate (%)	(RIADC017$_q$+RIADF559$_q$)/asset$_q$*100
Tier 1/2 Ratio (%)	(RBCT1J$_q$+RBCT2$_q$)/RWAJT$_q$*100
Reserve share (%)	chfrb$_q$/asset$_q$*100
Uninsured deposit share (%)	(depdom$_q$-depins$_q$)/depdom$_q$*100
Time deposit share (%)	ntrtime/asset$_q$*100
Wholesale share (%)	(frepp$_q$+idobrmtg$_q$+subnd$_q$)/liab$_q$*100

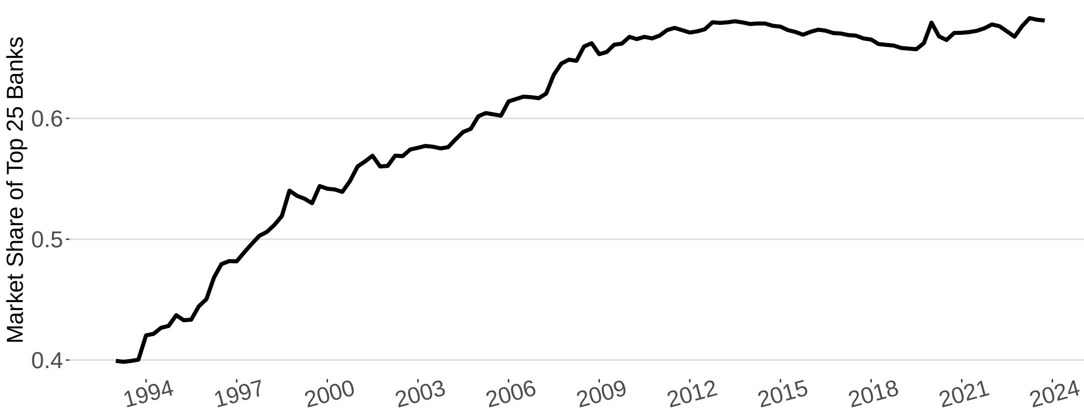
Notes: We follow the variable definitions from the FDIC's Statistics on Depository Institutions. See SDI.

B Additional Figures and Tables: Supporting Evidence and Alternative Channels

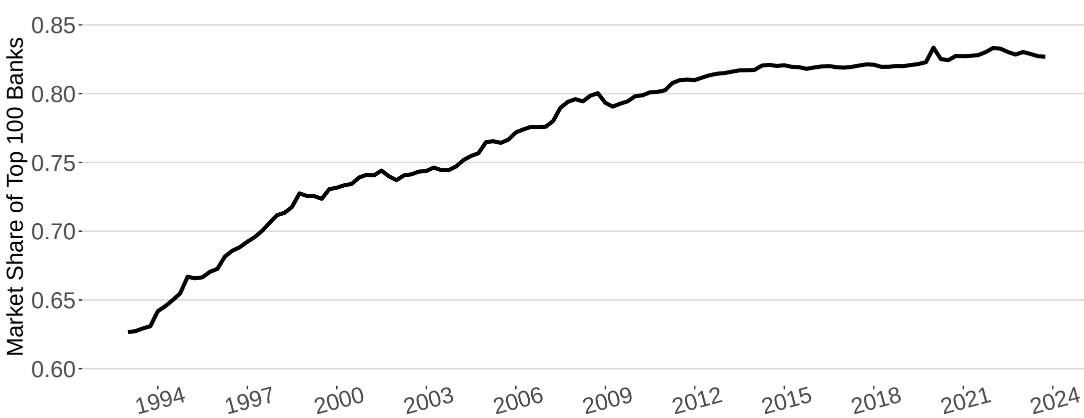
B.1 Figures

Figure B.1: Market Share of Top Banks

(a) Top 25



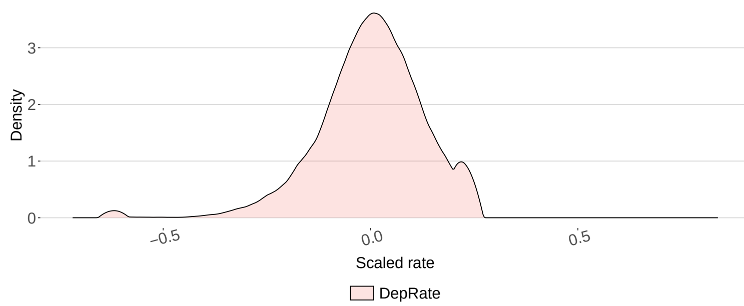
(b) Top 100



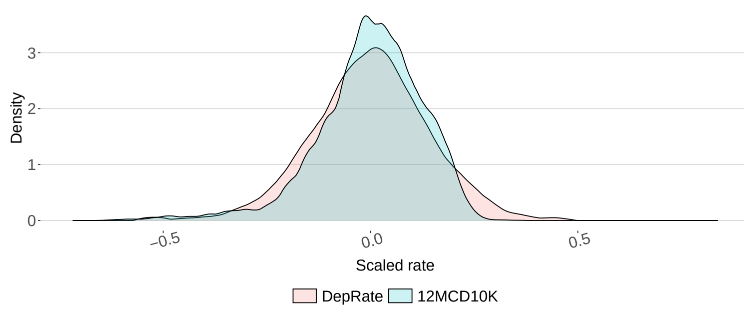
Notes: This figure presents the market share of the top 25 banks (in panel a) and top 100 banks (in panel b) from 2001Q1 through 2023Q4. Market share is measured by total assets. The top 25 (top 100) banks are defined according to bank size in each quarter. The data used to construct this figure comes from the Call Reports.

