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 in line with market rates, hold shorter-term assets, and primarily earn lending spreads by taking more credit risk through personal and business loans; and low-rate banks, which offer interest-insensitive and low deposit rates, hold a higher proportion of long-term assets (e.g., MBSs), and make fewer loans. This divergence leads to a significant shift of deposits towards high-rate banks as market rates rise, thereby reducing the sector's overall capacity for maturity transformation and concentrating credit risk among high-rate banks. Our evidence suggest that technological advancements contribute to the divergence: high-rate banks operate primarily online and attract less sticky depositors. In response, low-rate banks lower rates through the retention of relatively stickier 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 rates 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 rates were similar to today's, the spread between the 75th and 25th percentiles of deposit rates among the top 25 banks was around 70 bps, whereas today it is around 350 bps. The bimodal distribution of today's deposit rates highlights two distinct types of banks: high-rate banks, which offer deposit rates that are near market interest rates, and low-rate banks, which pay low deposit rates that are very insensitive to market 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 begin by examining 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 reduce long-term real estate loans and hold shorter maturity securities that match the duration of their deposits. However, these banks earn larger lending spreads by taking on greater credit risks, primarily through personal and commercial and industrial (C&I) lending. As high-rate banks become more prominent over the last 10 to 15 years, we simultaneously see significant changes in the behavior of low-rate banks. In particular, they offer deposit rates that are lower and far *less* sensitive to changes in interest rates than before, and they substantially shift their asset allocation from lending to households and businesses towards holding safe and long-duration assets (e.g., mortgage backed securities).

Recognizing the emergence of these two types of banks is critical for understanding the transmission of monetary policy, the banking sector's capacity for maturity transformation, and its ability to provide liquidity and credit going forward. Monetary policy affects deposit distribution between these banks: when rates rise, the rate gap between high- and low-rate banks widens, prompting deposits to shift towards high-rate banks. As high-rate banks typically engage in lending

[1] We primarily concentrate on the largest 25 banks for several key reasons. First, we adhere to the Federal Reserve's definition of large banks, as outlined here, with one key modification: we focus on the bank holding company, which determines 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 largest banks are disproportionately important for speaking to aggregate lending. Third, small banks are regulated very differently than large banks in our sample. 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.

at much shorter maturities – the average asset maturity for these banks is four years less than that of low-rate banks – increases in interest rates lower the extent of maturity transformation performed by the banking sector. At the same time, high-rate banks lend more to households and businesses, thereby assuming greater credit risk. Should deposits continue shifting towards high-rate banks, particularly in a prolonged high interest rate environment, the banking sector's capacity to absorb duration risk will likely diminish significantly, and credit risk will concentrate within high-rate banks. This shift could reshape 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, which is firstly proposed and causally identified by Jiang, Yu and Zhang (2022). They argue that digital disruption enables banks to operate without physical branches, influencing divergent strategies in branch operations and deposit rate settings.[2] Consistently, we observe that high-rate banks, since 2009, have experienced a 65% greater reduction in the number of branches compared to low-rate banks, accompanied by a 46% 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 online and 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 110 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 observed emerging heterogeneity in the banking sector is partly due to the rise of high-rate banks, a significant portion also stems from low-rate banks behaving quite differently than they used to. For example, low-rate banks used to have a deposit rate sensitivity of around 0.58, and this figure has fallen to around 0.12 for the recent two rate hiking cycles. That is, for every 100 basis points increase in the Federal funds rate, low-rate banks now pass along only 12 basis points

[2] Specifically, Jiang, Yu and Zhang (2022) show that the rollover of 3G network infrastructure results in the divergence in 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 depositors, compared to 58 basis points previously. In turn, their deposits act more like fixed rate liabilities, and hence these banks hold *longer* duration and safer securities than they previously did. One potential explanation is that as some banks transition to operating online, low-rate banks that maintain physical branches are left with stickier depositor bases and/or depositors who highly value in-person banking services. 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.

To rationalize above findings, we provide a simple model in the style of Salop (1979) and Allen and Gale (2004). We analyze the strategies of two banks competing for deposits and determining loans with varying 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 significant macro implications. First, it affects how monetary policy is transmitted through the banking sector. A key aspect highlighted in the literature is that as interest rates increase, deposits flow from banks to money-market funds, leading to an aggregate contraction in bank lending (Drechsler, Savov and Schnabl, 2017). However, within a diverging banking sector, our analysis reveals a different dynamic: when interest rates rise, deposits disproportionately flow out of low-rate banks. Given that these low-rate banks primarily focus on lending to long-term but safe assets, like MBSs, we show that a one percentage point increase in the Federal Funds rate causes these banks to reduce their MBS share by 0.56%. In contrast, high-rate banks, which have a larger portfolio of personal and C&I loans, experience a significant increase in their share of these loan categories. Specifically, for every one percentage point increase in the Federal Funds rate, high-rate banks experience a 0.53% and 0.32% rise in personal and C&I loans, respectively. This is because high-rate banks are less sensitive to rate increases and may even attract more deposits as rates rise, enabling them to expand their lending activities. We further show 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 small businesses.

This perspective also sheds light on why a significant credit crunch has not materialized despite the recent series of sharp interest rate increases initiated by the Federal Reserve starting in 2022. These increases were accompanied by annual deposit outflows of over 8%, the largest in percentage terms since the data began in 1973. Despite these pronounced outflows, a credit crunch has not occurred thus far. This can be attributed to the disproportionate impact of the rate hikes on low-rate banks, leading to a substantial reduction in their holdings of treasuries and agency MBSs. In contrast, high-rate banks have experienced minimal effects, with nearly negligible deposit outflows, allowing their lending activities to both households and businesses to remain largely unaffected on an aggregate scale.

Second, our paper suggests the need for a reevaluation of how bank risk is assessed. 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 manifest under different economic conditions. Interest rate risk becomes particularly acute during Federal Funds rate hikes, often associated with stronger economic periods, whereas credit risk escalates during economic downturns, which may trigger reductions in the Federal Funds rate. Current regulatory practices may not adequately consider this heterogeneity, which could have significant implications for systemic risk assessment and monetary interventions.

Third, 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 20% 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 particularly relevant today, as more banks opt to operate without physical branches and engage in fierce competition in deposit rate setting, driven by the preferences of younger customers who are more sensitive to rates and place less value 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.

It is worth noting that we focus on the largest 25 banks in our analysis, all of which offer online and mobile banking services. This distinguishes our work from previous research on digitization in banking, which often used the presence of mobile banking as a criterion for digital banks. For example, Koont, Santos and Zingales (2023) classify digital banks based on the number of reviews for the bank's mobile app. By their definition, all top 25 banks, which have widely used mobile apps, are considered digital. Additionally, while our study concentrates on the top 25 banks by size, our main results can be generalized to the top 100 banks and even all banks.

Overall, our evidence suggests that the growing divergence within the banking sector is connected to the advent of e-banking services. However, the rise of e-banking services coincides with the Financial Crisis of 2008, prompting concerns that our findings may be influenced by shifts during the 2008 crisis. We explore alternative explanations, primarily focusing on regulatory changes and liquidity injections from the Federal Reserve. Our findings show that these factors are insufficient in explaining the divergence observed in the banking sector.

Related Literature Our paper contributes to several strands of 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. We delve beyond aggregate measures to examine how changes in interest rates influence deposit flows across different 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 migrate from low-rate to high-rate banks, sustaining lending to personal and C&I loans, which high-rate banks increasingly hold. Thus, tracking aggregate deposit flows from the banking sector misses a substantial amount of flows within the banking sector. Understanding this heterogeneity is crucial for assessing the banking sector's capacity for maturity transformation, liquidity provision, and credit extension.

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. In contrast, Erel et al. (2023) examine a sample of purely online banks and find that these banks tend to offer higher rate and attract more deposits as 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 underscores potential fragility in the banking sector, as discussed in recent studies by Haddad, Hartman-Glaser and Muir (2023) and Drechsler et al. (2023). Last, we focus on the asset side of banks' balance sheets, in addition to the liabilities side, presenting evidence on how monetary policy is transmitted across different types of assets.

Broadly, we explore how digital disruption affects the banking sector. Previous research, such as Buchak et al. (2018), has highlighted how regulatory arbitrage has contributed to the rapid expansion of shadow banks. Our study illustrates the profound effects of technology within the banking sector itself. Jiang, Yu and Zhang (2022) show that digital disruption drives branch closures, leading to a divergence in branch operation strategies and deposit rate setting among banks. Some banks continue to rely on physical branches and can charge higher rents on both deposits and loans, while others operate remotely, offering services at lower rents. This study highlights the significant implications of these changes for financial inclusion. Relatedly, Haendler (2022) show that small community banks are slow to adopt mobile banking, losing both deposits and small business lending, while Koont (2023) demonstrate that mid-sized banks, after adopting mobile banking, grow faster and attract more uninsured deposits. Our paper complements theirs by providing evidence of how these digital disruptions lead to heterogeneous asset and liability management strategies across banks and draw implications on monetary policy transmission and the capacity of the banking sector to engage in maturity transformation and to provide loans to households and businesses.

Relatedly, our paper adds to the understanding of heterogeneity in the banking sector. While the existing literature extensively examines deposit rate distribution within banks (e.g., Radecki, 1998; Heitfield, 1999; Biehl, 2002; Heitfield and Prager, 2004; Park and Pennacchi, 2008; Granja and Paixao, 2021), less work focuses on the distribution of deposit rates across banks. Recent research by Iyer, Kundu and Paltalidis (2023) explores variations in deposit rates across banks within a region, suggesting that these variations may indicate a gradual buildup of liquidity shortages. Expanding on this view, our study finds that the banking sector exhibits 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. In addition to 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). 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. Our study offers a comprehensive perspective on the heterogeneity in both the liability and asset sides of banks in recent decades. Despite heterogeneity across banks, we emphasize the alignment between their liability and asset allocation within banks — beyond maturity matching (Drechsler, Savov and Schnabl 2021), we highlight the matching between franchise value and banks' risk-taking behaviors.

Lastly, we provide a new angle to view the banking industry. 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 businesses – they take deposits and lend to risky businesses, while low-rate banks behave more like long-term bond funds.

2 Motivating Fact: Divergence in Deposit Rates

We document a salient pattern in banking over the past decade: the increasing dispersion of deposit rates. Prior to 2009, deposit rates among large banks were fairly uniform, as evidenced by a low standard deviation. However, the subsequent period has witnessed a significant shift. Today, deposit rates display a bimodal distribution, characterized by two distinct peaks and a substantial economic divergence in rates.

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

the 12-month certificate of deposit ("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. Later analysis considers additional measures. In 2006Q3, deposit rates exhibited a unimodal distribution, with similar mean and median values, and low standard deviation.[3] However, subsequent rate cycles (2019Q1 and 2023Q4) show a shift towards bimodality with diverging 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 0.62 to 2.05.

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 demonstrates a significant shift in the distribution of banks' asset shares. Before 2009, the majority of bank assets – more than 60% – were linked to rates offered close to the sample average. However, by 2023Q4, this landscape had changed dramatically: only 4% of assets corresponded to rates between 0.75 and 1.25 times the average, while 75% of assets were linked to rates below 0.75 times the average, and 21% were associated with rates exceeding 1.25 times the average, as per the classification on CD rate in panel (a). A similar trend is observed based on the DepRate classification in panel (b). Additionally, the divergent patterns in deposit rates persist across the entire banking spectrum over an extensive sample period, as illustrated 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 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.

[3] In 2006Q3, the average Federal Fund rate was 5.25%. Among the top 25 banks, the average CD rate was 4.09%, with a corresponding median of 3.95%; and the average DepRate was 3.11%, with a corresponding median of 2.99%.

3 Data and Methodology

In this section, we first 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.[4]

3.1 Data

Bank data. We compile quarterly bank balance sheet and income statement data from the Reports of Condition and Income (Call Reports) spanning from 2001Q1 to 2023Q4. This data is aggregated to the bank holding company (BHC) level for banks under the same BHC, using RSSDHCR as the identifier. For standalone banks, we use RSSDID as the identifier. We supplement this with data from the FDIC Statistics on Depository Institutions (SDI), which provides comprehensive financial and operational information on all FDIC-insured institutions quarterly. Detailed information on data construction and variable definitions can be found in 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.[5] 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.[6] 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 provides a more robust and representative picture of rate setting activity across the BHC.[7]

[4] 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.

[5] 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.

[6] 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.

[7] Appendix Table B.1 indicates that deposit rates are primarily determined at the BHC level. BHC fixed effects

Branch data. We use 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 and data from the FDIC Survey of Consumer Use of Banking and Financial Services. Specifically, we use US Census data to compute the average customer age for each bank by weighting the average age in a county based on the number of branches in each county every quarter. 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. The survey is conducted biannually from 2009, and we use data from the 2013, 2015, 2017, and 2019 waves.

3.2 Methodology

Our analysis aims to document the emergence of two distinct types of banks in the industry, categorized based on the deposit rates they offer. We further explore how other characteristics like branch service provision, asset allocation, and loan portfolio risk profiles have evolved for these categories. Importantly, our findings do not suggest that deposit rates directly dictate all other operational decisions of banks, such as branch operations and lending. These factors are all endogenous decisions made by banks. Instead, we propose that two divergent business models have developed alongside the rise of e-banking, with each type of bank adopting a business model that is reflected across various aspects of their operations. We utilize deposit rates as the primary basis for classification due to their frequent updates and reliable empirical measurement, offering a timely and observable metric for differentiation. For simplicity, we categorize them as "high-rate" and "low-rate" banks. We describe our classification method in the following section.

The empirical strategy employed resembles a difference-in-differences (DiD) design. Our baseline empirical specification is the following:

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

where i and q indicate the bank and quarter-year, respectively, and $\mathbb{1}_{\text{High-rate}_i}$ denotes whether bank i is a high-rate bank, Post_t denotes the post-2009 period. We include two control variables, the return

alone explain as much of the variation in deposit rates as bank-level fixed effects.

on assets and the Tier 1 and 2 capital ratio from the previous quarter. Moreover, we weight each observation by the asset size each quarter, ensuring that the estimated effect reflects the aggregate effect of designated bank type. 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.

In the main analysis, we concentrate on the largest 25 BHCs based on their total assets of the quarter, in line with the Federal Reserve's definition of large banks, as outlined here. We select 2009 as the cutoff year because Figure 2 shows the emergence of two distinct types of banks, distinguished by deposit rates, beginning 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, we thoroughly explore the robustness of the cutoff choices, and expand the analysis to include a broader set of banks.

The β coefficient quantifies the divergence in $Y_{i,q}$ between high- and low-rate banks post-2009 relative to the pre-2009 era. Importantly, β by itself does not pinpoint which type of bank primarily drives this divergence, as both are expected to adapt their strategies over time. To illustrate these strategic differences more clearly, we employ time-series plots that aggregate the balance sheets of banks within each category, thus providing a visual representation of the distinct adjustments each type of bank has made.

3.3 Classification of High- and Low-rate Banks

We classify the top 25 banks each quarter based 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. Lastly, to ensure consistent bank categorization and avoid misinterpretation based on temporary fluctuations, we smooth the combined rank using one-year rolling averages.[8]

[8] 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

We classify banks using this ranking, considering the skewed distribution depicted in Figure 1, which illustrates a smaller number of high-rate banks relative to low-rate banks. To address this asymmetry, we designate banks ranked in the top tercile as high-rate banks and the remaining banks as low-rate banks. Consequently, each quarter, we have 8 high-rate banks and 17 low-rate banks. Consistent with Table 1, examples of high-rate banks in the 2023 Q4 include Citi and Ally Bank, while low-rate banks encompass Bank of America and JP Morgan. It is worth noting that although the classification is relatively persistent, we do observe shifts in bank types over the years. For instance, Goldman Sachs transitioned from a low-rate bank to a high-rate bank in 2012, and Capital One underwent a similar shift in 2008. For detailed classifications of each group of banks, we refer readers to the Appendix Table B.3.

The marked divergence in rate-setting behaviors between high-rate and low-rate banks raises a critical question: What factors influence a bank's decision to adopt a high-rate or low-rate strategy? In Appendix Table B.4, we investigate what characteristics prior to 2009 influenced their classification as high-rate or low-rate banks post-2009. To achieve sufficient statistical power, we focus on banks ranked among the top 100 banks over our sample. Our analysis reveals that banks with a higher ratio of branches to deposits, fewer branches, a larger share of insured deposits, and operations in demographically younger counties during the earlier part of our sample period were more likely to become high-rate banks after 2009.