Figure B.2: Dispersion of Deposit Rates for All Banks

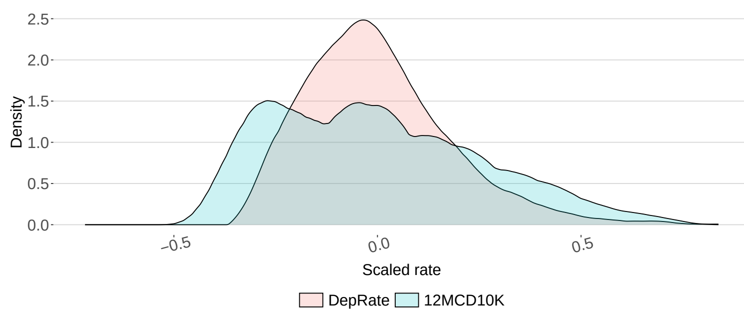
(a) 1995Q2



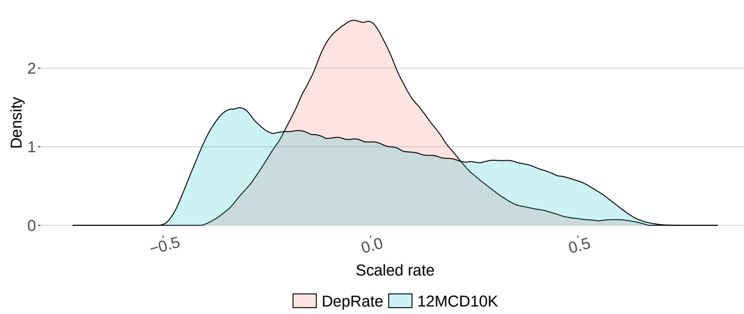
(b) 2006Q3



(c) 2019Q1



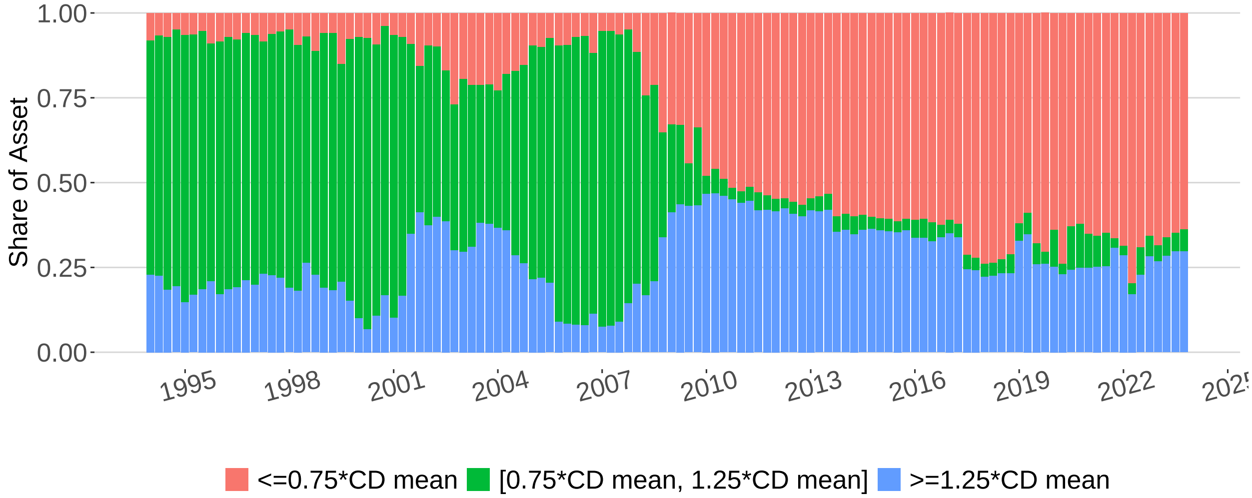
(d) 2023Q4



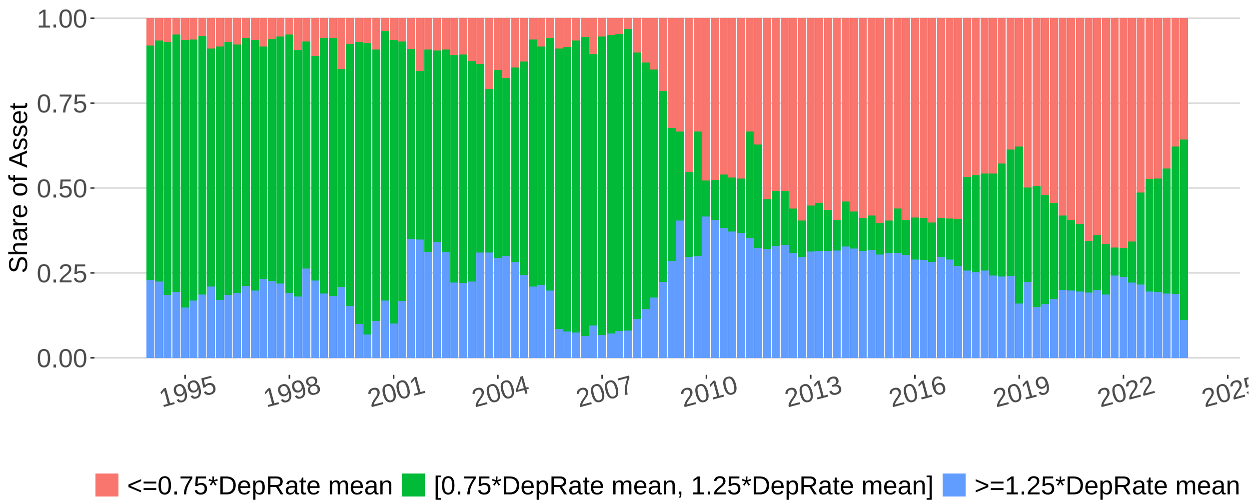
Notes: This figure depicts kernel density plots of the scaled and demeaned 12-month certificate of deposit rates of at least $10,000 (CD) and the scaled and demeaned deposit rates (DepRate) derived from Call Reports provided by all banks at 1995Q2, 2006Q3, 2019Q1, and 2023Q4, representing the peak of four recent rate-hiking cycles. The scaled and demeaned CD rates (DepRate) are computed by first scaling the CD rates (DepRate) using the Market Yield on U.S. Treasury Securities at 1-Year Constant Maturity (DGS1 series in FRED), and subsequently demeaning the scaled rates.

Figure B.3: Asset Distribution of All Banks

(a) Classification based on CD



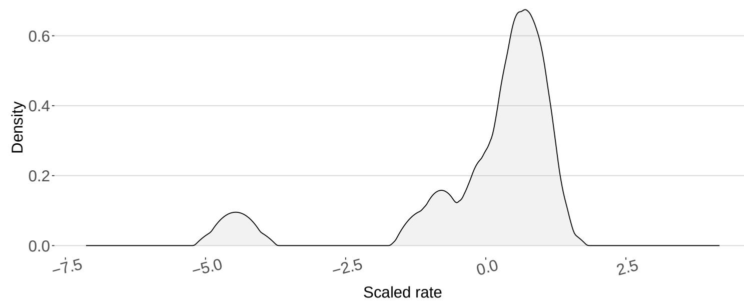
(b) Classification based on DepRate



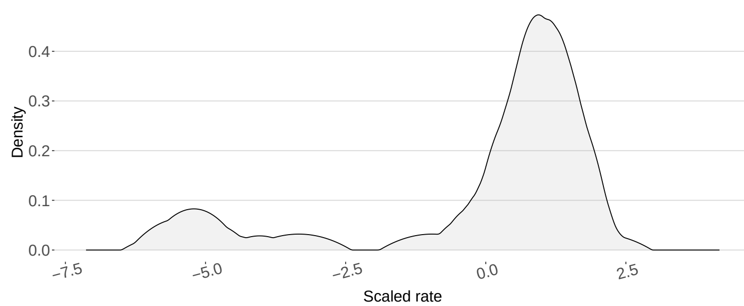
Notes: This figure illustrates the distribution of bank assets among three categories for all banks: banks with deposit rates below 0.75 times the sample average, banks with deposit rates within the range of 0.75 times to 1.25 times the sample average, and banks with deposit rates exceeding 1.25 times the sample average. Panel a and b present asset distribution classified based on 12-month certificate of deposit rates of at least $10,000 (CD) and deposit rates (DepRate) calculated from Call Reports. If the CD bank rate is unavailable, the classification is determined based on DepRate in Panel a. To maintain comparability with Appendix Figure B.2, the sample average is calculated as the average rate of the top 25 banks within each quarter.

Figure B.4: Dispersion of Branch/Deposits Ratio for Top 25 Banks

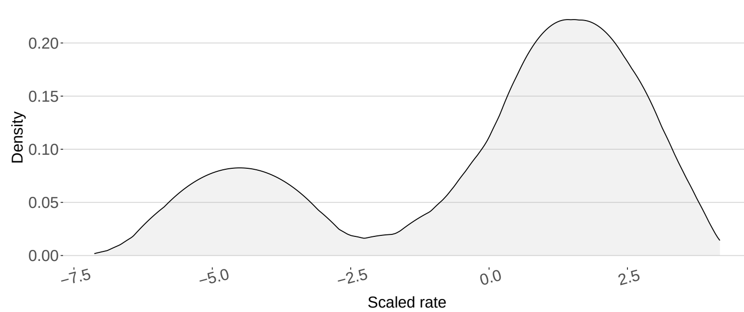
(a) 1995Q2



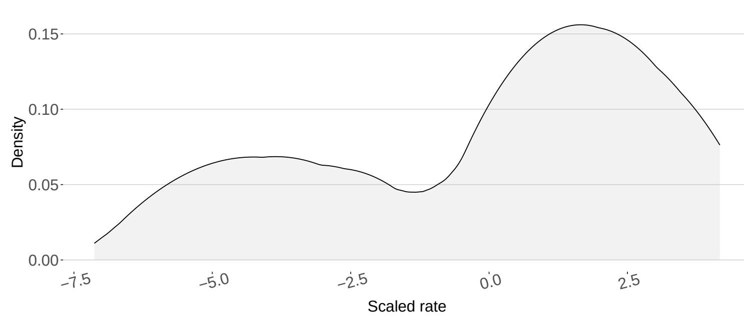
(b) 2006Q3



(c) 2019Q1



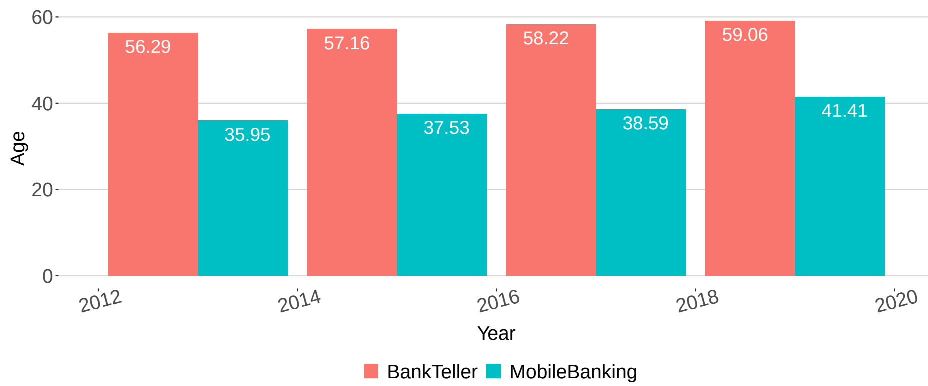
(d) 2023Q4



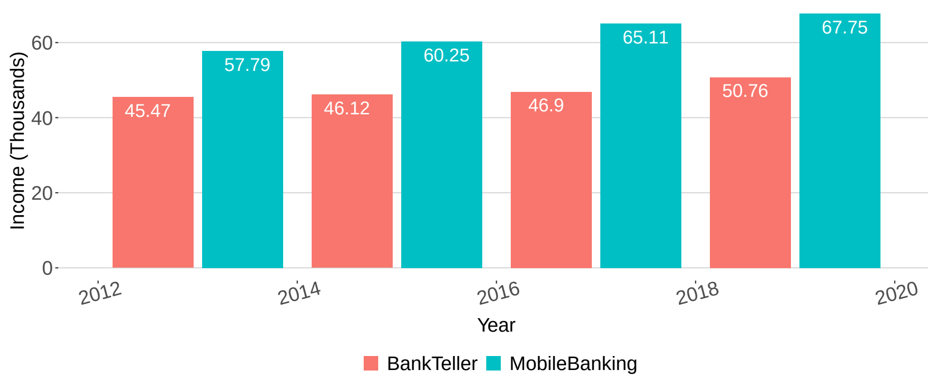
Notes: This figure displays kernel density plots of the demeaned logarithm of branch deposits by the top 25 banks at the peak of each interest rate hiking cycle. Figures a, b, c and d illustrate the kernel density at the following quarters: 1995Q2, 2006Q3, 2019Q1, and 2023Q4, respectively. The top 25 banks are determined based on bank size at the beginning of each quarter.

Figure B.5: Characteristics of Households Using Branches v.s. Mobile Banking

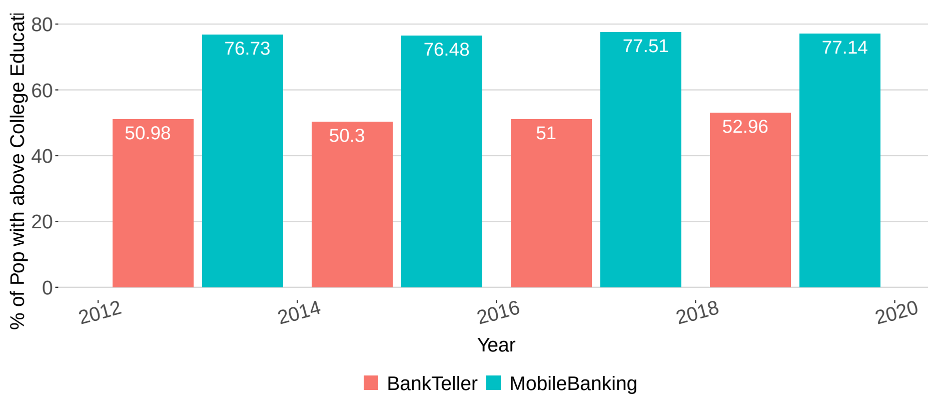
(a) Age



(b) Income



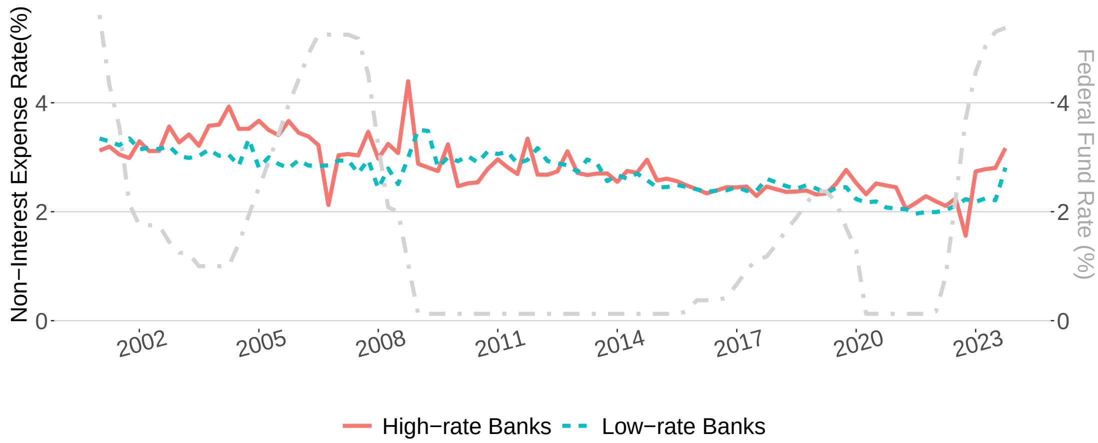
(c) Education



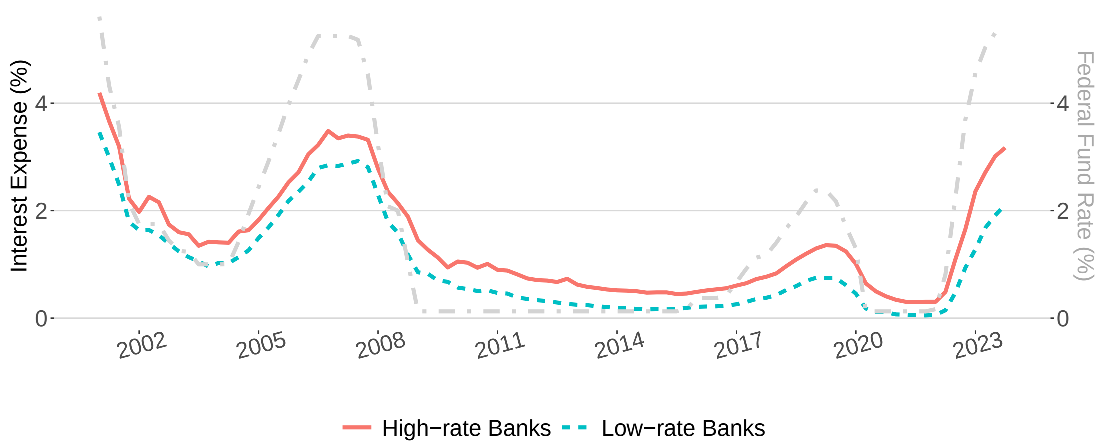
Notes: These figures present the characteristics of households utilizing bank tellers versus mobile banking as their primary means of accessing banking services. The data is derived from the FDIC Survey of Consumer Use of Banking and Financial Services. Respondents were asked to specify their most common method of accessing their accounts, choosing from options such as "Bank teller," "ATM/Kiosk," "Telephone banking," "Online banking," "Mobile banking," and "Other." Panels A, B, and C depict the average age, average income, and the proportion of households with education beyond the college level for households utilizing bank tellers and mobile banking to access banking services over the years.

Figure B.6: Interest and Non-interest Expense Rate

(a) Non-interest Expense Rate



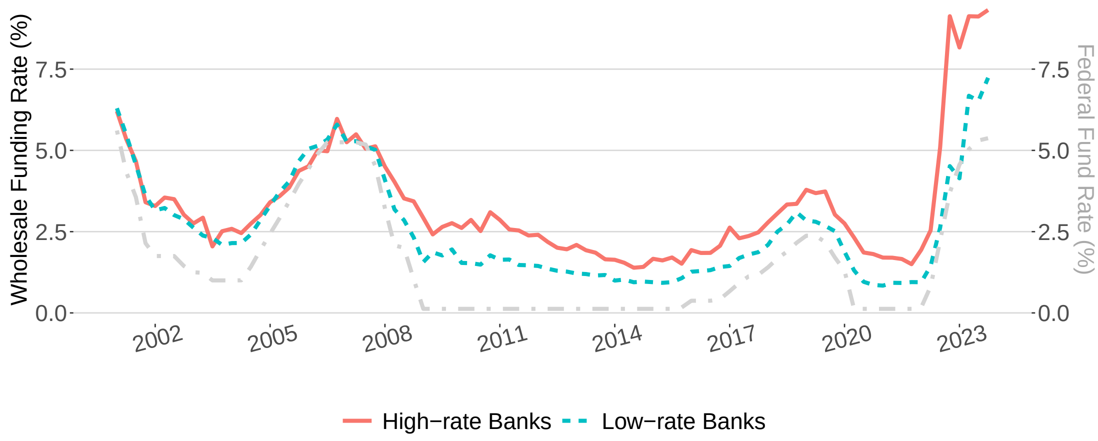
(b) Interest Expense Rate



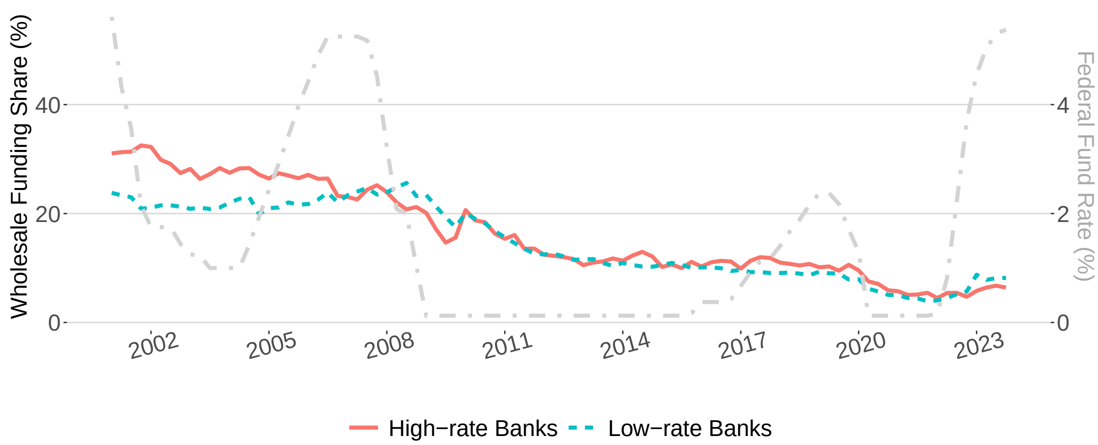
Notes: The figures plot the non-interest expense rate and interest expense rate of high- and low-rate banks among the top 25 banks from 2001Q1 through 2023Q4. See Appendix Table A.1 for more details on the construction of key variables. A bank is categorized as a *high-rate* bank if its average rank, calculated based on the 12MDC10K rate and deposit rate from the Call Report, falls within the top tercile.