4 Diverging Banking Sector

Panel A of Table 2 compares key characteristics of high-rate and low-rate banks across two distinct periods: 2001-2007 and 2017-2023.[9] Before 2009, high-rate banks typically operated fewer branches and held assets with shorter maturities compared to low-rate banks. However, after 2009, the gap between the two bank types in these aspects widened further. Additionally, high-rate banks exhibited significantly higher net interest margin (NIM) rates and charge-off rates post-2009. Notably, the divergence is mostly driven by shifts in low-rate banks. For example, the NIM rate of high-rate banks remained around 2.9% throughout the years, while that of low-rate banks decreased from 2.9% to 2.3%. A similar pattern is observed in other statistics.

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).

[9] A similar analysis for the 2008-2016 period is presented in Appendix Table B.2.

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 of average 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 if the Federal funds rate reaches more than 5%, while they adjusted CD rates similarly to other high-rate banks, such as Citi and Goldman Sachs, before 2009.

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 compares the branches operated by high- and low-rate banks, yielding two key observations. First, from the beginning of our sample, high-rate banks consistently maintain a lower number of branches compared to low-rate banks. Second, while the number of branches remains relatively stable for low-rate banks throughout the entire period, high-rate banks experience an over 63% decline in the number of branches in the post-2009 era (note that the figure is on a log scale).[10]

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-deposits ratio indicates that a bank has more branches relative to its deposit size, suggesting a broader physical presence and possibly higher operating costs. Conversely, a lower ratio implies a lesser reliance on physical branches to raise deposits. Figure 4b shows that while the branch deposit ratio has fallen for both low-rate and high-rate banks, it has fallen at a much steeper rate for high-rate banks. This suggests that high-rate

[10] We estimate the percentage changes from the log-level estimates using: $e^{-\beta} - 1$. A logarithmic change from 8 to 7 implies $e^{-1} - 1 = -0.63$.

banks are operating with less reliance on physical branches.[11]

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 stable number of branches. It is worth noting that all 25 banks in our sample offer e-banking services, including mobile and online banking. The reliance of *physical branches* serves as the key determinant of this change.

Moreover, the two types of banks appear to cater to distinct customer demographics. We find that high-rate banks tend to locate their much smaller number of branches in demographically younger counties. Figure 4c shows the time series of the average age of the population in areas with high-rate and low-rate bank branches, indicating a diverging trend after 2009. Prior to 2009, both bank types operated branches in areas with similar average ages. However, high-rate banks are increasingly concentrating their branches in regions with an average age roughly 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 FDIC Survey of Consumer Use of Banking and Financial Services. We find that physical branches tend to attract a clientele that is older, less educated, and has a lower income compared to mobile banking users.[12]

While the figures illustrate clear time-series trends, they cannot definitively establish the statistical significance of the divergence or rule out systemic changes within the banking sector. To address these limitations, we employ a regression analysis based on Equation (1) and present the results in Table 3. Consistent with the trends observed above, we find that high-rate banks report about a 65% additional reduction in the number of branches, about a 46% additional decline in the branch deposit ratio, and a 0.3-year additional decline in the average age after 2009, in comparison to low-rate banks. These magnitudes are stable even after accounting for aggregate shocks through quarter fixed effects, as indicated in the even numbered columns.

Given our finding that the number of branches for low-rate banks has remained unchanged since 2009, it may seem puzzling that these banks now charge customers more (offering lower

[11] 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.

[12] Between 2012 and 2018, the average age of households using physical branches increases by 2.77 years (4.92%), while the average age of households using mobile banks increases by 1.46 years (3.65%) over the same period. The average income of households using physical branches also increases 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.

deposit rates) compared to the pre-2009 period. We highlight two potential explanations. One possibility is that the operational costs for high-rate banks have risen, partly due to their provision of both traditional in-person banking services through branches and e-banking services (note that we are focused on the top 25 banks, all of which offer e-banking). Another plausible explanation is that low-rate banks may implement 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 examine the non-interest expense as a ratio of asset between the two types of banks in column 1 of Appendix Table B.5 to assess whether low-rate banks exhibit higher operating costs compared to high-rate banks. Our findings indicate that low-rate banks do not exhibit higher non-interest expenses, contradicting the marginal cost-based hypothesis. In the next section, we examine the differences on the asset side of banks' balance sheets.

4.3 Divergence on Asset Composition

Figure 5 presents an overview of the asset composition within high- and low-rate banks, revealing distinct patterns in their investment strategies. As of 2023, low-rate banks have allocated 56% of their assets to relatively long-term investments such as treasuries, mortgage-backed securities (MBSs), and real estate, representing a moderate increase over the sample period. In contrast, they have dedicated only 26% of their assets to personal lending and C&I loans, with the remaining assets categorized as "other." In contrast, high-rate banks have allocated 37% of their assets to treasuries, MBSs, and real estate lending, while their share of personal and C&I lending has risen to approximately 38% by 2023. These findings suggest that low-rate banks tend to hold longer-term assets, primarily in the form of MBSs and real estate loans, while high-rate banks focus more on traditional lending to firms and households, albeit at shorter maturities. We delve deeper into these trends to examine how the asset mix aligns with these banks' liability structures – for example, because low-rate banks have near "fixed rate" liabilities, they are better able to hold long duration fixed-rate assets.

We begin by studying banks' net interest margins. We first show that high-rate banks have a slightly higher net interest margin, despite offering higher deposit rates. Since net interest margin is the difference between interest earned (for example, on loans), and interest paid (for example, on deposits), this immediately indicates that high-rate banks earn higher rates on their assets. We show this comes from credit risk in the form of riskier lending. In contrast, we show these high-rate banks have shorter maturity on the asset side and thus engage in less maturity transformation.

These findings are in line with the broad patterns shown in Figure 5.

4.3.1 Net Interest Margin

Figure 6 presents a comparison of the changes in interest expense rate, interest income rate, and NIM rate for high-rate and low-rate banks in our sample. In Figure 6a, a consistent difference in interest expense rate is evident, with high-rate banks incurring significantly higher costs throughout the sample period. This gap widens notably during the recent two rate hike cycles.[13] Similarly, Figure 6b demonstrates that prior to 2009, high- and low-rate banks generate comparable levels of interest income rate. However, a significant divergence emerges after 2009. Consequently, the NIM rate which represents the difference between interest income rate and interest expense rate, does not decline for high-rate banks which have higher interest expense rate. In fact, Figure 6c reveals a diverging pattern in NIM rate between the two banks. Using a DiD specification, we find that high-rate banks maintain a roughly 55 basis-point advantage relative to low-rate banks after 2009. These patterns suggest that high-rate banks tilt their portfolio towards higher-yielding assets.[14]

4.3.2 Asset Reallocation

Banks can pursue higher yields through two primary strategies: taking on more credit risk or investing in longer-maturity assets to capture the term premium. In this section, we delve into the portfolio holdings of high-rate banks and low-rate banks to analyze how banks allocate their portfolios to seek high yields.

We classify loans into four categories: personal loans, commercial and industrial (C&I) loans, real estate loans, and other loans, and we divide securities into two categories: mortgage-backed securities (MBS) and other securities.[15] Table 4 examines how each share shifts for high-rate and

[13] The divergence in interest expense rate is not as pronounced as compared to the rate gap in Figure 3. This is due to the fact that, aside from the interest paid on a range of deposit products, including demand deposits, interest expense also includes wholesale funding costs, as well as interest paid on bonds or other debt securities. This offers a more comprehensive view of the overall cost of funds for a bank, as it encompasses borrowings from various sources, not solely limited to customer deposits. Moreover, as interest accrues over time and payments are spread out, the pattern of interest expenses tends to change more gradually compared to the CD rate. Therefore, the resulting divergence in patterns is less pronounced.

[14] As shown in the previous section, both high-rate and low-rate banks exhibit similar non-interest expense rates, indicating that high-rate banks' higher NIM rates are not used to offset higher non-interest expenses. Furthermore, we observe no significant difference in non-interest income rates between the two types of banks (see column 2 of Appendix Table B.5). This suggests that differences in fee income do not drive the divergence in NIM rates. Instead, other factors must be contributing to the observed differences in NIM rates between high-rate and low-rate banks.

[15] As shown in Figure 5, 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

low-rate banks. Since 2009, compared to low-rate banks, high-rate banks have tilted their portfolio allocation to personal loans by approximately 7.6%, C&I loans by about 3.4%, and other loans by around 2.2%. In contrast, they have decreased their holdings in real estate loans and MBSs by roughly 12.5% and 3.1%, respectively, during the same period. These changes represent a significant divergence from pre-2009 trends. For example, the difference in personal loan holdings was only 2.4% before 2009, and C&I loan holdings exhibited minimal disparity. Furthermore, high-rate banks previously held a larger share of real estate loans compared to low-rate banks.

The final two rows of Table 4 shed light on credit risk and maturity considerations within the asset portfolios of high-rate and low-rate banks. The charge-off rate reflects the percentage of loans or credit accounts a bank deems uncollectible. These are removed from the bank's books as losses, serving as a crucial indicator of the bank's portfolio credit quality. Generally, personal loans and C&I loans carry higher credit risk compared to other loan types and MBSs, which are backed by the U.S. government. Therefore, the observed increase in personal and C&I loan holdings by high-rate banks suggests they are taking on significantly more credit risk by shifting their assets towards these higher-risk loan categories. On the other hand, real estate loans and MBSs have much longer maturities compared to other loan types, which are typically floating-rate with repricing dates of one year or less.[16] Consequently, by reducing their holdings of real estate loans and MBSs, high-rate banks reduce 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 appear to be taking on more credit risk, while low-rate banks are more engaged in maturity transformation. The next two sections provide a deeper examination of these two aspects of risk, offering further insights into the distinct approaches adopted by high-rate and low-rate banks.

4.3.3 Credit Risk

As discussed above, credit risk is primarily associated with loan portfolios, as securities like Treasuries and MBSs often benefit from government backing. As high-rate banks tilde towards personal and C&I loans, they may expose themselves to more credit risk.

To confirm this hypothesis, we start with examining the overall return of loans portfolios. Consistent with the observed pattern in interest income, Figure 7a reveals a similar divergence in loan rates across banks. Both low-rate and high-rate banks report similar loan rates, ranging

agricultural production and farmers, loans to foreign governments and official institutions etc.

[16] 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.

between 6% and 8% before 2009. Afterwards, although the lending rate of high-rate banks remains stable, that of low-rate banks decreases to a range of 4% to 6% as overall interest rates decline. By the end of our sample, high-rate banks charge loan rates of approximately, 10% compared to 6% for low-rate banks. This divergence pattern is further supported by the results in column 1 of Panel A in Table 5, as per the regression model specified in Equation (1).

To calculate the credit spread in loans, we subtract the equivalent maturity Treasury yield from the loan rate, isolating the portion of the loan rate that reflects the borrower's creditworthiness, or credit risk premium. Figure 7b shows the evolution of credit spreads over time for two types of banks. Similar to loan rates, we observe a significant divergence in credit spreads post-2009, exceeding 200 basis points by the end of the sample period. Column 2 of Panel A in Table 5 reinforces this observation, showing a 1.1% increase in credit spreads for high-rate banks compared to low-rate banks after 2009. This increase is economically significant, being 34% higher than the sample average credit spread of 3.2%. This suggests that high-rate banks generate a higher spread from riskier lending activities.

We further provide direct evidence that high-rate banks assume higher credit risk by looking at proxies for default risk. Elevated default risk leads to portfolio losses, which are reflected in the charge-off rate. Figure 7c compares the charge-off rate for high-rate and low-rate banks. Consistent with our previous findings, we observe that the charge-off rate for high-rate banks is much higher than for low-rate banks after 2009. Towards the end of the sample period, high-rate banks report a charge-off rate that is more than three times of low-rate banks. This diverging pattern is further confirmed in column 3 of Panel A in Table 5.

Banks have the flexibility to not only adjust their portfolio allocations but also to manage credit risk within each loan category. anel B of Table 5 provides a detailed breakdown of post-2009 charge-off rates across loan types. High-rate banks assume more credit risk, with a 0.3% higher charge-off rate for personal loans and 0.1% higher for other loans compared to low-rate banks after 2009. These differences are statistically significant and economically meaningful, representing a 13% rise above the sample average for personal loans.

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 columns 3 and 4 of Appendix Table B.5 and Appendix Figure B.6, high-rate banks pay significantly higher wholesale funding rates and utilize a smaller proportion of it compared to low-rate banks after 2009. These findings further support that the market perceive a higher risk for high-rate banks.

In sum, high-rate banks compound more credit risk than low-rate banks. This occurs not just through a shift towards riskier assets, but also by taking on demonstrably higher credit risk *within* those asset classes themselves.

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 Table 4.

Figure 8a confirms that the average maturity of assets held by low-rate banks is significantly higher than that of high-rate banks, particularly after 2009. Before 2009, the average maturity of assets in low-rate banks was approximately 6 years, which is 50% longer than the 4-year maturity reported for high-rate banks. After 2009, the average maturity of assets in low-rate banks gradually increases to almost 8 years, representing a 33% increase. In contrast, the average maturity of assets held by high-rate banks remains around 4 years. Thus, by the end of 2023, the average maturity of assets held by low-rate banks is nearly twice as long as that in high-rate banks. Similarly, we compare the share of short-term assets – the proportion of a bank's assets that mature within one year – and find that high-rate banks hold a higher share of short-term assets than low-rate banks in Figure 8b. While the share of short-term assets for high-rate banks hovers around 50-55% across the whole sample period, the share of short-term assets for low-rate banks declines from 50% to 40% by the end of 2023.

Panel A of Table 6 examines the significance of the divergence in asset maturities between the two types of banks. Prior to 2009, high-rate banks typically held assets with maturities that were, on average, 1.7 years shorter and comprised a 5.6% larger share of short-term assets compared to low-rate banks. Post-2009, the analysis reveals that high-rate banks continued to maintain loans and securities with significantly shorter maturities – approximately 0.7 years less on average (approximately 12% lower than the sample average) – and a 3.3% higher proportion of short-term assets than low-rate banks. These findings demonstrate that low-rate banks tend to hold assets with longer maturities relative to their high-rate counterparts.

Panel B further investigates changes in maturities within a subset of assets that have maturity information.[17] The results demonstrate that, post-2009, high-rate banks hold MBSs with maturities that are 1.2 years shorter and treasuries with maturities that are 1.6 years shorter compared to low-rate banks. In essence, the combination of these two trends – a shift towards longer-maturity assets

[17] MBSs typically exhibit the longest maturity, exceeding 17 years, followed by real estate loans with an average maturity of around 12 years, treasuries with a 6-year maturity, and other loans with an average maturity of approximately 2 years (also see Appendix Figure B.7).

and increased maturities within existing long-term holdings – contributes to the higher average maturity observed in low-rate banks, as previously discussed.

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 documented divergence indicates that banks with high interest rates and low interest rates respond differently to changes in interest rates, which may have implications for how monetary policy is transmitted to these different types of banks. This section investigates the implications of a diverging banking sector on monetary policy transmission (Section 5.1) and aggregate banking sector outcomes (Section 5.2).

5.1 Transmission of Monetary Policy

This section delves into the differential responses of the two types of banks to monetary policy, assessing its effects on both prices and quantities. Monetary policy changes can be viewed as shocks to the banking system, providing additional evidence of the shifts in banks' asset allocations, as demonstrated in the preceding section.

5.1.1 Rate Sensitivity to Federal Funds Rate Changes

We begin our analysis by examining how the deposit rates of both high-rate and low-rate banks respond to adjustments in the Federal Funds rate across three rate-hiking cycles within our sample. Specifically, we calculate the deposit rate sensitivity, defined as the ratio of the cumulative change in deposit rates to the respective change in the Federal Funds Target rate.

Figure 9 illustrates the deposit rate sensitivity across three rate-hiking cycles for CD rates, savings deposit rates, and DepRate. During the first cycle from 2004Q3 to 2007Q4, both low-rate and high-rate banks exhibited similar deposit rate sensitivities. However, significant divergence occurred in the subsequent cycles, though average sensitivities remained relatively stable. In these later cycles, low-rate banks barely adjusted their deposit rates in response to Federal Funds rate hikes, leading to deposit rate sensitivities close to zero. Conversely, high-rate banks significantly increased their deposit rates, resulting in a strongly positive deposit rate sensitivity.

We test these relationships through the following regression framework:

$$\begin{aligned}\Delta Y_{i,q} = {} & \alpha + \beta_1 \times \Delta \text{Fed Funds}_q \times \mathbb{1}(\text{High-rate}_{i,q}) \times \text{Post}_q + \beta_2 \times \Delta \text{Fed Funds}_q \times \mathbb{1}(\text{High-rate}_{i,q}) \\ & + \beta_3 \times \Delta \text{Fed Funds}_q \times \text{Post}_q + \beta_4 \times \mathbb{1}(\text{High-rate}_{i,q}) \times \text{Post}_q + \beta_5 \times \Delta \text{Fed Funds}_q \\ & + \beta_6 \times \mathbb{1}(\text{High-rate}_{i,q}) + \beta_7 \times \text{Post}_q + \beta_8 \times Controls_{i,q-1} + \varepsilon_{i,q}, \end{aligned} \tag{2}$$

where ΔFed Funds$_q$ denotes the quarterly change in the Federal Funds Target Rate and $\Delta \text{Y}_{i,q}$ denotes the quarterly change in different deposit rates.