Figure B.7: Wholesale Funding

(a) Wholesale Funding Rate



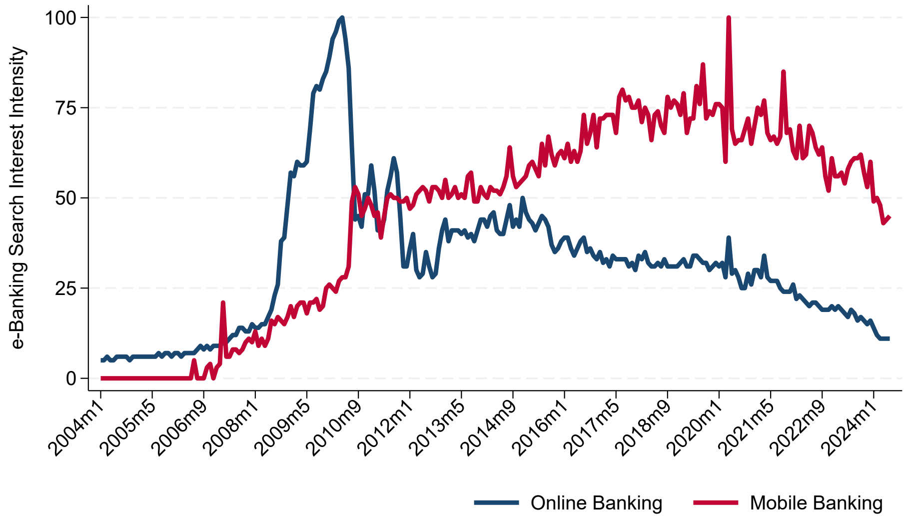
(b) Wholesale Funding Share



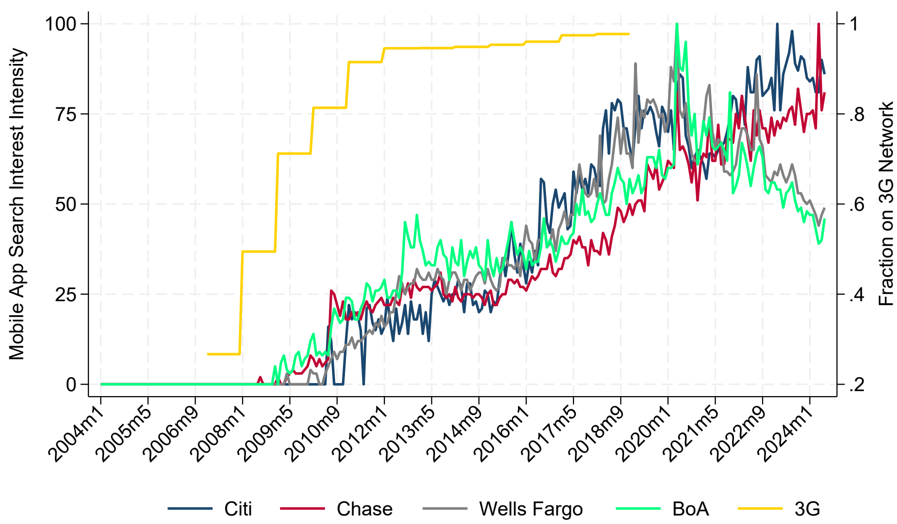
Notes: The figures plot the wholesale funding share (in panel A) and rate (in panel B) of high- and low-rate banks among the top 25 banks from 2001Q1 through 2023Q4. The wholesale funding includes federal funds purchased and repurchase agreements, subordinated debt, and other borrowed funds. See Appendix Table A.1 for more details on the construction of key variables. A bank is categorized as a *high-rate* bank if its average rank, calculated based on the 12MDC10K rate and deposit rate from the Call Report, falls within the top tercile.

Figure B.8: e-Banking Adoption 2004-2024

(a) Online and Mobile Banking



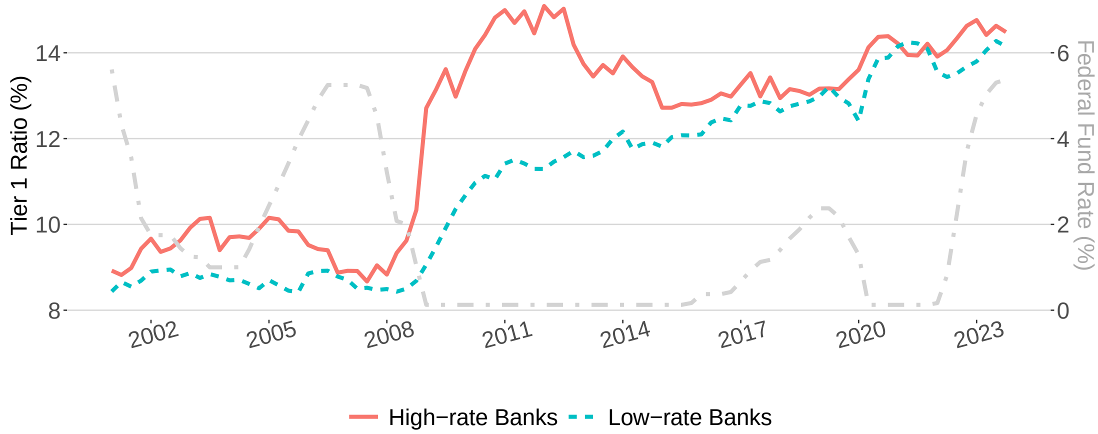
(b) 3G & Top 4 Banks: Mobile Apps



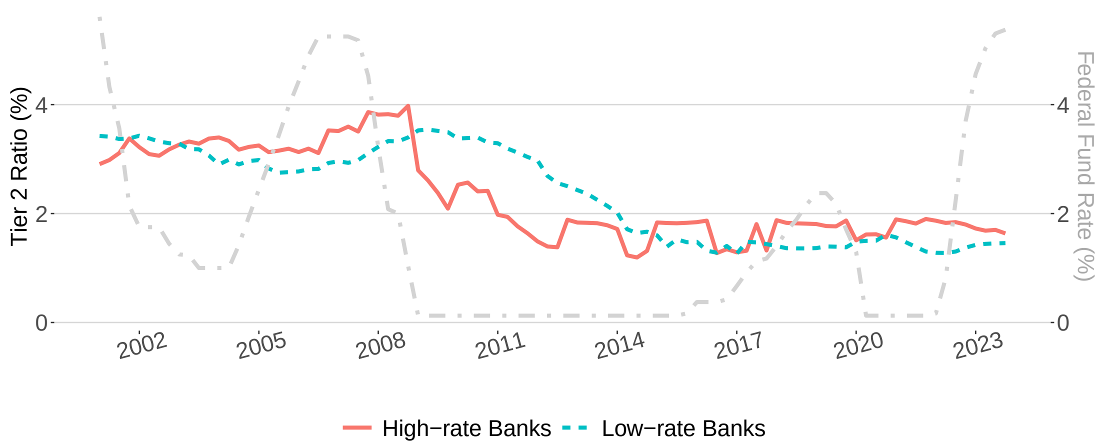
Notes: This figure plots the search interest intensity for online banking and mobile banking. Appendix Figure B.8a plots the search interest intensity for "online banking" (blue) and "mobile banking" (red) from 2004 through 2024. Figure B.8b plots the search interest intensity for "Citi App" (blue), "Chase App" (red), "Wells Fargo App" (gray), and "Bank of America App" (green), along with the fraction of the US population on a 3G network (yellow). The search interest intensity numbers represent search interest relative to the highest point on the chart for the given region and time; a value of 100 is the peak popularity for the term; a value of 50 means that the term is half as popular and a score of 0 means there was not enough data for this term. Search interest intensity data is from GoogleTrends. 3G coverage data is from Collins Bartholomew's Mobile Coverage Explorer.