The first three columns of Table 7 reveal a striking divergence in deposit rate sensitivity between two types of banks subsequent to 2009. Taking CD rates as an example, we observe that post-2009, the average deposit rate sensitivity for banks offering higher rates stands at 0.476, in stark contrast to a mere 0.123 for banks with lower rates.[18] This indicates that a 1 percentage point increment in the Federal Funds rate correlates with an additional 0.35 percentage point uptick in deposit rates for high-rate banks in the period after 2009. Conversely, prior to 2009, the deposit rate sensitivities were 0.580 for low-rate banks and 0.582 for high-rate banks, respectively. Hence, the divergence pattern primarily stems from low-rate banks reducing their deposit rate sensitivity, while high-rate banks only slightly increase theirs. We see similar patterns for savings rate sensitivity and interest expense rate sensitivity.

The greater sensitivity of high-rate banks to interest expense rates does not necessarily imply greater interest rate risk. Column 4 shows that these banks benefit from relatively higher interest income rates during periods of rising rates post-2009. Consequently, the sensitivity of the net

[18] The calculation of the average rate sensitivity for high-rate banks is derived from the sum of 0.351 - 0.457 + 0.002 + 0.580, whereas for low-rate banks, it is calculated from 0.580 - 0.457.

interest margin (NIM) presented in column 5 does not demonstrate a notable difference between high- and low-rate banks. This aligns with findings from Section 4.3, which indicate that high-rate banks typically invest in short-term, floating-rate assets, thereby reducing their interest rate risk.

For robustness, we control for common macroeconomic factors using quarter fixed effects in Appendix Table B.6, confirming that the observed differences in betas between high- and low-rate banks are indeed driven by post-2009 changes.

5.1.2 Deposits Reallocation During Monetary Policy Cycles

The divergence in deposit rate sensitivities across the two types of banks significantly influences the reallocation of deposits during monetary policy cycles.

Figure 10 compares the deposit growth for high-rate and low-rate banks over the past three rate hiking cycles.[19] We find that high-rate and low-rate banks exhibit similar deposit growth in the first rate hiking cycle between 2004Q3 and 2007Q4. However, in the last two rate hiking cycles, high-rate banks exhibit significantly higher deposit growth than low-rate banks, suggesting that there is substantial reallocation of deposits when interest rates rise. As interest rates rise, the deposit spread between high- and low-rate banks widens, and deposits flow towards high-rate banks. During the rate hiking period from the 2015Q4 to 2019Q4, high-rate banks experienced a cumulative deposit growth exceeding that of their low-rate counterparts by more than 6.5%. The same trend is observed in the most recent rate hiking cycle, from 2022Q1 to 2023Q4, where low-rate banks experienced negative deposit growth, while high-rate banks remained almost unaffected. This observation demonstrates the significant influence of monetary policy on the allocation of deposits across high-rate and and low-rate banks.

We assess the extent of deposit reallocation using Equation (2). Given the potential for slow-moving deposit flows, we investigate the relation between *annual* deposit growth and annual changes in the Federal Funds rate, comparing high-rate and low-rate banks before and after 2009. Furthermore, we control for the impact of the 2008 Financial Crisis by incorporating a dummy variable for the year 2008 in our analysis.

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 one percentage point increase in the Federal funds rate corresponds with a 0.50 percentage point increase in annual deposit growth for

[19] Mergers and acquisitions (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 by using the formula: $\log \frac{(\text{Deposits}_t - \text{Acquired Deposits}_t)}{\text{Deposits}_{t-1}}$. More details can be found in Appendix A.

high-rate banks compared to their low-rate counterparts. This marks a notable shift from the period before 2009, when an increase in the Federal Funds rate led to deposit outflows from both types of banks, consistent with Drechsler, Savov and Schnabl (2017). Post-2009, however, high-rate banks have ceased to experience such outflows.[20]

Robustness To address potential concerns that our findings might be influenced by banks switching categories, we fix the set of top 25 banks at the start of each rate-hiking period. Appendix Figure B.8 confirms that our results remain robust.

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 investigate the growth trajectories of personal loans, C&I loans, real estate loans, and MBSs across various monetary policy cycles. Specifically, we analyze the annual changes in the share of each asset category by regressing these changes against annual fluctuations in the Federal Funds Rate. We focus on changes in asset share rather than volume growth, because the higher deposit growth observed in high-rate banks after rate hikes typically suggests increased growth in their asset classes. This method allows us to assess whether high-rate banks, upon receiving increased deposits, allocate more capital disproportionately towards asset categories that facilitate better balance sheet alignment.[21]

The results, detailed in columns 3-10 of Table 8, reveal that high-rate banks predominantly direct incoming deposits toward personal and C&I loans, whereas low-rate banks tend to divest from MBSs following deposit withdrawals when interest rates rise. Specifically, columns 3 and 5 demonstrate that, after 2009, a one percentage point increase in the Federal Funds rate corresponds to a 0.53% increase in the share of personal loans (column 3) and a 0.32% increase in the share of C&I loans (column 5) for high-rate banks.[22] Conversely, deposit withdrawals from low-rate banks

[20] The effect size for high-rate banks is calculated as -0.032 = 0.501 - 0.350 + 0.004 - 0.187.

[21] 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 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.

[22] The calculation of the magnitude of the effect is derived from columns 3, and 5 of Table 8. Specifically, the magnitude for high-rate banks post-2009 is calculated by aggregating four coefficients involving the term ΔFFar_y. For

result in a reduction of MBS shares within these institutions. Specifically, a one percentage point increase in the Federal Funds rate leads to a 0.56% decrease in the share of MBSs, as shown in column 9.[23] The robustness of these results is further reinforced after controlling for quarter fixed effects in even columns.

This analysis also serves as stronger evidence supporting the distinct asset allocation strategies between two types of banks. In line with our findings documented in Table 4, the results demonstrate that high-rate banks take on considerable credit risk in personal and C&I loans compared to low-rate banks, which prefer safer, longer-maturity assets such as MBSs. Generally, the larger deposit growth in high-rate banks, triggered by an increase in rates, translates into significant growth in personal and C&I lending sectors where high-rate banks are more actively involved.

These findings challenge the conventional view that an increase in the Federal Funds rate generally results in a contraction of bank lending. Our results indicate that rising interest rates lead to a reallocation of deposits from low-rate banks towards high-rate banks, influencing credit provision. Specifically, while a rise in the Federal Funds rate leads low-rate banks to reduce their securities holdings, it simultaneously encourages high-rate banks to increase their credit offerings to households and small businesses.

Finally, a potential concern is whether the observed increases in lending are driven by increased demand from households or firms, rather than an expansion of loan supply from high-rate banks experiencing significant deposit growth. Appendix Table B.7 alleviates this concern by showing that lending rates across these categories do not differ significantly between banks or over time, suggesting that diverging patterns are not driven by varying demand across banks. While not definitive, this evidence strongly suggests the interpretation that higher Federal Funds rates prompt high-rate banks to expand credit provision in personal and C&I loans, while significantly reducing low-rate banks' credit provision to MBSs.

Overall, our findings reveal a stark contrast in how high-rate and low-rate banks respond to monetary policy shifts, with significant consequences for the allocation of credit and the overall economy. In the following section, we delve deeper into the implications of this phenomenon.

5.2 Aggregate Implications

Explaining the Absence of a Large Credit Crunch for Recent Rate Hikes The current rate hiking cycle saw a sharp increase in interest rates beginning in early 2022 from roughly 0% to

instance, in the context of personal loans, the effect size for high-rate banks is calculated as 0.525% = 0.622% - 0.411% -0.172% + 0.486%.

[23] The magnitude is calculated as -0.56% = -0.31% + -0.25%.

around 5.25%. Concurrently, aggregate deposit growth declined substantially as shown in Panel A of Figure 11.[24] The annual decline in aggregate deposit growth of 8-10% is the largest deposit outflow in percentage terms since the H8 data series began in 1973 (the FRED database) and was accompanied by disruptions in the banking sector with 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 behaviors 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, as high-rate banks focus lending relatively more on personal loans, we find that the growth rate in personal loans is negatively correlated with aggregate deposit growth in Panel C of Figure 11.[25]

This finding underscores the importance of considering heterogeneity among banks to understand aggregate effects and to identify potential areas where credit contraction may occur. Since 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.[26] Thus, our analysis 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 compositions of the two bank types, 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

[24] We use total deposits DPSACBM027SBOG less large time deposits LTDACBM027NBOG.

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

[26] 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 4.26% during 2020-2021 but fell to 3.08% 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.

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 20% higher credit risk.[27] This shift could increase credit risk concentration within the 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. Though both risks can precipitate bank runs, their dynamics differ significantly. As shown in Jiang et al. (2023), interest rate risk becomes particularly salient during Federal Fund rate hikes, typically occurring in stronger economic conditions, whereas credit risk escalates during economic downturns, prompting potential Federal Fund rate reductions. The existing regulatory capital requirements may not fully account for the differential risks within the banking sector.

6 Mechanisms and Robustness

Our analysis has uncovered several key facts: (1) a widening gap in deposit rates, (2) divergent branching strategies, and (3) disparate asset management approaches among banks. While our findings suggest that this divergence began in 2009, coinciding with the emergence of e-banking services, the direct impact of technology on this trend requires further investigation. In this section, we present additional evidence that corroborates the link between e-banking innovations and the observed divergence, and demonstrates the robustness of our findings through alternative methodological approaches. Furthermore, we explore alternative explanations for this divergence, thereby strengthening the validity of our conclusions.

6.1 e-Banking and the Divergence

This section explores the role of technological adoption in driving the divergence within the banking sector. 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

[27] As of the fourth quarter of 2023, the weighted average maturities for high- and low-rate banks were 4.29 and 7.36 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 0.3 years, representing a reduction of 5%, benchmarked to the average maturity of 6 years. Similarly, the credit spreads for high- and low-rate banks are 4.54% and 1.38%, 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 0.32%, representing a 17% increase from the average of 1.92%.

stable (Appendix Figure B.9a). However, a significant surge in search volume occurred around 2009, indicating a growing interest in e-banking channels. For instance, mobile banking searches climbed from an index of 17 in January 2009 to 26 by December (out of 100), and online banking searches jumped from 56 to 89 during the same period.[28] This trend aligns with the emergence and growing popularity of mobile banking apps from major banks (e.g., Citi, JP Morgan Chase), see Appendix Figure B.9b. Google search trends for these apps began in 2008 and intensified through 2009. Additionally, the widespread adoption of 3G technology, crucial for mobile banking activity, coincides with the surge in online and mobile banking interest.[29] These trends collectively indicate that e-banking began to gain significant popularity around 2009.

To substantiate that technology contributes to the divergence, we first demonstrate in column 1 of Table 10 that high-rate banks increase their IT expenditure including data processing and telecommunications expenses by 1.8% more than low-rate banks after 2009. Furthermore, we refine our analysis by substituting the binary "Post" variable – which marks the onset of the technological era – with continuous measures of Google search intensity for mobile banking and the 3G coverage ratio. We then retest our main findings, as presented in rows (2) and (3) of Table 9. The robustness of these results reinforces the argument that technological adoption is a significant driver of the observed divergence.

6.2 Robustness of Divergence Pattern

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

Choice of Cutoff Year Considering that technological innovation was not instantaneous, but rather a gradual process, we conduct two robustness checks to confirm that our findings do not hinge on the specific choice of 2009 as the cutoff year. First, we adjust the cutoff year to 2010, as shown in row (4) of Table 9, and second, we exclude the years 2008-2011, as detailed in row (5), to mitigate any potential confounding effects from the Great Financial Crisis. In both cases, our findings remain robust.

Alternative Specifications To verify the robustness of our findings under different weighting schemes, we apply equal weights in row (6) and show that our findings remain consistent. Additionally, we control for unobserved bank-specific factors by incorporating BHC fixed effects in row (7). We find consistent results, with the exception of column 4, which indicates that high-rate

[28] 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.

[29] 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.

banks do not experience an increase in personal and C&I loan shares after 2009, once level effects are removed.

To understand the change, we compare column 4 to column 7, both of which illustrate how personal and C&I loan allocations change between banks. The significant positive result in column 7 suggests that high-rate banks indeed experience greater growth in loan shares when rates increase. Given that the years from 2009 to 2016 in our post period are in a zero-rate regime, one potential reason for the inconsistency between columns 4 and 7 is that high-rate banks experience *lower* personal and C&I loan share growth when the market rate is close to zero. Indeed, data confirms this hypothesis: from 2009 to 2016, the average annual loan growth rate for high-rate banks was -0.83%, whereas it was -0.07% for low-rate banks. In contrast, from 2017 to 2023, the average annual loan growth rate for high-rate banks became positive at 0.17%, while it turned to -0.7% for low-rate banks. Therefore, high-rate banks experience higher loan share growth when rates increase, but not when the market rate is close to zero.

Overall, these robustness results confirm that the observed divergence in bank behavior represents a fundamental shift within the industry, rather than being attributable to pre-existing bank characteristics.

Alternative Classification Methods We also address concerns regarding our bank classification methodology in rows (8) to (11) of Table 9. Our primary analysis employs both CD rates and deposit rates, capitalizing on their complementary strengths. However, we acknowledge potential limitations with CD rates, including their product-specific nature and limited applicability across banks. To validate the robustness of our findings, we conduct additional analyses using only the DepRate in row (8) of Table 9, which confirms our baseline results. The extensive data series available for DepRate also allows us to expand our analysis across an extended sample period starting from 1994 (row 9), include the top 100 bank holding companies (BHCs) in row (10), and include all BHCs in row (11). 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.

6.3 Alternative Explanations

While our evidence suggests a link between the emergence of e-banking services and the growing divergence in the banking sector, we also examine alternative explanations for this phenomenon, including regulatory changes, post-Financial Crisis liquidity injections, and differences in the distribution of insured and uninsured deposits, as well as variations in savings and CD account holdings between high-rate and low-rate banks.

Regulatory Changes Following the 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. Basel III required a 3% Tier 1 supplementary leverage ratio for large BHCs with assets over $250 billion, while the Dodd-Frank Act applied Enhanced Prudential Regulation (EPR) to all BHCs with assets above $50 billion. Despite all top 25 banks in our sample exceeding the $50 billion mark, only about one-third have assets surpassing $250 billion. 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 may not be the primary driver of the sector's divergence.[30]

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, as depicted in Figure B.7a, low-rate banks maintained a slightly higher proportion of MBSs and Treasuries. Diamond, Jiang and Ma (2023) argues 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 in column 3 of Table 10 and Appendix Figure B.11, 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 observed divergences, such as risk-taking behaviors and deposit flows, especially if high-rate banks have enhanced their screening technology over time. Nevertheless, if this hypothesis held, 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

[30] Appendix Figure B.10 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.

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.12 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 wholly 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 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 observed might be attributed to differences in time deposit shares rather than fundamentally distinct business models across banks.

We examine this hypothesis in the analysis presented in column 5 of Table 10 and Appendix Figure B.13, which reveals 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 business loans in our sample. Building on the analysis of Figure 1 from Supera (2021), we extend the sample through 2023Q4 in Appendix Figure B.14. 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 high shares of time deposits influence changes in C&I loans, we adapted 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.8 suggest that, although time deposits might explain changes in personal and real estate loans before 2009 (see columns 2 and 6), 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.9. 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.

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 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.[31] 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.

[31] 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.

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 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.

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 elevates the bank's exposure to the risk of default.[32]

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

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

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.

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:[33]

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

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 above results 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 only offer *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

[33] 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.

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 riskier loan portfolios that promise higher returns to maximize profits.

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 need to 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 the emergence of two distinct types of banks in the last decade: high-rate banks, which align their deposit rates with market interest rates, and low-rate banks, whose deposit rates are less responsive to market interest rates. Despite the aggregate deposit rate sensitivity of the banking sector showing minimal change, there is now a clear bimodal distribution in deposit rates.

We show that high-rate banks have a limited physical branch presence and maintain short-term assets, earning their margins primarily through higher credit risk. In contrast, low-rate banks engage extensively in maturity transformation, holding longer-term, interest-sensitive assets while incurring lower credit risk. When market rates rise, significant deposits shifts from low- to high-rate banks, prompting low-rate banks to divest MBSs holdings, while high-rate banks increase lending, particularly in personal and C&I loans. Therefore, a nuanced understanding of how deposits are distributed between high- and low-rate banks is crucial for a full appreciation of the deposit and lending channels of monetary policy, beyond simply tracking total bank deposits.