Figure B.9: Tier 1 and Tier 2 Ratios

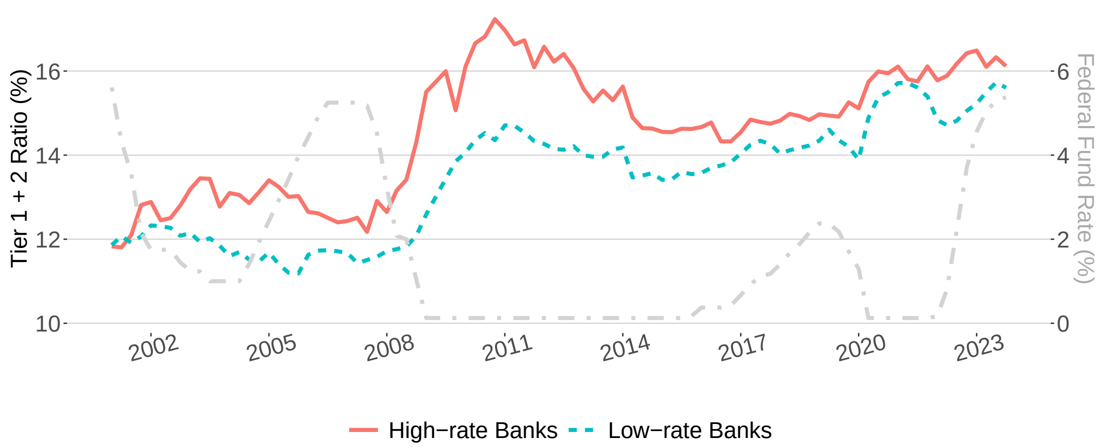
(a) Tier 1 Ratio



(b) Tier 2 Ratio

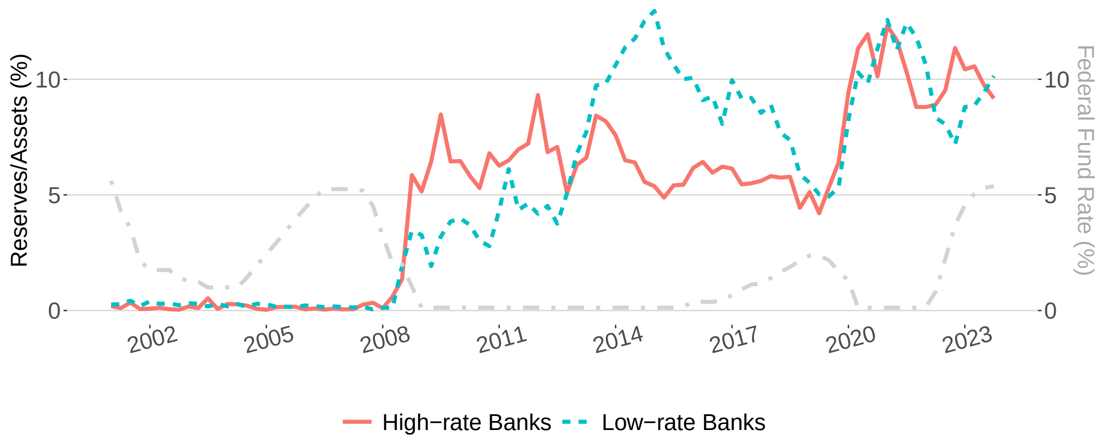


(c) Tier 1+2 Ratio



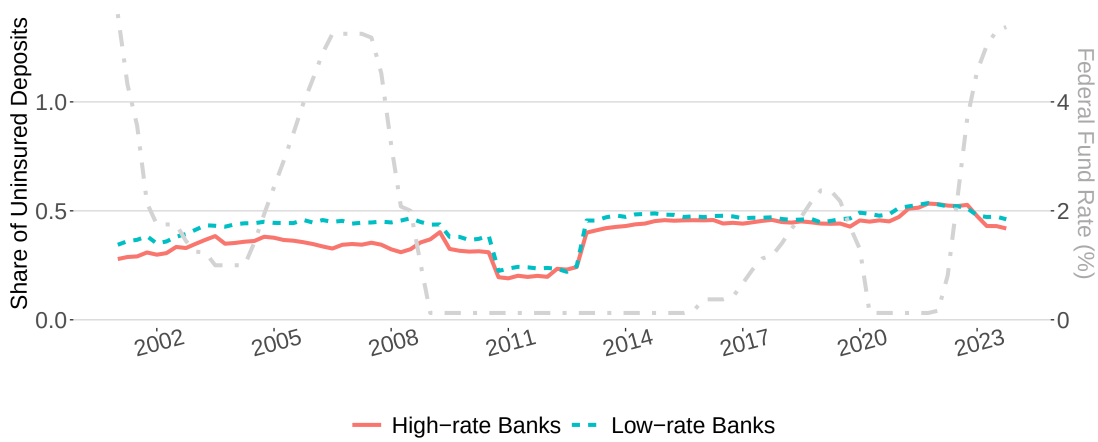
Notes: This figure compares the Tier 1/2 ratio of high- and low-rate banks among the top 25 banks from 2001Q1 through 2023Q4. See Appendix Table A.1 for more details on the construction of key variables. The left y-axis represents the quarterly average Federal Fund Target rate (FFTar). A bank is categorized as a *high-rate* bank if its average rank, calculated based on the CD rate and deposit rate from the Call Report, falls within the top tercile.

Figure B.10: Reserves



Notes: This figure compares the reserve holding of high- and low-rate banks among the top 25 banks from 2001Q1 through 2023Q4. See Appendix Table A.1 for more details on the construction of key variables. The left y-axis represents the quarterly average Federal Fund Target rate (FFTar). A bank is categorized as a *high-rate* bank if its average rank, calculated based on the CD rate and deposit rate from the Call Report, falls within the top tercile.

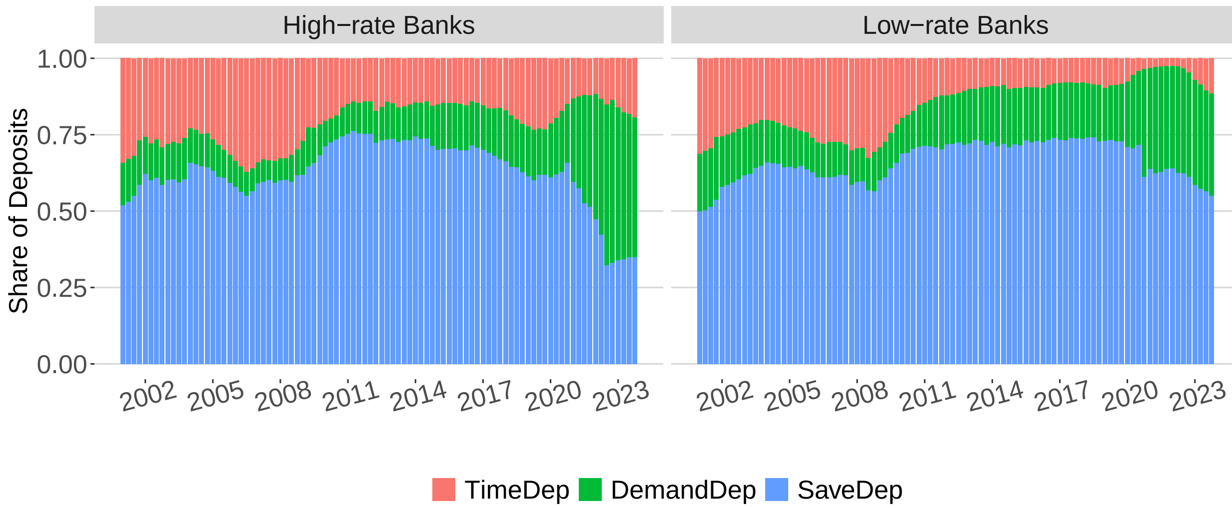
Figure B.11: Uninsured Deposit Share



Notes: This figure compares the uninsured deposit share of high- and low-rate banks among the top 25 banks from 2001Q1 through 2023Q4. See Appendix Table A.1 for more details on the construction of key variables. The left y-axis represents the quarterly average Federal Fund Target rate (FFTar). A bank is categorized as a *high-rate* bank if its average rank, calculated based on the CD rate and deposit rate from the Call Report, falls within the top tercile.

Figure B.12: Deposits Decomposition

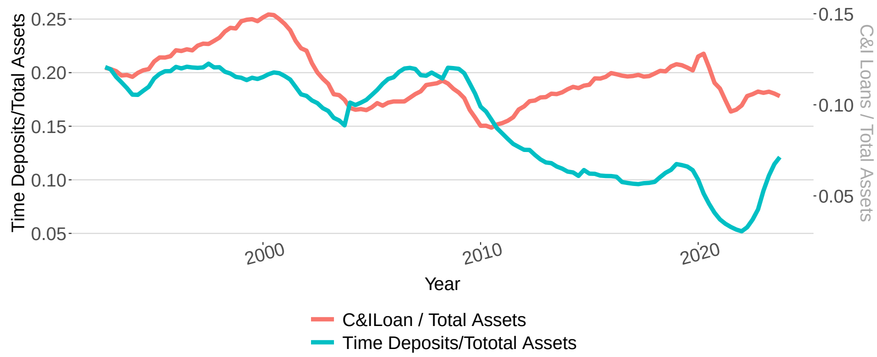
(a) Share of Deposits



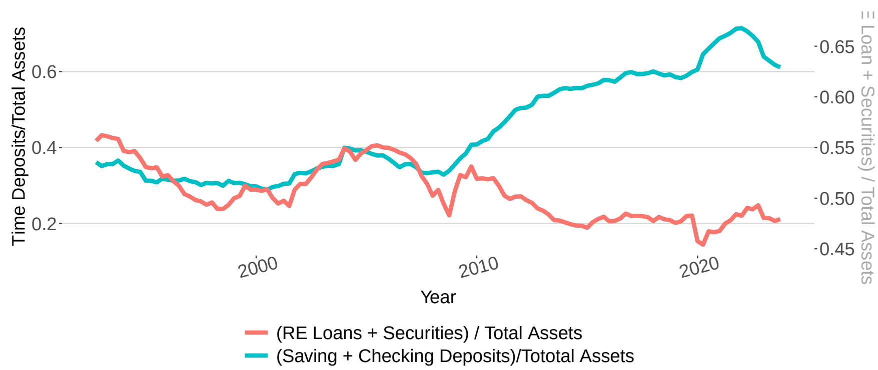
Notes: This figure compares the deposit composition of high- and low-rate banks among the top 25 banks from 2001Q1 through 2023Q4. See Appendix Table A.1 for more details on the construction of key variables. A bank is categorized as a *high-rate* bank if its average rank, calculated based on the CD rate and deposit rate from the Call Report, falls within the top tercile.

Figure B.13: Extension of Figure 1 from Supera (2021) to 2023Q4

(a) C&I Loans vs. Time Deposits



(b) Real Estate Loans and Securities vs. Savings and Checking Deposits



Notes: This figure extends Figure 1 of Supera (2021) to 2023Q4. Panel (a) plots the time-series evolution of C&I loans versus time deposits of all banks, expressed as a share of total assets. Panel (b) plots the time-series evolution of real estate loans and securities versus savings deposits of all banks, also expressed as a share of total assets.

B.2 Tables

Table B.1: Variation in Branch Deposit Rates across Largest Banks and BHCs

	(1) Time FE	(2) RSSD FE	(3) BHC FE	(4) RSSD+Time FE	(5) BHC+Time FE	(6) RSSD×Time FE	(7) BHC×Time FE
R^2	0.9056	0.0657	0.0674	0.9320	0.9423	0.9423	0.9636
adj. R^2	0.9056	0.0588	0.0669	0.9315	0.9422	0.9363	0.9626
N	916,859	910,276	57,545	910,276	57,545	513,270	57,401

Notes: This table reports the R^2, adj R^2 and number of observations from regressing the 12-month certificate of deposit rate at the Branch × Bank × Quarter-Year level on quarter-year fixed effects (column 1), RSSD fixed effects (column 2), BHC fixed effects (column 3), RSSD and quarter-year fixed effects (column 4), BHC and quarter-year fixed effects (column 5), RSSD × quarter-year fixed effects (column 6), and BHC × quarter-year fixed effects (column 7).

Table B.2: Summary Statistics

Panel A: High v.s. Low-rate Banks Comparison

	2008-2016		
	High	Low	Diff
CD (%)	0.80	0.44	0.36***
DepRate (%)	0.88	0.43	0.45***
Asset ($B)	298.17	429.14	-130.96
Insured Deposits Share (%)	41.68	49.41	-7.73***
# Branches	831	4051	-3220***
$\log(\frac{\#\text{ Branches}}{\text{Deposits}})$	-0.01	1.37	-1.38***
NIM rate (%)	3.17	2.64	0.53***
Maturity (Years)	3.91	5.95	-2.04***
Charge-off Rate (%)	1.89	1.27	0.62***

Panel B: Correlation Matrix of Rates

	DepRate	SAV	CD	MM
DepRate	1.000	0.653	0.904	0.815
SAV	0.653	1.000	0.694	0.764
CD	0.904	0.694	1.000	0.847
MM	0.815	0.764	0.847	1.000

Notes: Panel A compares various metrics between high- and low-rate banks among the top 25 banks between 2008Q1 to 2016Q4. CD refers to the 12-month certificate of deposit rate on accounts with at least $10,000, collected from RateWatch. DepRate is the deposit rate calculated from the Call Reports. The share of insured deposits, NIM rate, quarterly growth of deposits, maturity of loans and securities, charge-offs of loans are extracted from the Call Reports. Additionally, we count the number of branches for each bank using the Statement of Deposits (SOD). A bank is categorized as a *high-rate* bank if its average rank, calculated based on the 12MDC10K rate and deposit rate from the Call Report, falls within the top tercile. The averages, weighted by its asset size in the previous quarter, are reported separately for the two types of banks, as well as their difference. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively. Panel B presents the correlation matrix of various measures of the deposit rate. SAV refers to the savings rate and MM refers to the money market account rate on accounts with at least $25,000. Both are recorded by RateWatch.