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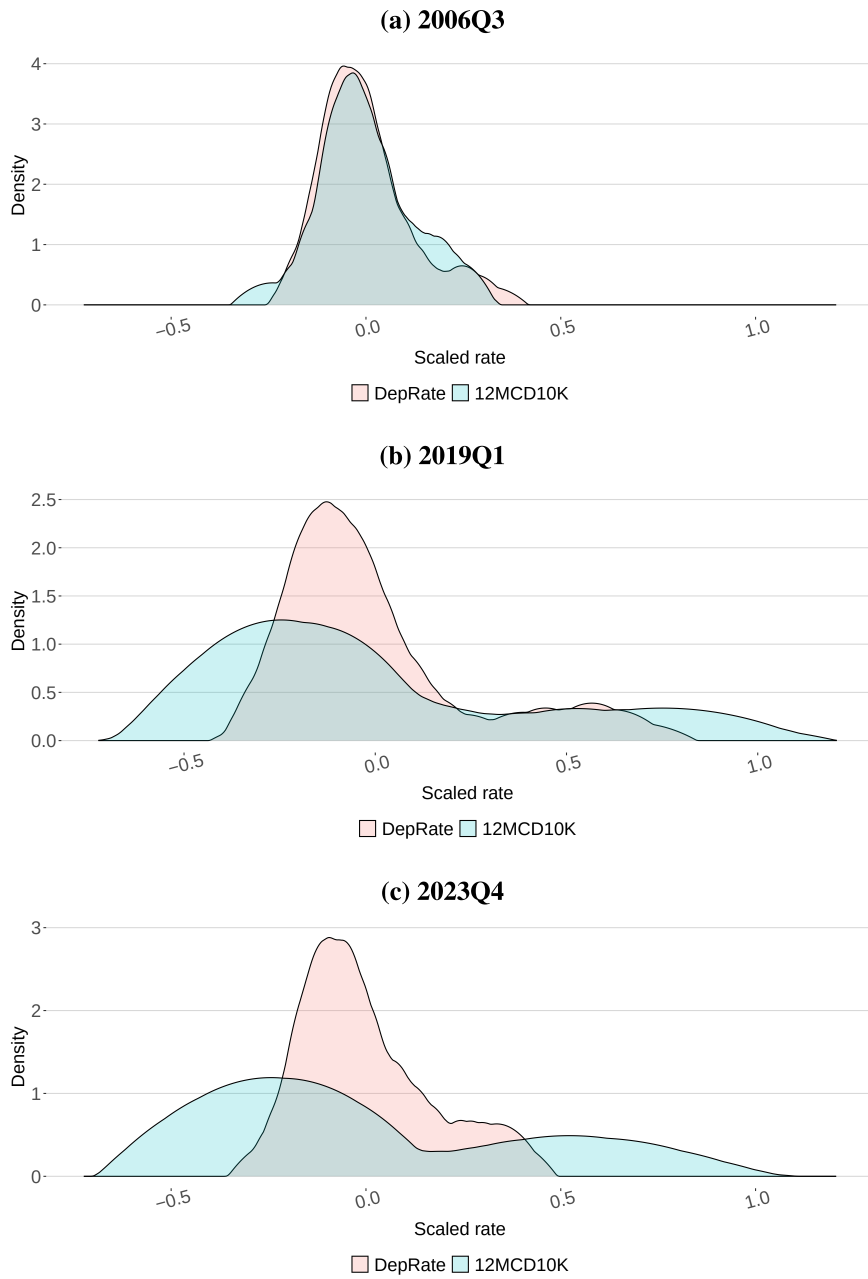
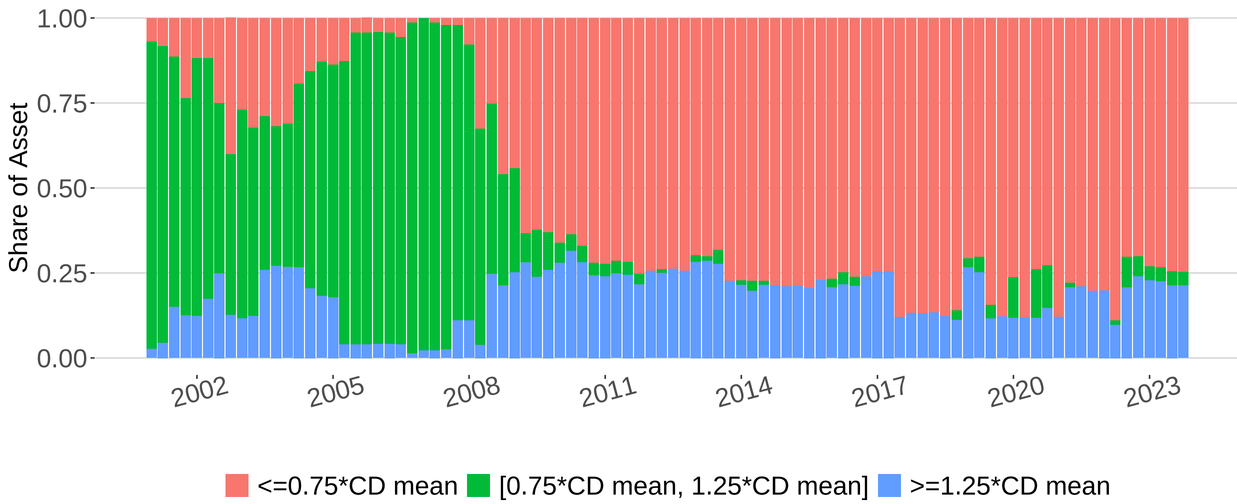
Figure 1: Dispersion of Deposit Rates for Top 25 Banks



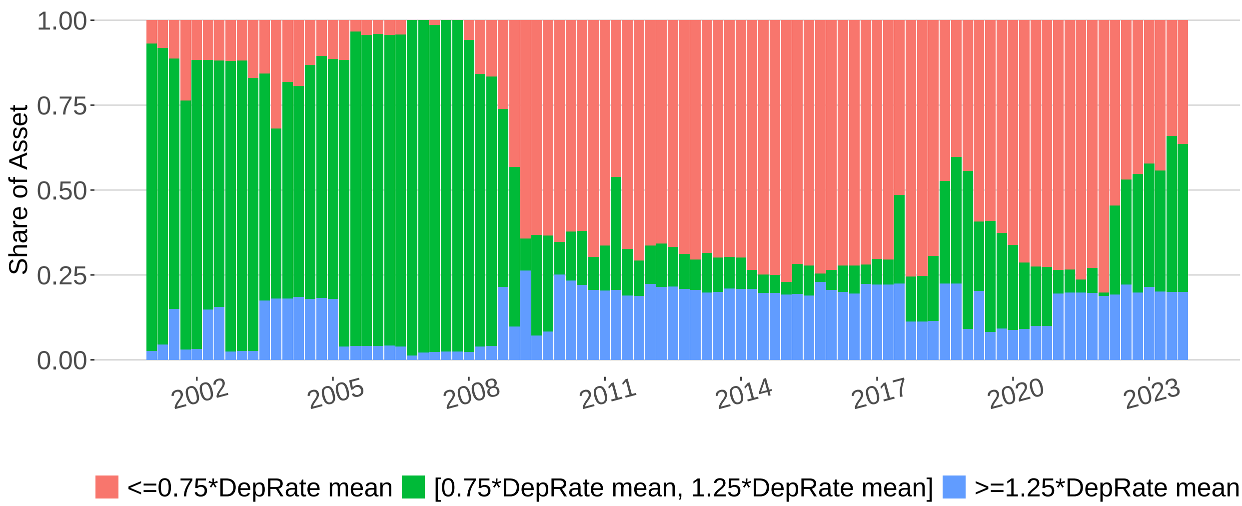
Notes: This figure depicts kernel density plots of the scaled and demeaned 12-month certificate of deposit rates of at least $10,000 (CD) and the scaled and demeaned deposit rates (DepRate) derived from Call Reports provided by the top 25 banks at 2006Q3, 2019Q1, and 2023Q4, representing the peak of 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



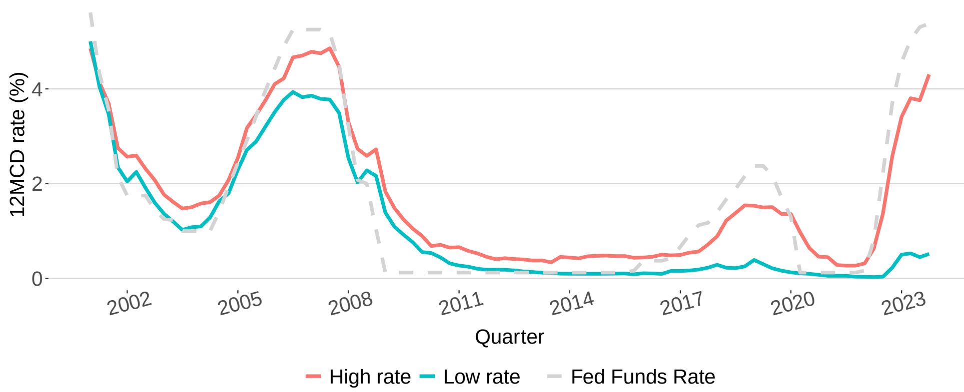
(b) Classification based on DepRate



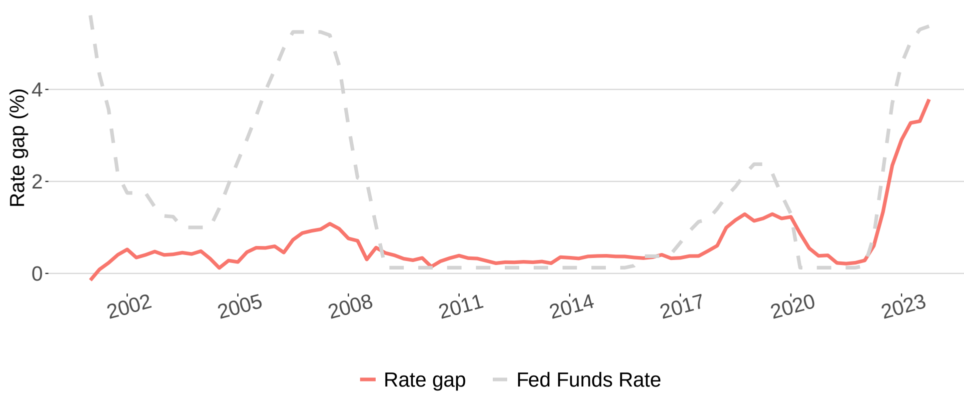
Notes: This figure illustrates the distribution of bank assets among three categories for the top 25 banks: banks with deposit rates below 0.75 times the sample average, banks with deposit rates within the range of 0.75 times to 1.25 times the sample average, and banks with deposit rates exceeding 1.25 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

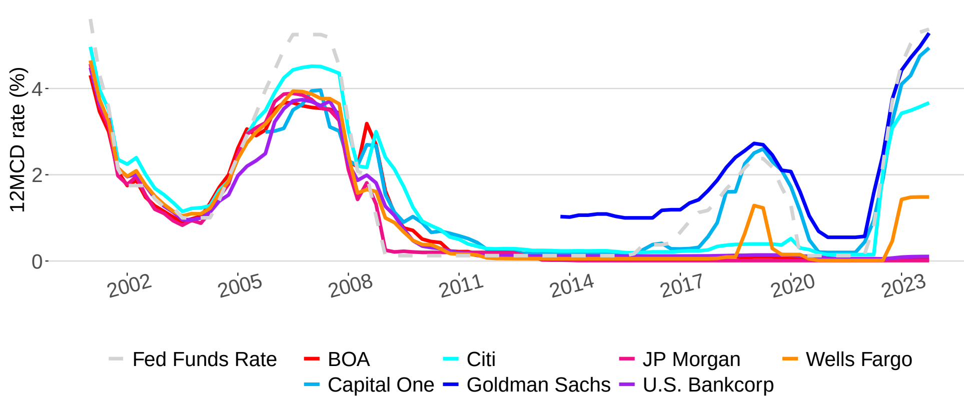
(a) Rate



(b) Rate Gap



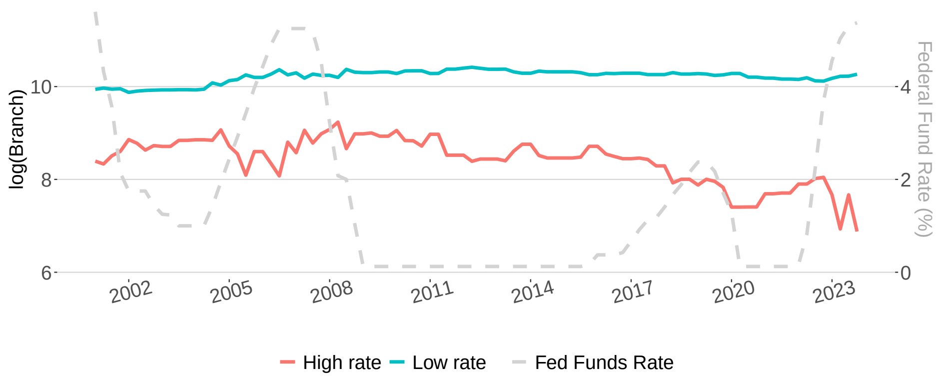
(c) Rate by Bank for Select Banks



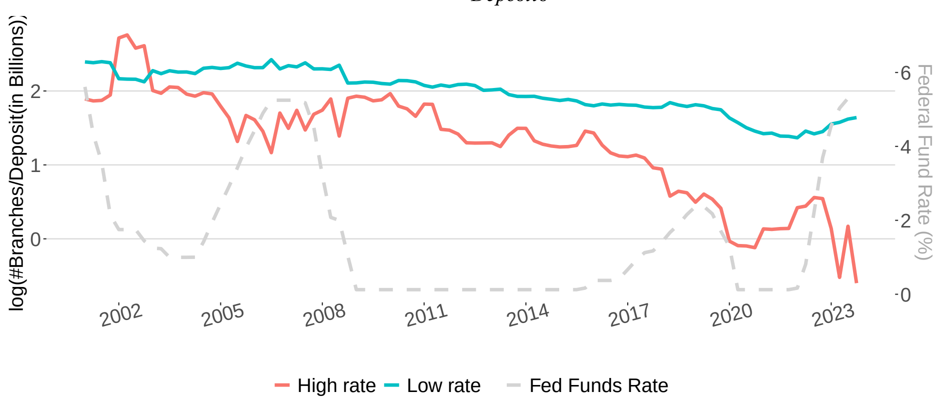
Notes: This figure characterizes the dispersion of deposit rates of high- and low-rate banks from 2001Q1 through 2023Q4 among the top 25 banks. We construct the time-series for each bank type by taking an average of the banks' CD rates, weighted by assets. Figure 3a presents a time-series plot of average CD for *high-rate* (blue) and *low-rate* (red) banks. Figure 3b presents the gap in the CD rates between high-rate and low-rate banks. Figure 3c presents the CD rate by bank. 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 4: Branches

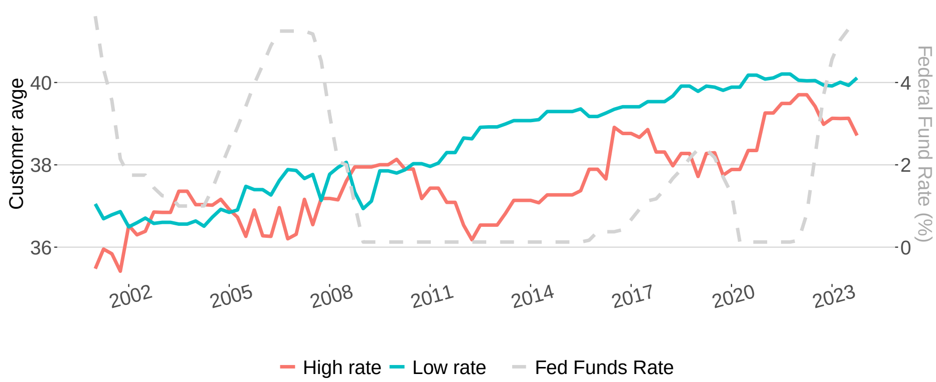
(a) Growth of Branches



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



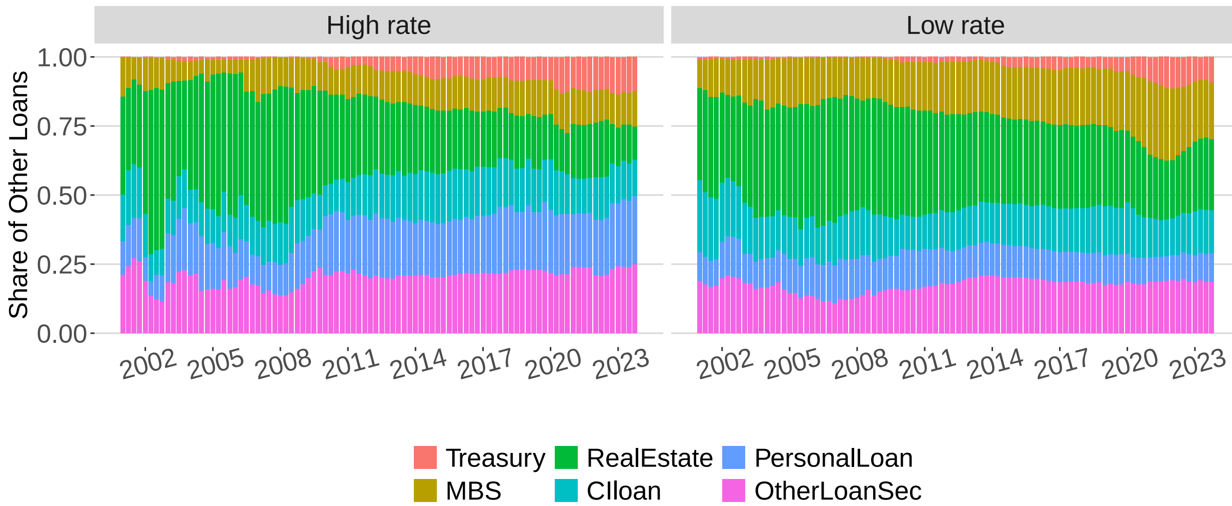
(c) Branch-weighted County Average Age



Notes: This figure compares branches operating by high- and low-rate banks among the top 25 banks from 2001Q1 through 2022Q2, which is the quarter where the most recent SOD data ends. Figure 4a presents the log-transformed number of branches 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: Portfolio Composition