Table B.3: Classification of Banks

Classification of Banks

High-rate Banks	Low-rate Banks
Ally Financial	Banco Santander
American Express	Bank of Montreal
Banco Bilbao Vizcaya Argentaria	Bank of New York
Capital One	Barnett Banks
Citi	Bank of America
Countrywide Financial	Charles Schwab
Deutsche Bank	Citizens Bank
First Hawaiian	Comerica Incorporated
Goldman Sachs	Fifth Third Bank
ING Group	First Citizens Bancshares
MBNA Corporation	First Republic Bank
Mitsubishi UFJ Financial Group	Fleetboston Financial Corporation
Morgan Stanley	HSBC
National City	Huntington
Potrero Hill Branch	JP Morgan
RBS Holdings	Keybank
Southtrust Corporation	M&T Bank
Suntrust Bank	Mellon Financial Corporation
Washington Mutual	Merrill Lynch
	North Fork Bancorporation
	Northern Trust
	PNC
	Regions Financial
	State Street Bank
	SVB
	TD Bank
	Thuist
	U.S. Bankcorp
	Wachovia
	Wells Fargo

Notes: Table presents the classification for the top 25 banks in the sample from 2001Q1 to 2023Q4.

Table B.4: What Predicts the Bank Type?

	$\mathbb{1}(\text{High-rate}_{2009-2023})$	
	Top 25	Top 100
	(1)	(2)
$\log(\frac{\text{Branches}}{\text{Deposit}})_{2001-2008}$	-0.071*	-0.040*
	(0.041)	(0.022)
$\log(\text{Asset})_{2001-2008}$	-0.146*	-0.101***
	(0.082)	(0.030)
Reserve $\text{share}_{2001-2008}$	-2.300	-1.159
	(1.398)	(0.747)
Insured $\text{dep}_{2001-2008}$	0.656	0.282
	(0.463)	(0.226)
$\Delta\text{Dep}_{2001-2008}$	-0.008	-0.001
	(0.012)	(0.005)
$\text{ROA}_{2001-2008}$	-0.162	-0.000
	(0.123)	(0.005)
$\text{Tier1/2}_{2001-2008}$	-0.005	0.000
	(0.013)	(0.001)
CI $\text{Loan}_{2001-2008}$	-0.017	0.000
	(0.011)	(0.004)
Personal $\text{Loan}_{2001-2008}$	0.008	0.004
	(0.011)	(0.003)
$\text{MBS}_{2001-2008}$	-0.028**	-0.002
	(0.011)	(0.005)
RE $\text{Loan}_{2001-2008}$	-0.008	0.004
	(0.009)	(0.003)
Constant	4.191**	2.121***
	(1.898)	(0.615)
Adjusted R^2	0.323	0.187
Observations	38	175

Notes: This table examines the characteristics of banks between 2001 and 2008 to predict their classification from 2009 to 2023, focusing on those that entered the top 25 (Column 1) and top 100 (Column 2) rankings. The analysis uses a dependent variable indicating whether a bank is classified as high-rate. Independent variables include average characteristics such as log-transformed branch-to-deposit ratios, log-transformed assets, reserve ratios, share of insured deposits, annual deposit growth rates, ROA, Tier 1/2 capital ratios, and shares of commercial, personal, real estate loans, and MBS. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

Table B.5: Transmission of Monetary Policy (Robustness Check with Quarter FE)

	Liabilities			Assets	Assets - Liability
	ΔCD	ΔSav	ΔInterest Expense	ΔInterest Income	ΔNIM
	(1)	(2)	(3)	(4)	(5)
ΔFed Funds$_q\times$ $\mathbb{1}$(High-rate) $\times$Post	0.375***	0.211***	0.124***	0.309***	0.137***
	(0.107)	(0.042)	(0.022)	(0.032)	(0.039)
ΔFFTar$\times$ $\mathbb{1}$(High-rate)	0.040	0.004	0.028***	-0.154***	-0.174***
	(0.029)	(0.022)	(0.011)	(0.029)	(0.032)
$\mathbb{1}$(High-rate)$\times$Post	0.012	0.018	0.013	-0.011	-0.005
	(0.113)	(0.049)	(0.029)	(0.065)	(0.064)
$\mathbb{1}$(High-rate)	0.075	0.021	-0.016	0.018	0.022
	(0.067)	(0.032)	(0.021)	(0.057)	(0.056)
Controls+Quarter FE	✓	✓	✓	✓	✓
Adjusted R^2	0.281	0.215	0.149	0.071	0.040
Observations	1,820	1,768	2,300	2,300	2,300
Mean of Dep. Variable (level %)	0.850	0.217	0.915	3.616	2.658

Notes: This table reports the estimated coefficients from the following regression specification:

$$\begin{aligned}\Delta Y_{i,y} &= \delta_q + \Delta\text{Fed Funds}_y \times \mathbb{1}(\text{High-rate}_i) \times \text{Post}_q + \Delta\text{Fed Funds}_y \times \mathbb{1}(\text{High-rate}_i)\\ &+ \Delta\text{Fed Funds}_y \times \text{Post}_q + \times\mathbb{1}(\text{High-rate}_i) \times \text{Post}_q + \Delta\text{Fed Funds}_y + \mathbb{1}(\text{High-rate}_i)\\ &+ \Delta\text{Fed Funds}_y \times \mathbb{1}(\text{High-rate}_i) \times \text{Crisis} + Controls_{i,q-1} + \varepsilon_{i,q},\end{aligned}$$

where i and q indicate the bank and quarter-year, respectively, ΔFed Funds$_y$ denotes the one-year change in the Federal Funds Target Rate, $\mathbb{1}(\text{High-rate}_i)$ denotes whether bank i is a high-rate bank, Post$_q$ denotes the post-2009 period, Crisis is an indicator for year 2008. Controls include ROA$_{i,q-1}$ and Tier 1/2$_{i,q-1}$, which represent the return on assets and the Tier 1/2 capital ratio from the previous quarter, respectively. The dependent variable, $\Delta Y_{i,y}$ is the one-year change in the CD rate in column (1), the change in the saving rate in column (2), the change in interest expense in column (3), the change in net interest income in column (4), and the change in NIM in column (5). All dependent variables are winsorized at the 1% and the 99% levels. The CD and saving rates comes from RateWatch. The change in interest expense, interest income and NIM are computed from the Call Reports. See Table A.1 for more details on the construction of key variables. A bank is categorized as a *high-rate* bank if its average rank each quarter, calculated based on the CD rate and deposit rate from the Call Report, falls within the top tercile. Each observation is weighted by its asset size from the previous quarter. Standard errors (in parentheses) are clustered at the quarter-year levels and are accounted for autocorrelation consistent errors using Driscoll-Kraay with 4-quarter lags. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

Table B.6: Changes in Lending Rates During Monetary Policy Cycles

	ΔPersonal Loan Rate$_{i,y}$	ΔC&I Loan Rate$_{i,y}$	ΔRE Loan Rate$_{i,y}$	ΔMBS Rate$_{i,y}$
	(1)	(2)	(3)	(4)
ΔFed Funds$_y\times$ $\mathbb{1}$(High-rate) $\times$Post	0.199	0.097*	0.160	0.268
	(0.435)	(0.051)	(0.141)	(0.162)
ΔFed funds$_y\times$ $\mathbb{1}$(High-rate)	-0.119	-0.258***	-0.192	-0.238
	(0.430)	(0.040)	(0.137)	(0.146)
$\mathbb{1}$(High-rate)$\times$Post	0.955	-0.142	-0.267	-0.746*
	(0.841)	(0.100)	(0.306)	(0.410)
$\mathbb{1}$(High-rate)	-0.566	0.170*	0.329	0.686*
	(0.827)	(0.087)	(0.301)	(0.399)
Quarter FE	✓	✓	✓	✓
Adjusted R^2	0.027	0.021	0.023	0.033
Observations	2,059	2,157	2,127	2,015
Mean of Dep. Variable (level %)	7.706	3.960	4.221	3.170