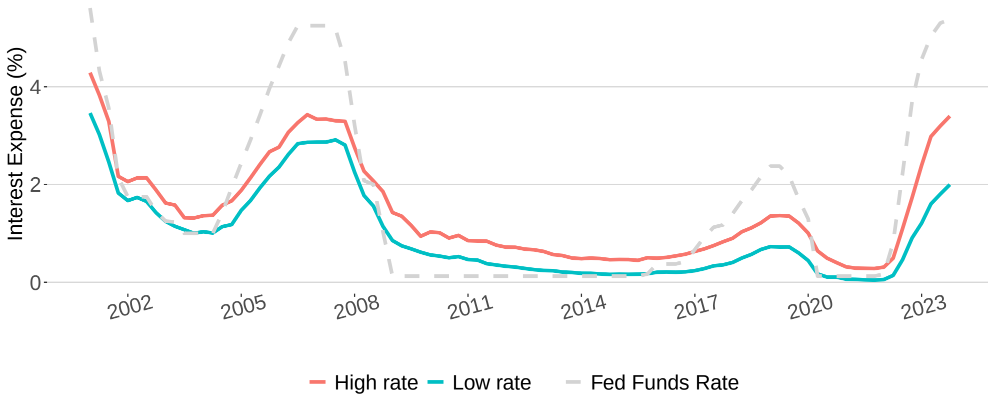
(a) Share of Assets



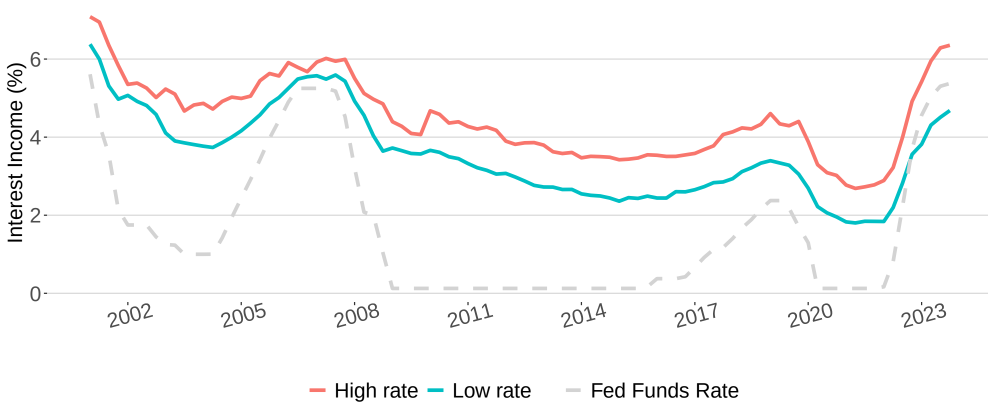
Notes: This figure compares the portfolio characteristics of high- and low-rate banks among the top 25 banks from 2001Q1 through 2023Q4. Figure examines the portfolio composition of high-rate and low-rate banks; share of treasuries, mortgage-backed securities, real estate loans, and C&I loans loans, 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 6: Net Interest Margin

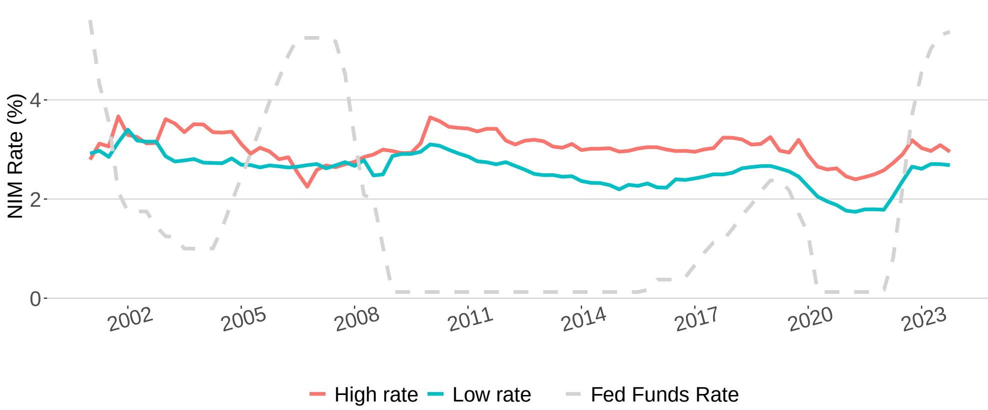
(a) Interest Expense



(b) Interest Income



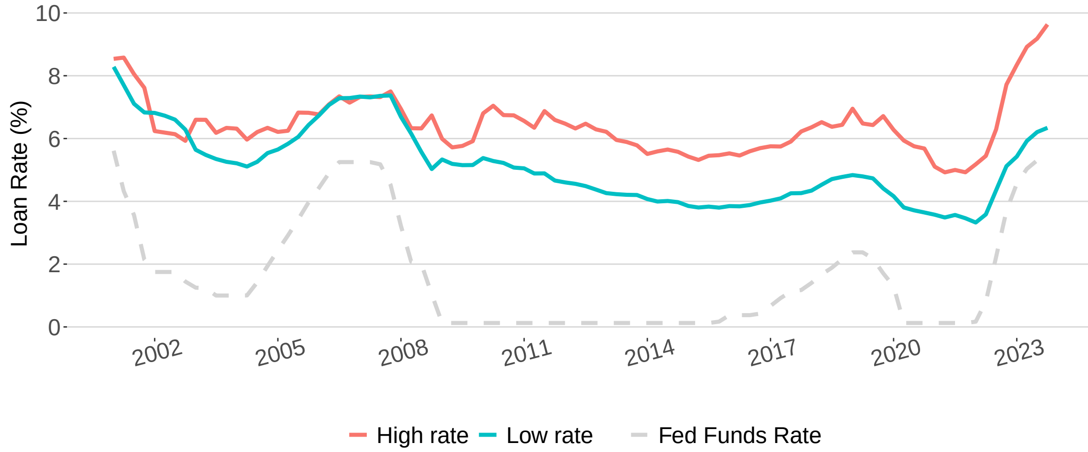
(c) NIM



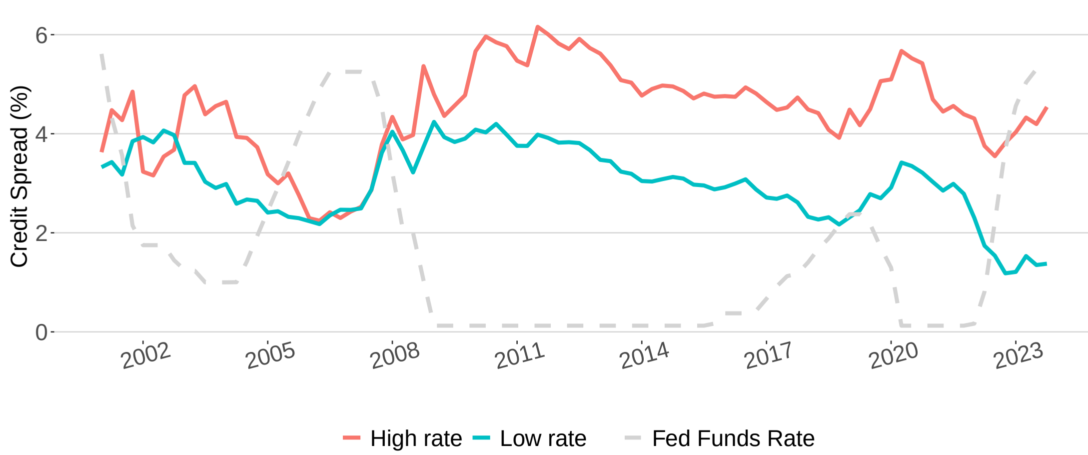
Notes: This figure compares the interest expense, interest income, and net interest margin of high- and low-rate banks among the top 25 banks from 2001Q1 through 2023Q4. Figure 6a presents the interest expense (%) of high- and low-rate banks. Figure 6b presents the interest income (%) of high- and low-rate banks. Figure 6c presents the net interest margin (NIM) 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 each quarter, calculated based on the CD rate and deposit rate from the Call Report, falls within the top tercile.

Figure 7: Credit Risk

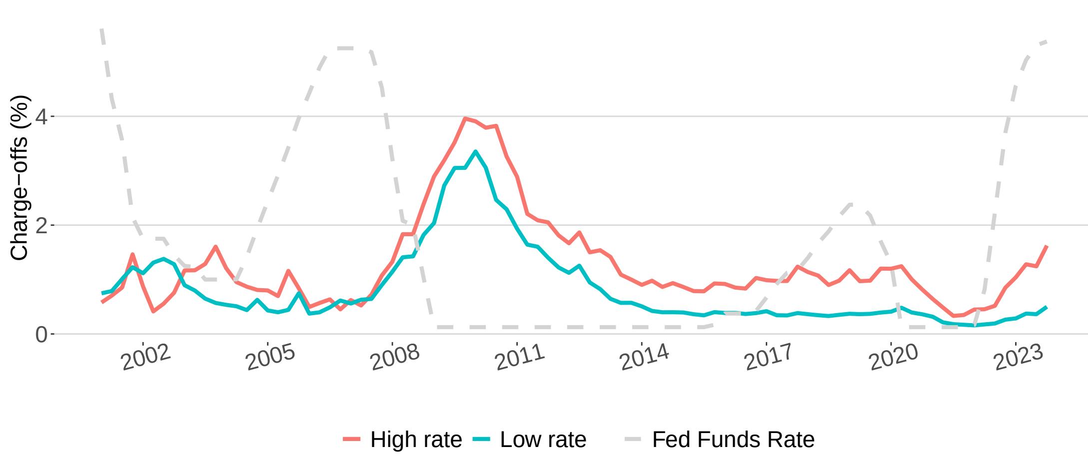
(a) Loan rate



(b) Credit spread



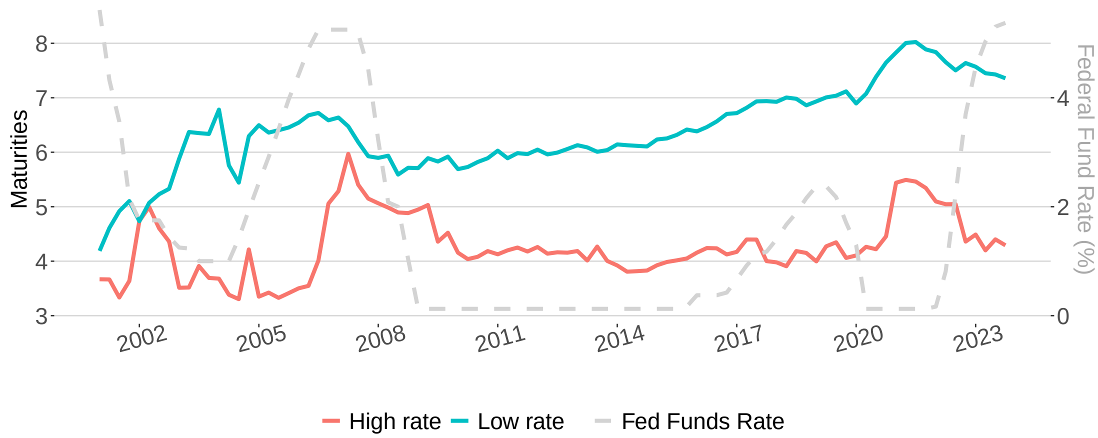
(c) Charge-offs



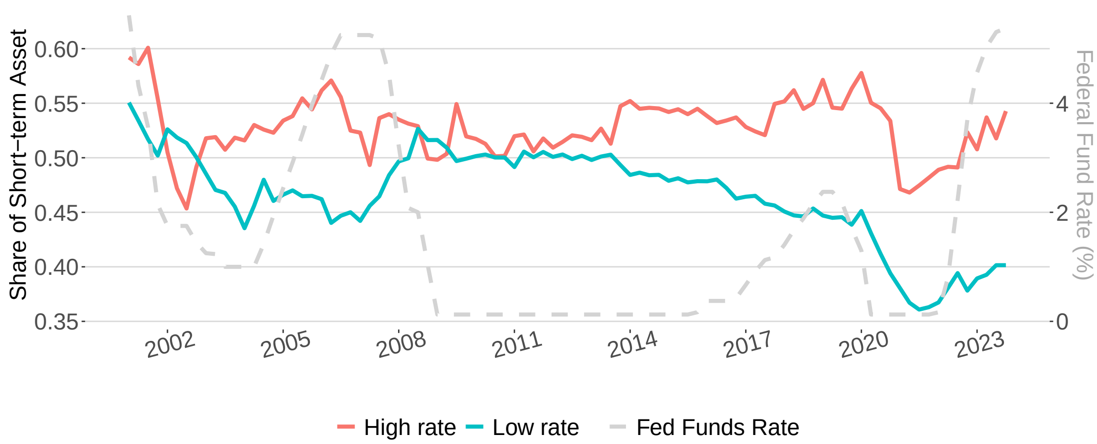
Notes: This figure compares the credit risk of high- and low-rate banks among the top 25 banks from 2001Q1 through 2023Q4. Figure 7a presents the loan rate (%) of high- and low-rate banks. Figure 7b presents the credit spread (%) of high- and low-rate banks. The credit spread is computed as the difference 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



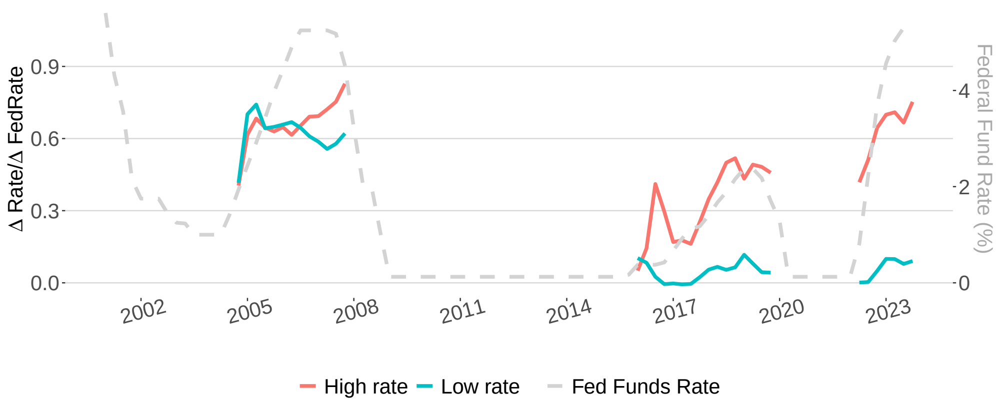
(b) Share of Short-Term Assets



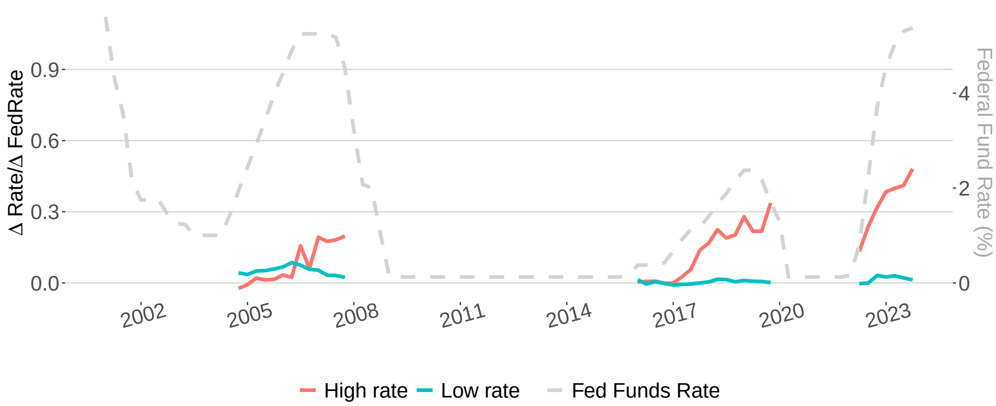
Notes: This figure compares the maturity risk of high- and low-rate banks among the top 25 banks from 2001Q1 through 2023Q4. Figure 8a presents the maturity (# of years) of high- and low-rate banks. Figure 8b presents the share of assets with less-than one-year maturity (short-term assets) for high- 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