Notes: This table reports the estimated coefficients from the following regression specification:

$$\begin{aligned}\Delta Y_{i,y} = {} & \delta_q + \Delta\text{Fed Funds}_y \times \mathbb{1}(\text{High-rate}_i) \times \text{Post}_q + \Delta\text{Fed Funds}_y \times \mathbb{1}(\text{High-rate}_i) \\ & + \Delta\text{Fed Funds}_y \times \text{Post}_q + \times\mathbb{1}(\text{High-rate}_i) \times \text{Post}_q + \Delta\text{Fed Funds}_y + \mathbb{1}(\text{High-rate}_i) \\ & + \Delta\text{Fed Funds}_y \times \mathbb{1}(\text{High-rate}_i) \times \text{Crisis} + Controls_{i,q-1} + \varepsilon_{i,q},\end{aligned}$$

where i and q indicate the bank and quarter-year, respectively, ΔFed Funds$_y$ denotes the one-year change in the Federal Funds Target Rate, $\mathbb{1}$(High-rate$_i$) denotes whether bank i is a high-rate bank, Post$_q$ denotes the post-2009 period, Crisis is an indicator for year 2008. Controls include ROA$_{i,q-1}$ and Tier 1/2$_{i,q-1}$, which represent the return on assets and the Tier 1/2 capital ratio from the previous quarter, respectively. The dependent variable, $\Delta Y_{i,y}$ is the one-year change of personal loan rate (column 1), C&I loan rate (column 2), real estate loan rate (column 3) and MBS rate (column 4) of bank i, and are winsorized at the 1% and the 99% levels. A bank is categorized as a *high-rate* bank if its average rank each quarter, calculated based on the CD rate and deposit rate from the Call Report, falls within the top tercile. Each observation is weighted by its asset size from the previous quarter. Standard errors (in parentheses) are clustered at the quarter-year levels and are accounted for autocorrelation consistent errors using Driscoll-Kraay with 4-quarter lags. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

Table B.7: Reallocation of Lending During Monetary Policy Cycles (Including New Three-way Interactions)

	Pers. Loans		C&I Loans		RE Loans		MBS	
	$\Delta\log(Q_{i,y})$	$\Delta\text{Share}_{i,q}$	$\Delta\log(Q_{i,y})$	$\Delta\text{Share}_{i,q}$	$\Delta\log(Q_{i,y})$	$\Delta\text{Share}_{i,q}$	$\Delta\log(Q_{i,y})$	$\Delta\text{Share}_{i,q}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔFed Funds$_y\times$ $\mathbb{1}$(High-rate)$\times$Post	6.395***	0.999***	8.314***	0.560***	0.662	-0.436*	1.592	-0.532*
	(2.171)	(0.274)	(2.521)	(0.164)	(0.641)	(0.257)	(2.119)	(0.273)
ΔFFTar$_y\times$ $\mathbb{1}$(High-rate)	-3.918***	-0.735***	-6.686***	-0.475***	-1.291**	0.123	0.141	0.779***
	(1.462)	(0.236)	(1.333)	(0.123)	(0.495)	(0.154)	(2.007)	(0.237)
ΔFed Funds$_y\times$ $\frac{\text{TimeDep}_{i,q-1}}{\text{Asset}_{i,q-1}}\times$Post	-15.402	-4.151***	12.617	-0.751	9.983	-1.172	26.106	6.653**
	(11.366)	(1.503)	(16.544)	(1.687)	(9.008)	(1.679)	(28.565)	(3.159)
ΔFFTar$_y\times$ $\frac{\text{TimeDep}_{i,q-1}}{\text{Asset}_{i,q-1}}$	-8.412	2.553**	-18.904***	-0.983	-14.883**	-0.525	-16.623	-3.880
	(5.317)	(1.219)	(5.456)	(1.018)	(6.957)	(1.056)	(27.388)	(2.889)
Quarter FE+Controls	✓	✓	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.092	0.087	0.069	0.015	0.057	0.025	0.038	0.019
Observations	2,300	2,300	2,300	2,300	2,300	2,300	2,300	2,300
Mean of Dep. Variable (level)	4.575	13.375	4.293	15.181	2.190	29.619	5.978	16.994

Notes: This table reports the estimated coefficients from the following regression specification:

$$\begin{aligned}\Delta Y_{i,y} = \delta_q &+ \Delta\text{Fed Funds}_y \times \mathbb{1}(\text{High-rate}_i) \times \text{Post}_q + \Delta\text{Fed Funds}_y \times \mathbb{1}(\text{High-rate}_i)\\ &+ \Delta\text{Fed Funds}_y \times \text{Post}_q + \times\mathbb{1}(\text{High-rate}_i) \times \text{Post}_q + \Delta\text{Fed Funds}_y + \mathbb{1}(\text{High-rate}_i)\\ &+ \Delta\text{Fed Funds}_y \times \mathbb{1}(\text{High-rate}_i) \times \text{Crisis} + Controls_{i,q-1} + \varepsilon_{i,q},\\ &\Delta\text{Fed Funds}_y \times \frac{\text{TimeDep}_{i,q-1}}{\text{Asset}_{i,q-1}} \times \text{Post}_q + \Delta\text{Fed Funds}_y \times \frac{\text{TimeDep}_{i,q-1}}{\text{Asset}_{i,q-1}} + \varepsilon_{i,q},\end{aligned}$$

where i and q indicate the bank and quarter-year, respectively, ΔFed Funds Rate$_y$ denotes the one-year change in the Federal Funds Target Rate, $\mathbb{1}_{\text{High-rate}_i}$ denotes whether bank i is a high-rate bank, Post$_q$ denotes the post-2009 period, Crisis is an indicator for year 2008. Controls include ROA$_{i,q-1}$ and Tier $1_{i,q-1}$, which represent the return on assets and the tier 1 capital ratio from the previous quarter, respectively. To account for the channel proposed by Supera (2021), we incorporate three-way interactions of the time deposits to total assets from the previous quarter, $\frac{\text{TimeDep}_{i,q-1}}{\text{Asset}_{i,q-1}}$, with ΔFed Funds Rate$_y$ and Post$q$. We analyze two forms of dependent variables: 1) $\Delta\log(Q_{i,y})$, representing the logarithmic change in quantity, and 2) $\Delta\text{Share}_{i,q}$, denoting the change in share. A bank is categorized as a *high-rate* bank if its average rank, calculated based on the CD rate and deposit rate from the Call Report, falls within the top tercile. Each observation is weighted by its asset size from the previous quarter. Standard errors (in parentheses) are clustered at the quarter-year levels and are accounted for autocorrelation consistent errors using Driscoll-Kraay with 4-quarter lags. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

Table B.8: Reallocation of Lending During Monetary Policy Cycles (Including Various Deposit Growth)

	Pers. Loans		C&I Loans		RE Loans		MBS	
	$\Delta\log(Q_{i,y})$	$\Delta\text{Share}_{i,q}$	$\Delta\log(Q_{i,y})$	$\Delta\text{Share}_{i,q}$	$\Delta\log(Q_{i,y})$	$\Delta\text{Share}_{i,q}$	$\Delta\log(Q_{i,y})$	$\Delta\text{Share}_{i,q}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔFed Funds$_y\times$ $\mathbb{1}$(High-rate)$\times$Post	5.342**	1.019***	7.570***	0.471***	0.379	-0.436*	0.564	-0.575**
	(2.139)	(0.246)	(1.870)	(0.143)	(0.704)	(0.243)	(2.429)	(0.278)
ΔFFTar$_y\times$ $\mathbb{1}$(High-rate)	-3.103**	-0.767***	-5.771***	-0.455***	-0.730	0.053	1.758	0.922***
	(1.507)	(0.219)	(0.981)	(0.100)	(0.496)	(0.155)	(2.293)	(0.264)
log(Time Dep.$_{i,y}$)	0.063**	0.004	0.011	0.001	0.071***	-0.001	0.022	-0.005
	(0.024)	(0.002)	(0.022)	(0.003)	(0.022)	(0.006)	(0.041)	(0.006)
log(Sav Dep.$_{i,y}$)	0.249***	0.013**	0.176**	-0.001	0.121***	-0.008	0.151**	-0.002
	(0.068)	(0.006)	(0.073)	(0.005)	(0.038)	(0.006)	(0.071)	(0.012)
log(Demand Dep.$_{i,y}$)	0.014	0.003	0.020	0.002	0.042*	-0.002	0.103***	0.004
	(0.039)	(0.004)	(0.030)	(0.003)	(0.023)	(0.007)	(0.031)	(0.005)
Quarter FE+Controls	✓	✓	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.106	0.077	0.070	0.012	0.073	0.022	0.048	0.015
Observations	2,300	2,300	2,300	2,300	2,300	2,300	2,300	2,300
Mean of Dep. Variable (level)	4.575	13.375	4.293	15.181	2.190	29.619	5.978	16.994

Notes: This table reports the estimated coefficients from the following regression specification:

$$\begin{aligned}\Delta Y_{i,y} = \delta_q &+ \Delta\text{Fed Funds}_y \times \mathbb{1}(\text{High-rate}_i) \times \text{Post}_q + \Delta\text{Fed Funds}_y \times \mathbb{1}(\text{High-rate}_i) \\ &+ \Delta\text{Fed Funds}_y \times \text{Post}_q + \times\mathbb{1}(\text{High-rate}_i) \times \text{Post}_q + \Delta\text{Fed Funds}_y + \mathbb{1}(\text{High-rate}_i) \\ &+ \Delta\text{Fed Funds}_y \times \mathbb{1}(\text{High-rate}_i) \times \text{Crisis} + Controls_{i,q-1} + \varepsilon_{i,q}, \\ &\log(\text{Time Dep.}_{i,y}) + \log(\text{Sav Dep.}_{i,y}) + \log(\text{Demand Dep.}_{i,y}) + \varepsilon_{i,q},\end{aligned}$$

where i and q indicate the bank and quarter-year, respectively, ΔFed Funds Rate$_y$ denotes the one-year change in the Federal Funds Target Rate, $\mathbb{1}_{\text{High-rate}_i}$ denotes whether bank i is a high-rate bank, Post$_q$ denotes the post-2009 period, Crisis is an indicator for year 2008. Controls include ROA$_{i,q-1}$ and Tier $1_{i,q-1}$, which represent the return on assets and the tier 1 capital ratio from the previous quarter, respectively. To accommodate the mechanism suggested by Supera (2021), we incorporate three control variables representing the annual logarithmic changes in time, savings, and demand deposits. We analyze two forms of dependent variables: 1) $\Delta\log(Q_{i,y})$, representing the logarithmic change in quantity, and 2) $\Delta\text{Share}_{i,q}$, denoting the change in share. A bank is categorized as a *high-rate* bank if its average rank, calculated based on the CD rate and deposit rate from the Call Report, falls within the top tercile. Each observation is weighted by its asset size from the previous quarter. Standard errors (in parentheses) are clustered at the quarter-year levels and are accounted for autocorrelation consistent errors using Driscoll-Kraay with 4-quarter lags. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