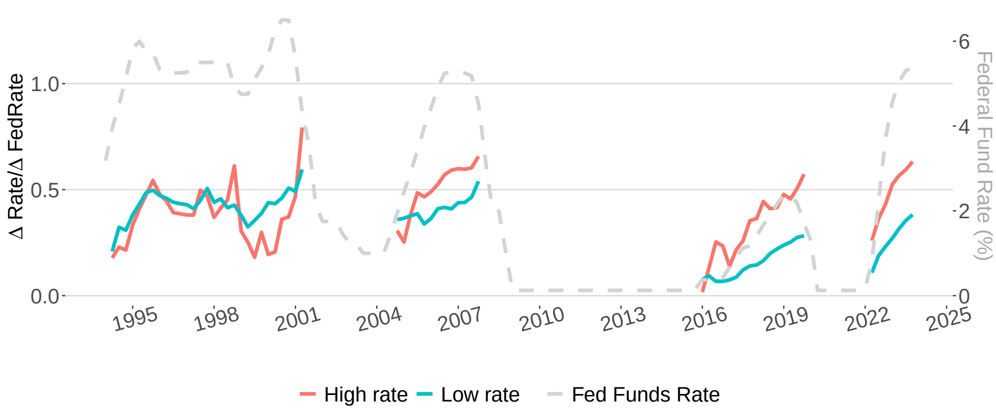
(a) CD



(b) SAV



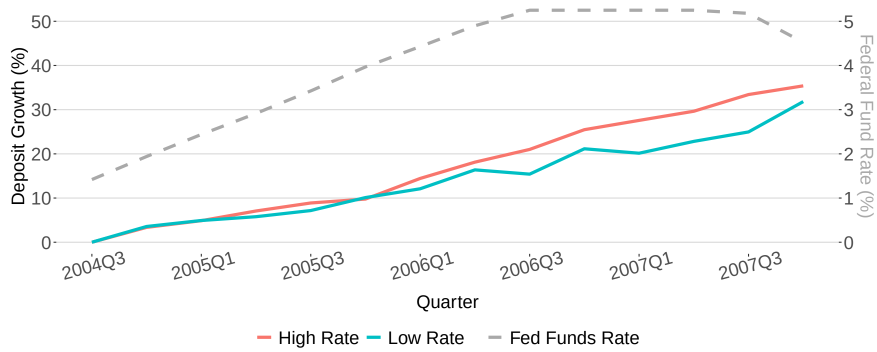
(c) DepRate



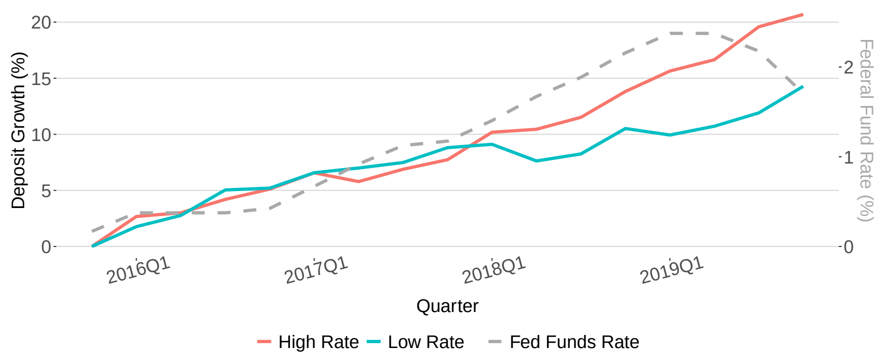
Notes: This figure compares the average deposit rate sensitivity of high- and low-rate banks among the top 25 banks over the three recent rate hiking cycles: 2004Q3 through 2007Q4, 2015Q4 through 2019Q4, and 2022Q1 through 2023Q4. Deposit rate sensitivity is defined as the ratio of the cumulative change 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

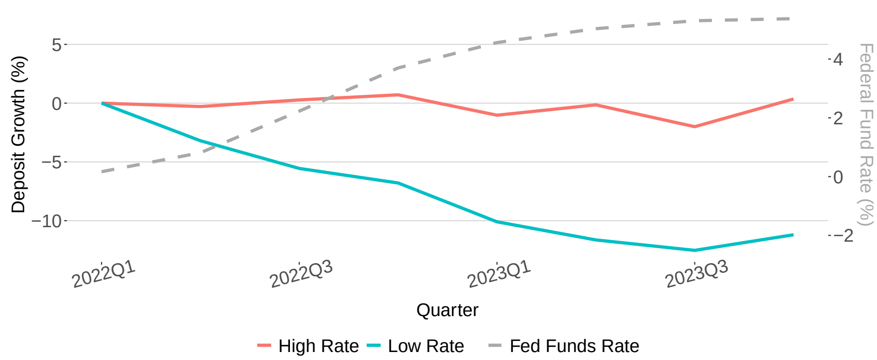
(a) 2004Q3-2007Q4



(b) 2015Q4-2019Q4



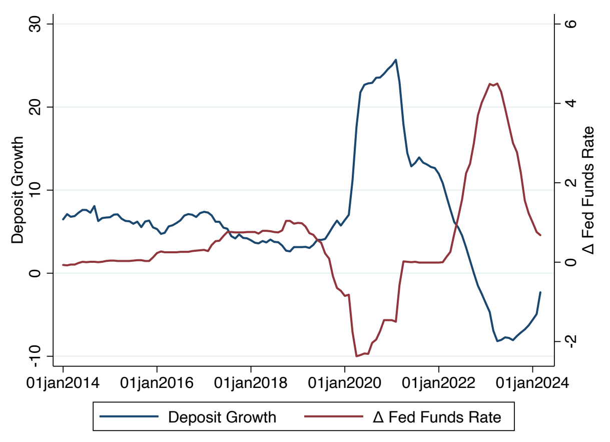
(c) 2022Q1-2023Q4



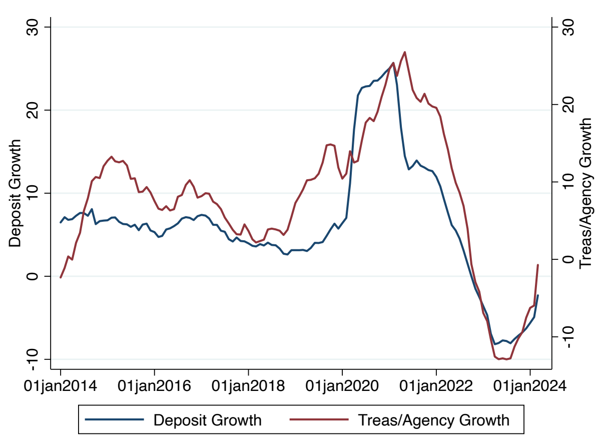
Notes: This figure compares the deposit growth of high- and low-rate banks among the top 25 banks over the three recent rate hiking cycles. Figures 10a, 10b, and 10c compare the deposit growth experienced by high-rate banks to that of low-rate banks from 2004Q3 through 2007Q4, from 2015Q4 through 2019Q4, 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

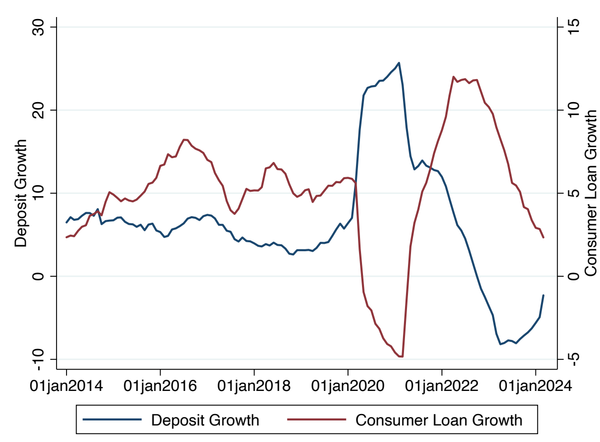
(a) Deposits and the Fed Funds



(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
MCD (%)	3.08	2.72	0.35*	1.30	0.21	1.09**
DepRate (%)	2.65	1.92	0.73***	1.24	0.50	0.74***
Insured Deposits Share	0.60	0.51	0.09	0.54	0.47	0.07
#Branches	769	1428	-659***	336	1645	-1309***
$\log(\frac{\text{\# Branches}}{\text{Deposits}})$	1.11	1.80	-0.69***	-1.72	0.27	-1.99***
NIM rate (%)	2.91	2.89	0.02	2.89	2.31	0.58***
Maturity (Years)	4.33	5.07	-0.73***	4.86	6.30	-1.45***
Charge-off Rate (%)	0.67	0.60	0.08	0.74	0.23	0.51***

Panel B: Deposit Rate

	Count	Mean	Stdev	Skewness	P5	P25	Median	P75	P95
CD	1,896	1.19	1.38	1.17	0.02	0.13	0.48	2.00	4.08
DepRate	2,300	1.11	1.07	1.15	0.04	0.23	0.75	1.72	3.28

Notes: Panel A compares various metrics between high- and low-rate banks among the top 25 banks from 2001Q1 to 2007Q4 and from 2017Q1 to 2023Q4. The comparison between 2008Q1 to 2006Q4 is reported in Tabel B.2. 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. 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. Standard errors 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. 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). Panel B presents the summary statistics for DepRate and CD from 2001Q1 to 2023Q4.

Table 3: Bank Branches

	log(# Branches)		$\log(\frac{\text{Branches}}{\text{Deposit}})$		Branch-weighted County Average Age	
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(High-rate)×Post	-1.048***	-1.027***	-0.624***	-0.637***	-0.319**	-0.257*
	(0.233)	(0.237)	(0.228)	(0.231)	(0.149)	(0.154)
$\mathbb{1}$(High-rate)	-0.466***	-0.455***	-0.357**	-0.337**	-0.275***	-0.374***
	(0.143)	(0.151)	(0.154)	(0.157)	(0.104)	(0.117)
Post	1.273***		0.260***		2.062***	
	(0.133)		(0.092)		(0.213)	
Controls	✓	✓	✓	✓	✓	✓
Quarter FE		✓		✓		✓
Adjusted R^2	0.282	0.284	0.378	0.331	0.305	0.158
Observations	2276	2276	2276	2276	1794	1794
Mean of Dep. Variable	7.044	7.044	0.759	0.759	38.785	38.785

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

$$Y_{i,q} = \delta_q + \beta_1 \times \mathbb{1}(\text{High-rate}_{i,q}) \times \text{Post}_q + \beta_2 \times \mathbb{1}(\text{High-rate}_{i,q}) + \beta_3 \times Controls_{i,q-1} + \varepsilon_{i,q},$$

where i and q indicate the bank and quarter-year, respectively, $\mathbb{1}(\text{High-rate}_{i,q})$ denotes whether bank i is a high-rate bank at quarter q, $Post_t$ 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 average customer age in columns (5)-(6). The branch-weighted county average age 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 for the 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	C&I loans	Real Estate	Other Loans	MBSs	Other Securities
	(1)	(2)	(3)	(4)	(5)	(6)
𝟙(High-rate)×Post	7.594***	3.421***	-11.928***	2.183***	-3.009**	1.738*
	(1.508)	(0.834)	(1.695)	(0.420)	(1.463)	(1.037)
𝟙(High-rate)	2.426*	-1.067	6.116***	-0.893**	-7.694***	1.112
	(1.428)	(0.678)	(1.530)	(0.383)	(1.385)	(0.858)
Quarter FE+Controls	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.214	0.144	0.157	0.013	0.229	0.193
Observations	2300	2300	2300	2300	2300	2300
Mean of Dep. Variable (%)	13.399	15.119	29.878	11.483	16.893	13.228
Charge-offs (%)	2.277	0.602	0.431	0.223	-	-
Maturity (years)	1.932	1.932	12.287	1.932	17.192	5.967

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

$$Y_{i,q} = \delta_q + \beta_1 \times \mathbb{1}(\text{High-rate}_{i,q}) \times \text{Post}_q + \beta_2 \times \mathbb{1}(\text{High-rate}_{i,q}) + \beta_3 \times Controls_{i,q-1} + \varepsilon_{i,q}$$

where i and q indicate the bank and quarter-year, respectively, $\mathbb{1}(\text{High-rate}_{i,q})$ denotes whether bank i is a high-rate bank at quarter q, $Post_t$ 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 for the 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	1.262***	1.080***	0.345***
	(0.190)	(0.255)	(0.107)
$\mathbb{1}$(High-rate)	0.679***	0.968***	0.257**
	(0.166)	(0.241)	(0.098)
Quarter FE+Controls	✓	✓	✓
Adjusted R^2	0.350	0.377	0.162
Observations	2300	2206	2300
Mean of Dep. Variable	5.137	3.238	0.847

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	0.092	0.074	0.312*	0.110**
	(0.082)	(0.071)	(0.170)	(0.052)
$\mathbb{1}$(High-rate)	0.136**	0.153***	0.669***	-0.066
	(0.057)	(0.057)	(0.153)	(0.049)
Quarter FE+Controls	✓	✓	✓	✓
Adjusted R^2	0.087	0.034	0.095	0.027
Observations	2271	2245	2293	2275
Mean of Dep. Variable	0.431	0.602	2.277	0.223

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

$$Y_{i,q} = \delta_q + \beta_1 \times \mathbb{1}(\text{High-rate}_{i,q}) \times \text{Post}_q + \beta_2 \times \mathbb{1}(\text{High-rate}_{i,q}) + \beta_3 \times Controls_{i,q-1} + \varepsilon_{i,q}$$

where i and q indicate the bank and quarter-year, respectively, $\mathbb{1}(\text{High-rate}_{i,q})$ denotes whether bank i is a high-rate bank at quarter q, $Post_t$ 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 for the 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	-0.707**	3.339**
	(0.349)	(1.540)
$\mathbb{1}$(High-rate)	-1.658***	5.602***
	(0.325)	(1.150)
Quarter FE+Controls	✓	✓
Adjusted R^2	0.281	0.144
Observations	2206	2206
Mean of Dep. Variable	5.937	47.773

Panel B: Maturity by Asset Class

	Real Estate Loans	Other Loans	MBSs	Treasuries
	(1)	(2)	(3)	(4)
$\mathbb{1}$(High-rate)×Post	-0.102	0.137	-1.231***	-1.619***
	(0.375)	(0.161)	(0.382)	(0.539)
$\mathbb{1}$(High-rate)	-0.856**	-0.285**	0.919***	-0.018
	(0.360)	(0.143)	(0.313)	(0.531)
Quarter FE+Controls	✓	✓	✓	✓
Adjusted R^2	0.081	0.142	0.021	0.080
Observations	2100	2206	2116	2165
Mean of Dep. Variable	12.287	1.932	17.192	5.967

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

$$Y_{i,q} = \delta_q + \beta_1 \times \mathbb{1}(\text{High-rate}_{i,q}) \times \text{Post}_q + \beta_2 \times \mathbb{1}(\text{High-rate}_{i,q}) + \beta_3 \times Controls_{i,q-1} + \varepsilon_{i,q},$$

where i and q indicate the bank and quarter-year, respectively, $\mathbb{1}(\text{High-rate}_{i,q})$ denotes whether bank i is a high-rate bank at quarter q, $Post_t$ 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 for the 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	SavRate	ΔInterest Expense	ΔInterest Income	ΔNIM
	(1)	(2)	(3)	(4)	(5)
ΔFed Funds$_q\times$ $\mathbb{1}$(High-rate) $\times$Post	0.351***	0.587***	0.133***	0.129***	-0.000
	(0.098)	(0.134)	(0.026)	(0.044)	(0.047)
ΔFed funds$_q\times$ $\mathbb{1}$(High-rate)	0.002	-0.312***	-0.015	-0.018	-0.037
	(0.080)	(0.062)	(0.022)	(0.034)	(0.041)
ΔFed funds$_q\times$Post	-0.457***	-0.055	-0.120***	0.109***	0.213***
	(0.109)	(0.044)	(0.032)	(0.033)	(0.040)
ΔFed funds$_q$	0.580***	0.090**	0.404***	0.347***	-0.043*
	(0.057)	(0.038)	(0.020)	(0.035)	(0.025)
$\mathbb{1}$(High-rate)$\times$Post	-0.007	0.169	-0.021*	-0.011	0.001
	(0.040)	(0.158)	(0.011)	(0.024)	(0.024)
$\mathbb{1}$(High-rate)	0.010	0.151**	0.014	0.017	0.010
	(0.037)	(0.061)	(0.010)	(0.022)	(0.022)
Post	-0.053	-0.028	-0.000	0.002	0.005
	(0.063)	(0.069)	(0.017)	(0.030)	(0.021)
Controls	✓	✓	✓	✓	✓
Adjusted R^2	0.507	0.143	0.629	0.434	0.102
Observations	1873	859	2300	2300	2300
Mean of Dep. Variable (level)	0.860	0.218	0.919	3.538	2.622

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

$$\begin{aligned}\Delta Y_{i,q} = \alpha &+ \beta_1 \times \Delta\text{Fed Funds}_q \times \mathbb{1}(\text{High-rate}_{i,q}) \times \text{Post}_q + \beta_2 \times \Delta\text{Fed Funds}_q \times \mathbb{1}(\text{High-rate}_{i,q}) \\ &+ \beta_3 \times \Delta\text{Fed Funds}_q \times \text{Post}_q + \beta_4 \times \mathbb{1}(\text{High-rate}_{i,q}) \times \text{Post}_q + \beta_5 \times \Delta\text{Fed Funds}_q \\ &+ \beta_6 \times \mathbb{1}(\text{High-rate}_{i,q}) + \beta_7 \times \text{Post}_q + \beta_8 \times Controls_{i,q-1} + \varepsilon_{i,q},\end{aligned}$$

where i and q indicate the bank and quarter-year, respectively, ΔFed Funds$_q$ denotes the change in the Federal Funds Target Rate, $\mathbb{1}$(High-rate$_{i,q}$) denotes whether bank i is a high-rate bank at quarter q, $Post_t$ denotes the post-2009 period. 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, $\Delta Y_{i,q}$ is the 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 for the 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

	Δlog(Deposit$_{i,y}$)		ΔPersonal Loan Share$_{i,y}$		ΔC&I Loan Share$_{i,y}$		ΔRE Loan Share$_{i,y}$		ΔMBS Share$_{i,y}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ΔFed Funds$_y\times$ $\mathbb{1}$(High-rate) $\times$Post	0.501***	0.499**	0.622***	0.667***	0.319**	0.302*	-0.060	-0.055	-0.286	-0.279
	(0.190)	(0.195)	(0.219)	(0.226)	(0.155)	(0.153)	(0.298)	(0.296)	(0.414)	(0.398)
ΔFed funds$_y\times$ $\mathbb{1}$(High-rate)	-0.350*	-0.346*	-0.411**	-0.451**	-0.370***	-0.338***	-0.239	-0.240	0.568	0.555
	(0.187)	(0.191)	(0.208)	(0.215)	(0.115)	(0.106)	(0.233)	(0.226)	(0.409)	(0.392)
ΔFed funds$_y\times$Post	0.004		0.486***		-0.362*		0.402*		-0.248*	
	(0.176)		(0.126)		(0.216)		(0.240)		(0.134)	
ΔFed funds$_y$	-0.187		-0.172*		0.736***		0.057		-0.306***	
	(0.166)		(0.091)		(0.157)		(0.103)		(0.088)	
$\mathbb{1}$(High-rate)$\times$Post	-1.534***	-1.553***	1.514***	1.467***	-0.794***	-0.769***	-0.778	-0.713	0.075	-0.045
	(0.453)	(0.475)	(0.445)	(0.443)	(0.261)	(0.275)	(0.603)	(0.612)	(0.962)	(0.991)
$\mathbb{1}$(High-rate)	1.588***	1.599***	-1.320***	-1.278***	0.660***	0.525**	0.718	0.624	-0.371	-0.239
	(0.446)	(0.468)	(0.426)	(0.419)	(0.214)	(0.230)	(0.492)	(0.509)	(0.936)	(0.964)
Post	-0.336		-0.679***		0.792		-2.647***		0.221	
	(0.307)		(0.237)		(0.615)		(0.451)		(0.404)	
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Quarter FE		✓		✓		✓		✓		✓
Adjusted R^2	0.088	0.035	0.111	0.065	0.109	0.010	0.118	0.013	0.040	0.008
Observations	2300	2300	2300	2300	2300	2300	2300	2300	2300	2300
Mean of Dep. Variable (level)	0.232	0.232	13.399	13.399	15.119	15.119	29.878	29.878	16.893	16.893

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

$$\Delta Y_{i,y} = \delta_q + \beta_1 \times \Delta\text{Fed Funds}_y \times \mathbb{1}(\text{High-rate}_{i,q}) \times \text{Post}_q + \beta_2 \times \Delta\text{Fed Funds}_y \times \mathbb{1}(\text{High-rate}_{i,q})$$
$$+ \beta_3 \times \Delta\text{Fed Funds}_y \times \text{Post}_q + \beta_4 \times \mathbb{1}(\text{High-rate}_{i,q}) \times \text{Post}_q + \beta_5 \times \Delta\text{Fed Funds}_y + \beta_6 \times \mathbb{1}(\text{High-rate}_{i,q})$$
$$+ \beta_7 \times \Delta\text{Fed Funds}_y \times \mathbb{1}(\text{High-rate}_{i,q}) \times \text{Crisis} + \beta_8 \times Controls_{i,q-1} + \varepsilon_{i,q},$$

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, $\mathbb{1}(\text{High-rate}_{i,q})$ denotes whether bank i is a high-rate bank at quarter q, 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 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 for the 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: Robustness

	log(#Branches) T3.(2) (1)	Credit Spread T5.(2) (2)	Maturity (years) T6.(1) (3)	Pers. & CI Loan Share T4.(1)&(2) (4)	Real Estate & MBS Share T4.(3)&(5) (5)	Δ Interest Expense T7.(3) (6)	$\Delta Deposit_{i,y}$ T8.(2) (7)	Δ Pers. & CI Loans Share T8.(4)&(6) (8)
(1) Original Results	-1.027***	1.080***	-0.707**	11.015***	-14.937***	0.133***	0.499**	0.969***
e-Banking and Divergence								
(2) Mobile Bank Google Search	-2.107***	1.565***	-1.583***	16.078***	-23.782***	0.202***	0.541	1.470***
(3) 3G Coverage	-1.384***	1.239***	-0.787*	12.358***	-16.885***	0.135***	0.509**	0.927***
Robustness of Cutoff 2009								
(4) Post≥2010	-1.181***	1.076***	-0.901***	10.113***	-14.587***	0.119***	0.163	0.748***
(5) Drop year 08-11	-1.194***	1.237***	-0.617*	12.310***	-15.250***	0.139***	0.477**	0.978***
Robustness of Specification								
(6) Equal Weights	-0.890**	0.772***	-0.388	16.662***	-21.011***	0.099***	0.761***	0.700***
(7) Add BHC FE	-0.370***	0.478*	-0.337	-2.362*	-1.711	0.128***	0.555**	0.921***
Using DepRate from Call Report to Classify Banks								
(8) Original Spec.	-0.946***	0.702***	-0.335	6.449***	-10.511***	0.129***	0.678***	1.391***
(9) 1994-2023	-0.531**	0.851***	-0.523**	7.876***	-10.325***	0.177***	0.552*	1.160***
(10) Top 100 BHCs	-0.810***	0.721***	-0.433**	7.627***	-9.859***	0.142***	0.285*	0.947***
(11) All BHCs	-0.754***	0.402***	-0.221	5.999***	-3.179***	0.112***	0.158	0.481**

Notes: This table conducts robustness checks for the main results, focusing on the key coefficients (first columns) of Table X column Y, denoted as T.X(Y). The different rows represent various robustness checks applied to the original results. The first row shows the original results. The second and third rows report results replacing "Post" by the 3G coverage ratio across the U.S and google search of mobile banking, respectively. The fourth row reports results where "Post" denotes the after-2010 period, and the fifth row reports results after dropping years from 2008 to 2011.
The sixth row reports results with equal weights, and the seventh row reports results after adding BHC fixed effects. Starting from row (8), we extend the sample in various ways and classify banks based on DepRate from Call Report. The eighth row reports results with original specification but new classification rule. The ninth row reports result with sample extended back to 1994. The last two rows report results using the top 100 banks and all banks, respectively. *, **, *** 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	0.017***	-0.111	-0.922	9.017***	3.599***
	(0.004)	(0.197)	(0.673)	(1.647)	(0.533)
$\mathbb{1}$(High-rate)	-0.001	1.144***	-0.413***	-7.591***	-0.857
	(0.003)	(0.143)	(0.126)	(0.928)	(0.995)
Quarter FE+Controls	✓	✓	✓	✓	✓
Adjusted R^2	0.142	0.055	0.034	0.039	0.050
Observations	1333	2300	2300	2300	2300
Mean of Dep. Variable	0.033	14.314	6.364	45.934	7.835

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

$$Y_{i,q} = \delta_q + \beta_1 \times \mathbb{1}(\text{High-rate}_{i,q}) \times \text{Post}_q + \beta_2 \times \mathbb{1}(\text{High-rate}_{i,q}) + \beta_3 \times Controls_{i,q-1} + \varepsilon_{i,q}$$

where i and q indicate the bank and quarter-year, respectively, $\mathbb{1}(\text{High-rate}_{i,q})$ denotes whether bank i is a high-rate bank at quarter q, $Post_t$ 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 for the 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

We construct our panel data at the bank-quarter level by combining data from the Survey of Depository Institutions (SDI) and Call Reports. Although the SDI data, sourced from Call Reports, aggregates variables from multiple reports, its coverage only goes up to 2022Q2. To extend our dataset to 2023Q4, we supplement the SDI data with additional data from the Call Reports.

In our analysis, we aggregate banks under the same Bank Holding Company (BHC). When a bank's type changes, we update our records using the latest BHC identifier from the RSSDHCR database. For example, when Capital One transitioned from a domestic entity to a BHC on October 1, 2004, we consistently applied the identifier 2277860 to all data prior to this date, ensuring continuity in our time series for banks undergoing classification changes.

Additionally, we account for mergers and acquisitions (M&As) when constructing growth variables, including growth of deposits, various of loans products. We source M&A data from the FFIEC's National Information Center and incorporate statistics on target banks from the Call Reports or SDI. We calculate the quarterly growth of variable Y as $\log \frac{(\mathrm{Y}_t - \text{Acquired } \mathrm{Y}_t)}{\mathrm{Y}_{t-1}}$. For annual growth, we calculate the cumulative quarterly growth after adjusting for M&As. This approach ensures that our analysis is not distorted by M&A activities.

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 (%)	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)	$(0.125*\text{scpt3les}_q+0.625*\text{scpt3t12}_q+2*\text{scpt1t3}_q$ $+4*\text{scpt3t5}_q+10*\text{scpt5t15}_q+20*\text{scptov15}_q)/\text{MBS}$
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)	$(0.125*\text{lnrs3les}_q+0.625*\text{lnrs3t12}_q+2*\text{lnrs1t3}_q$ $+4*\text{lnrs3t5}_q+10*\text{lnrs5t15}_q+20*\text{lnrsov15}_q)/\text{RELoan}$

Maturity$_{OtherLoan}$ (years)	(0.125*lnot3les$_q$+0.625*lnot3t12$_q$+2*lnot1t3$_q$ +4*lnot3t5$_q$+10*lnot5t15$_q$+20*lnotov15$_q$)/OtherLoan
Maturity (years)	(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$_q$)) / (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

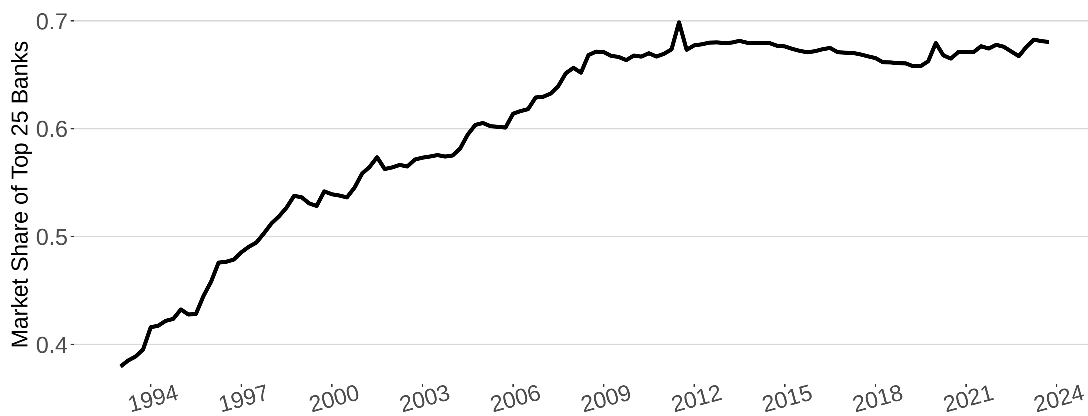
Notes: We follow the variable definitions from the FDIC's Statistics on Depository Institutions. See SDI.

B Additional Figures and Tables: Supporting Evidence and Alternative Channels

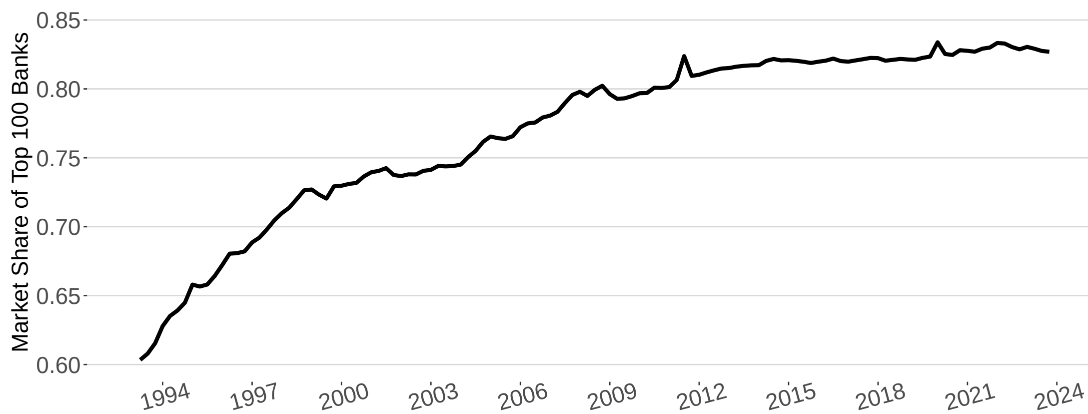
B.1 Figures

Figure B.1: Market Share of Top Banks

(a) Top 25



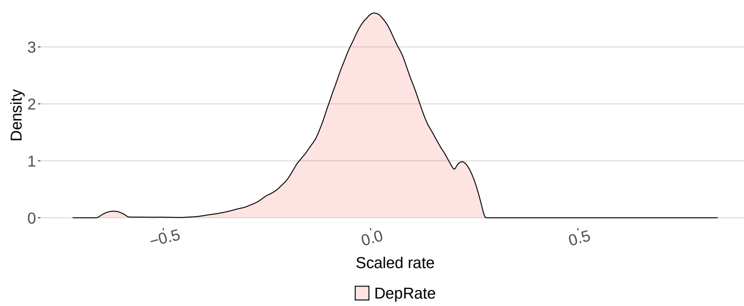
(b) Top 100



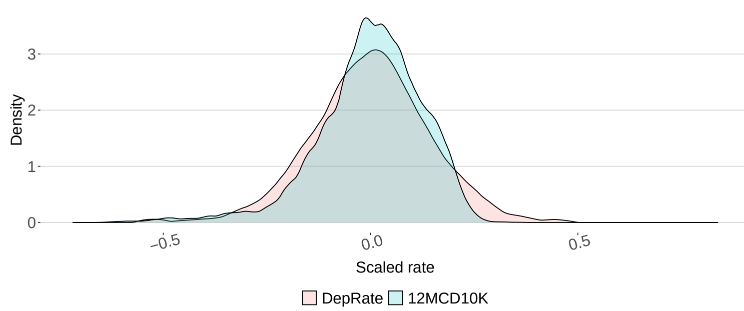
Notes: This figure presents the market share of the top 25 banks (in panel a) and top 100 banks (in panel b) from 2001Q1 through 2023Q4. Market share is measured by total assets. The top 25 (top 100) banks are defined according to bank size in each quarter. The data used to construct this figure comes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