Table B.9: Composition of Top25 Banks

	Top 25 Banks Before 2009	2017-2023 Top 25 Banks After 2009	Diff
CD (%)	0.32	1.40	-1.08***
DepRate (%)	0.61	1.02	-0.40*
Asset ($B)	667.14	228.38	438.76***
Insured Deposits Share (%)	42.42	67.58	-25.16***
# Branches	3020	102	2918***
$\log(\frac{\#\text{ Branches}}{\text{Deposits}})$	0.62	-3.60	4.22***
NIM rate (%)	2.52	2.24	0.28
Maturity (Years)	6.56	5.62	0.94
Charge-off Rate (%)	0.46	0.29	0.17

Notes: This table presents a comparison of various metrics reflecting the composition of the top 25 banks before and after 2009, focusing specifically on data from the period 2017Q1 to 2023Q4 to ensure the statistics are comparable. CD refers to the 12-month certificate of deposit rate on accounts with at least $10,000, collected from RateWatch. DepRate is the deposit rate calculated from the Call Reports. The share of insured deposits, NIM rate, quarterly growth of deposits, maturity of loans and securities, charge-offs of loans are extracted from the Call Reports. Additionally, we count the number of branches for each bank using the Statement of Deposits (SOD). A bank is categorized as a *high-rate* bank if its average rank, calculated based on the 12MDC10K rate and deposit rate from the Call Report, falls within the top tercile. The averages, weighted by its asset size in the previous quarter, are reported separately for the two types of banks, as well as their difference. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

C Proofs

C.1 Solving the Model without Remote Banking Services

Considering the symmetry of the banks, two banks position their branches equidistantly around a circle. Without loss of generality, we assume that Bank A is located at position 0, while Bank B is located at position $1/2$. Depositors located at s and $1-s$ has a distance s to bank A and $1/2-s$ to bank B. In the case, depositors located at $\tilde{s} = \frac{r_A - r_B + \eta/2}{2\eta}$ and $1-\tilde{s}$ are indifferent between bank A and B. This leads to the following demands for two banks:

$$D_A = \frac{\eta/2 + (r_A - r_B)}{\eta}, \qquad D_B = \frac{\eta/2 - (r_A - r_B)}{\eta}.$$

Solving the equations (3), the first order conditions with respect to deposit rates are

$$r_A = \frac{1}{2}(f - \eta/2 + l_A + r_B), \quad r_B = \frac{1}{2}(f - \eta/2 + l_B + r_A).$$

Solving the equations (3), the first order conditions with respect to risk levels are

$$p(l_A) + (f + l_A - r_A)p'(l_A) = 0, \quad p(l_B) + (f + l_B - r_B)p'(l_B) = 0.$$

Based on the first two questions, we have

$$f + l_A - r_A = r_A - r_B + \eta/2, \quad f + l_B - r_B = r_B - r_A + \eta/2.$$

This gives

$$p(l_A) + (r_A - r_B + \eta/2)p'(l_A) = p(l_B) + (r_B - r_A + \eta/2)p'(l_B) = 0.$$
$$\Longrightarrow p(l_A) - p(l_B) = \frac{\eta}{2}\Big(p'(l_B) - p'(l_A)\Big) + \frac{l_B - l_A}{3}\Big(p'(l_B) + p'(l_A)\Big).$$

If $l_A > l_B$, the left side of the equation becomes negative, owing to the condition $p'(\cdot) < 0$. In contrast, the right side remains positive because of $p''(\cdot) \leq 0$. Such a scenario is not feasible, leading to the conclusion that $l_A \leq l_B$. Applying the same reasoning, we can also deduce that $l_A \geq l_B$. Consequently, it follows that $l_A = l_B = l^*$, where $p(l^*) + \frac{\eta}{2}p'(l^*) = 0$, and $r_A = r_B = f + l^* - \eta/2$. Under the assumption that $p(l) = \alpha - l$, $l^* = \alpha - \frac{\eta}{2}$.

C.2 Solving the Model during Mobile Banking Era

We separately discuss all possible equilibria during mobile banking era.

- Case 1 {A: E-banking only, B: E-banking only}. In this case, two banks provide homogeneous deposit products, and hence the deposit market is perfectly competitive, resulting in 0 profit for both banks:

$$prof_A^1 = prof_B^1 = 0.$$

- Case 2 {A: Branch+E-banking, B: Branch+E-banking}. In this case, the banks maintain their symmetry. Proceeding with the methodology as in the baseline model, we derive the following results:

$$r_A = r_B = f + l^* - \eta/2 = r^*, \qquad prof_A^2 = prof_B^2 = \frac{\eta}{4}p(l^*) = \frac{\eta^2}{8} - \kappa,$$

where $-\frac{p'(l^*)}{p(l^*)} = \frac{2}{\eta} \Longrightarrow l^* = \alpha - \frac{\eta}{2}$, the same as in the case without mobile banking.

- Case 3 {A: Branch only, B: Branch+E-banking}. In this case, the objective functions of banks can be written as follows:

$$\max_{l_A, r_A} p(l_A)(f + l_A - r_A)\frac{\eta/2 + r_A - r_B - \gamma}{\eta} - \kappa,$$

$$\max_{l_B, r_B} p(l_B)(f + l_B - r_B)\frac{\eta/2 + r_B - r_A + \gamma}{\eta} - \kappa.$$

The equilibrium is characterized as

$$r_A = r^* + \frac{2\gamma}{5}, \quad r_B = r^* - \frac{3c_M + 2\gamma}{5}$$

$$l_A = l^* + \frac{\gamma}{5}, \quad l_B = l^* - \frac{\gamma}{5},$$

$$Prof_A^3 = \frac{(-2\gamma + 5\eta)^3}{1000\eta} - \kappa, \quad Prof_B^3 = \frac{(2\gamma + 5\eta)^3}{1000\eta} - \kappa.$$

- Case 4 {A: Branch only, B: E-banking only}. In this case, the objective functions of banks can be written as follows:

$$\max_{l_A, r_A} p(l_A)(f + l_A - r_A)\frac{\eta + 2r_A - 2r_B - 2\gamma}{\eta} - \kappa,$$

$$\max_{l_B, r_B} p(l_B)(f + l_B - r_B)\frac{2r_B - 2r_A + 2\gamma}{\eta}.$$

The equilibrium is characterized as

$$r_A = r^* + \frac{2\gamma + 2\eta}{5}, \quad r_B = r^* + \frac{-2\gamma + 3\eta}{5}$$

$$l_A = l^* + \frac{2\gamma + 2\eta}{10}, \quad l_B = l^* + \frac{-2\gamma + 3\eta}{10},$$

$$Prof_A^4 = \frac{(-2\gamma + 3\eta)^3}{500\eta} - \kappa, \quad Prof_B^4 = \frac{2(\gamma + \eta)^3}{125\eta}.$$

- Case 5 {A: Branch+E-banking, A: E-banking only}. In this case, the objective functions of banks can be written as follows:

$$\max_{l_A, r_A} p(l_A)(f + l_A - r_A)\frac{\eta + 2r_A - 2r_B}{\eta} - \kappa,$$

$$\max_{l_B, r_B} p(l_B)(f + l_B - r_B)\frac{2r_B - 2r_A}{\eta}.$$

The equilibrium is characterized as

$$r_A = r^* + \frac{2\eta}{5}, \quad r_B = r^* + \frac{3\eta}{5}, \quad r_B - r_A = \frac{\eta}{5} > 0$$

$$l_A = l^* + \frac{\eta}{5}, \quad l_B = l^* + \frac{3\eta}{10}, \quad l_B - l_A = \frac{\eta}{10}.$$

$$Prof_A^5 = \frac{(3\eta)^3}{500\eta} - \kappa, \quad Prof_B^5 = \frac{2(\eta)^3}{125\eta}.$$

The table below summarizes the profits of two banks under all possible scenarios. Then we can determine the Nash equilibria by comparing profits under different strategies.

		Bank B		
		Branch only	Branch+E-banking	E-banking only
Bank A	Branch only	$(\frac{\eta^2}{8} - \kappa, \frac{\eta^2}{8} - \kappa)$	$(Prof_A^3, Prof_B^3)$	$(Prof_A^4, Prof_B^4)$
	Branch+E-banking	$(Prof_B^3, Prof_A^3)$	$(\frac{\eta^2}{8} - \kappa, \frac{\eta^2}{8} - \kappa)$	$(Prof_A^5, Prof_B^5)$
	E-banking only	$(Prof_B^4, Prof_A^4)$	$(Prof_B^5, Prof_A^5)$	$(0, 0)$

We have $Prof_A^3 < \frac{\eta^2}{8} - \kappa$, $Prof_B^3 > \frac{\eta^2}{8} - \kappa$, $Prof_A^4 < Prof_A^5$, and $Prof_B^4 > Prof_B^5$. Then, we can solve the Nash equilibria when mobile banking option is available.

- If $Prof_B^5 > \frac{\eta^2}{8} - \kappa$, then Case 5 {A: Branch+E-banking, A: E-banking only} and its symmetric case {A: E-banking, A: Branch+E-banking} are Nash equilibria.
- If $Prof_B^5 < \frac{\eta^2}{8} - \kappa$, then Case 2 {A: Branch+E-banking, B: Branch+E-banking} is Nash equilibrium.