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

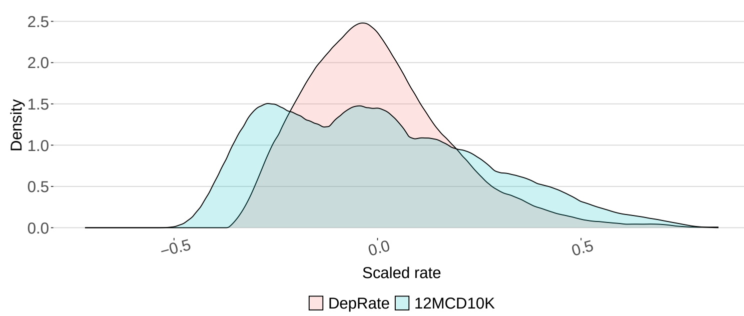
(a) 1995Q2



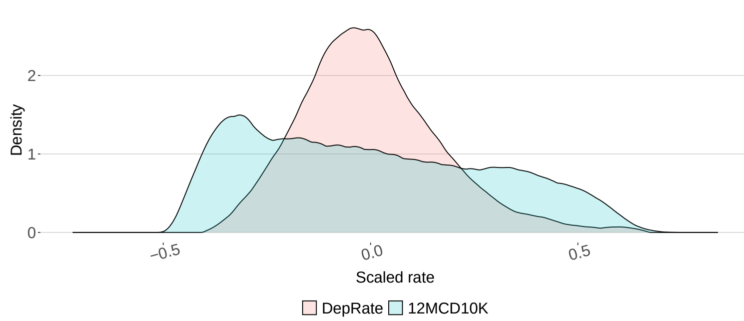
(b) 2006Q3



(c) 2019Q1



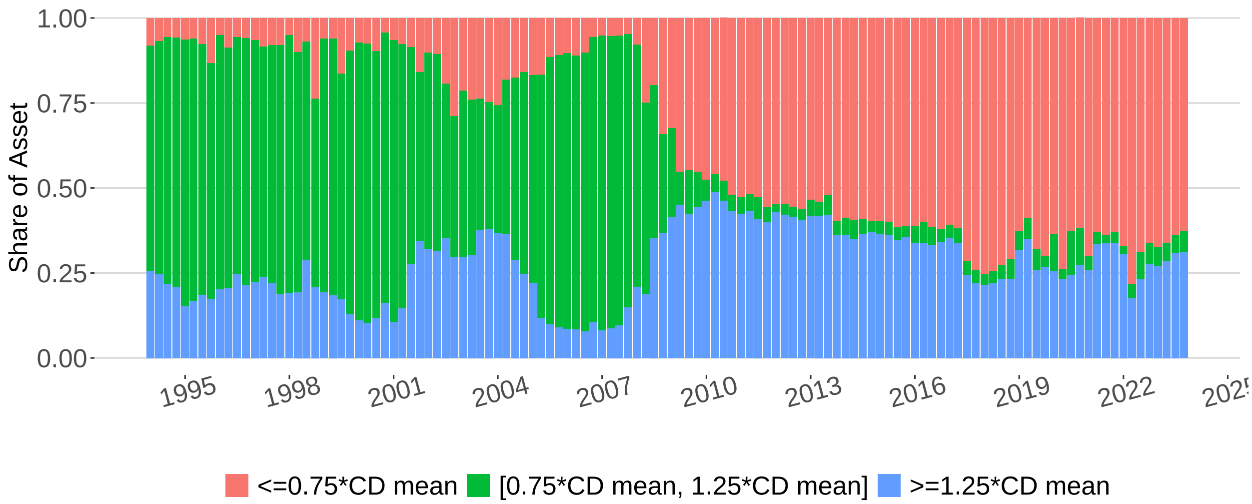
(d) 2023Q4



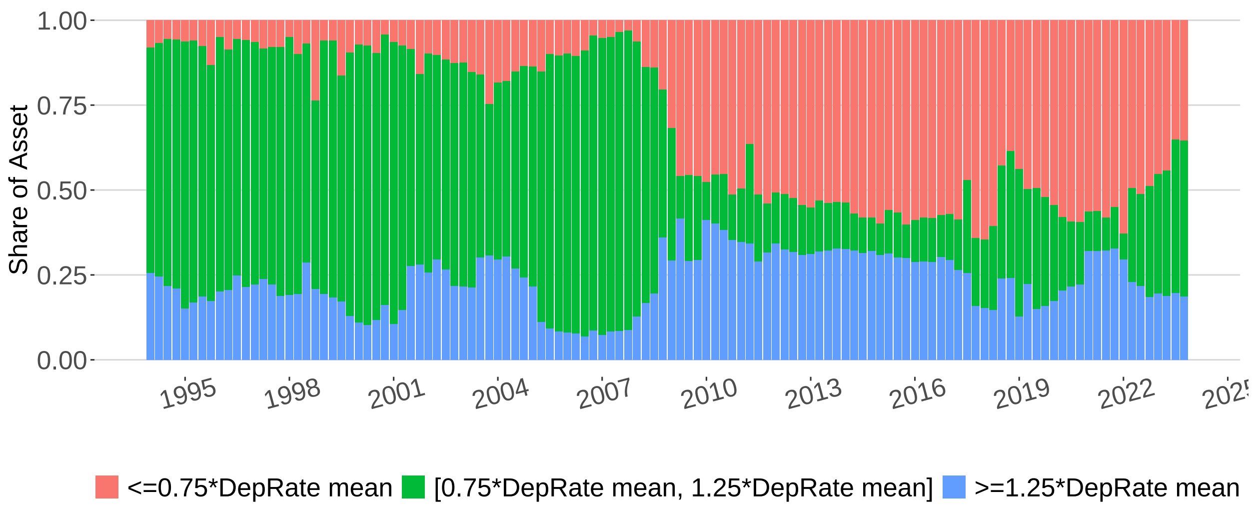
Notes: This figure depicts kernel density plots of the scaled and demeaned 12-month certificate of deposit rates of at least \$10,000 (CD) and the scaled and demeaned deposit rates (DepRate) derived from Call Reports provided by all banks at 1995Q2, 2006Q3, 2019Q1, and 2023Q4, representing the peak of 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



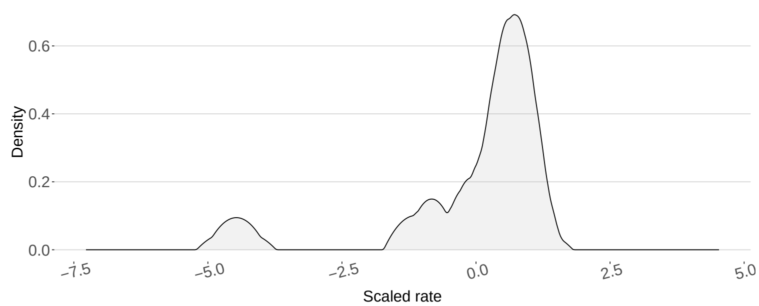
(b) Classification based on DepRate



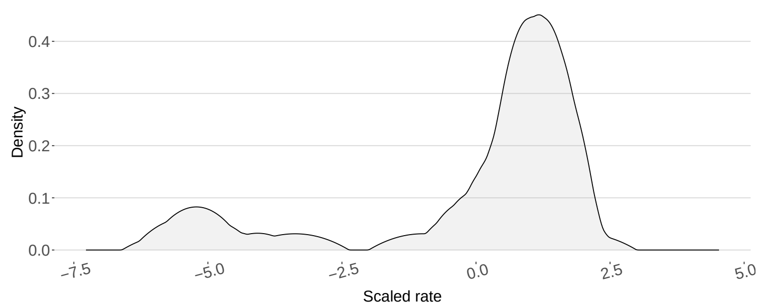
Notes: This figure illustrates the distribution of bank assets among three categories for all banks: banks with deposit rates below 0.75 times the sample average, banks with deposit rates within the range of 0.75 times to 1.25 times the sample average, and banks with deposit rates exceeding 1.25 times 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

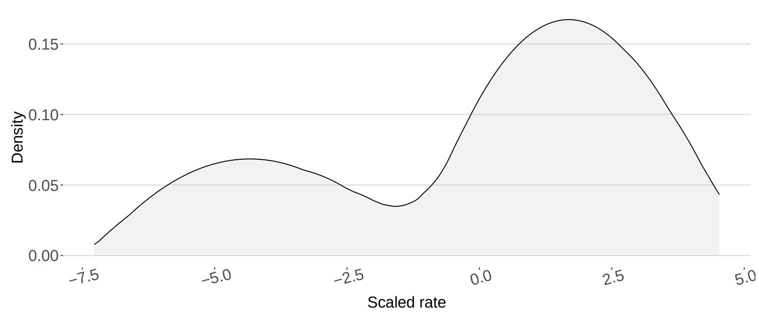
(a) 1995Q2



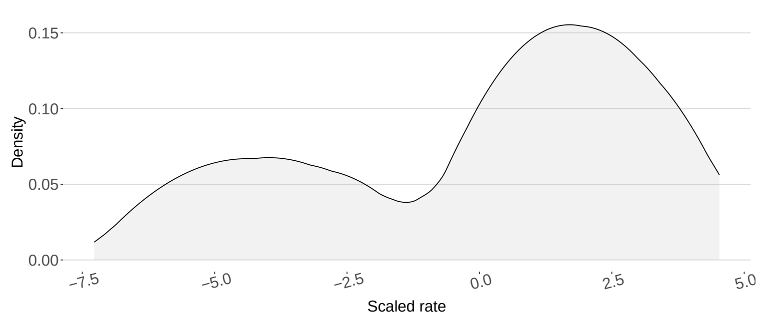
(b) 2006Q3



(c) 2019Q1



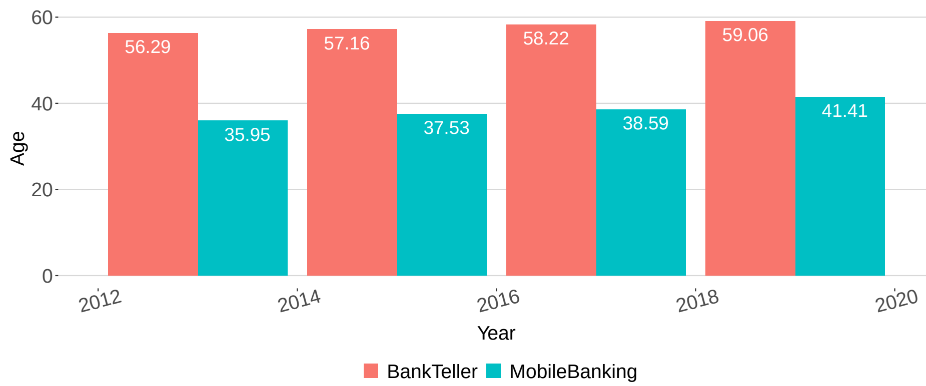
(d) 2023Q4



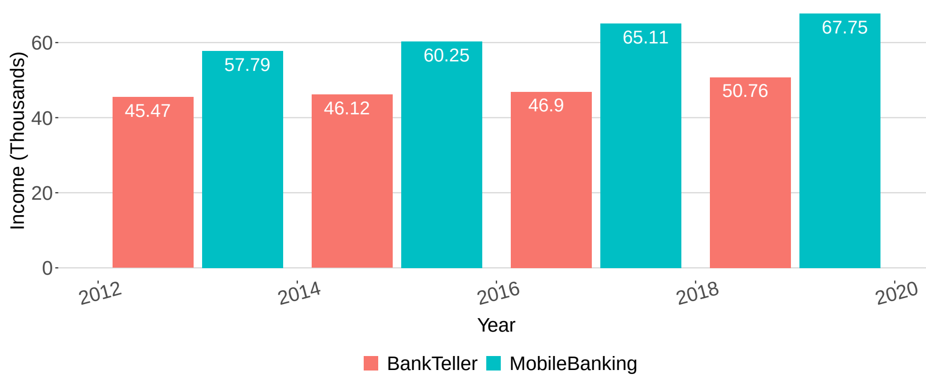
Notes: This figure displays kernel density plots of the demeaned logarithm of branch deposits by the top 25 banks at the peak of each interest rate hiking cycle. Figures a, b, c and d illustrate the kernel density at the following quarters: 1995Q2, 2006Q3, 2019Q1, and 2023Q4, respectively. The top 25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

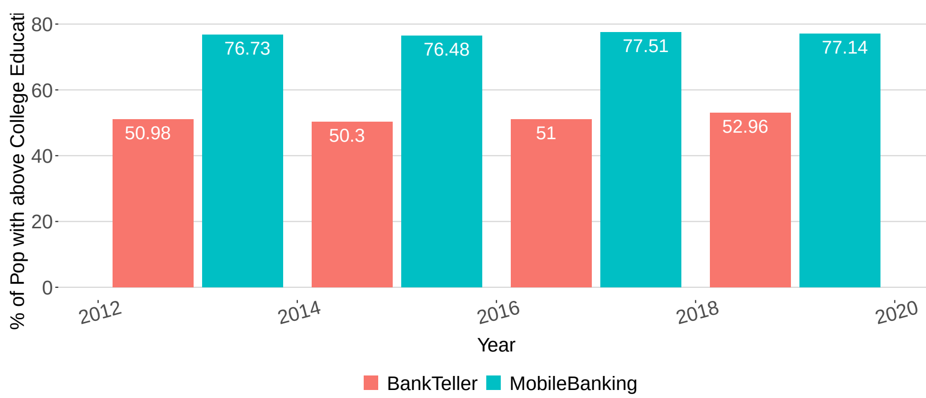
(a) Age



(b) Income



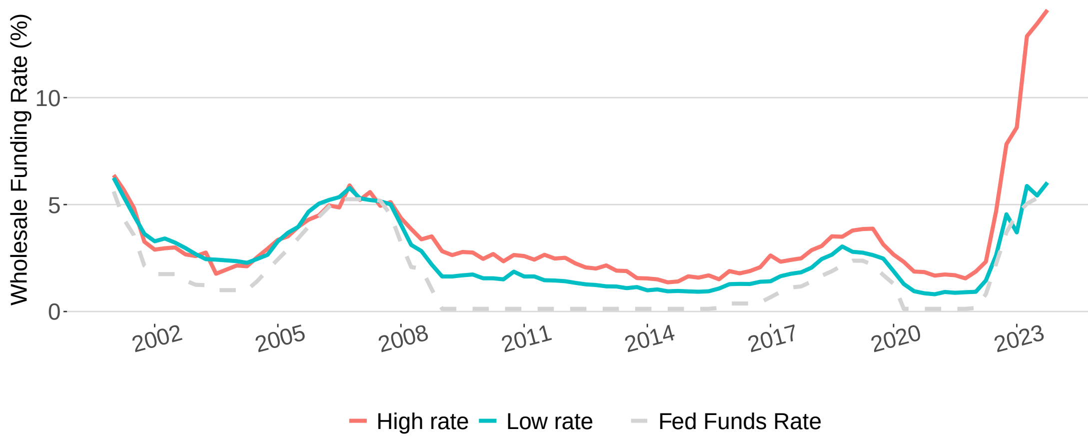
(c) Education



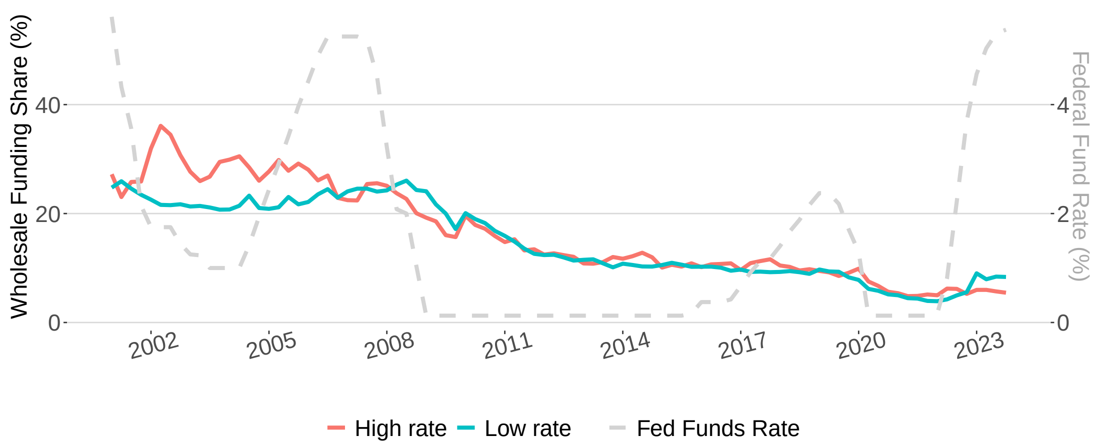
Notes: These figures present the characteristics of households utilizing bank tellers versus mobile banking as their primary means of accessing banking services. The data is derived from the FDIC Survey of Consumer Use of Banking and Financial Services. Respondents were asked to specify their most common 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: Wholesale Funding

(a) Wholesale Funding Rate



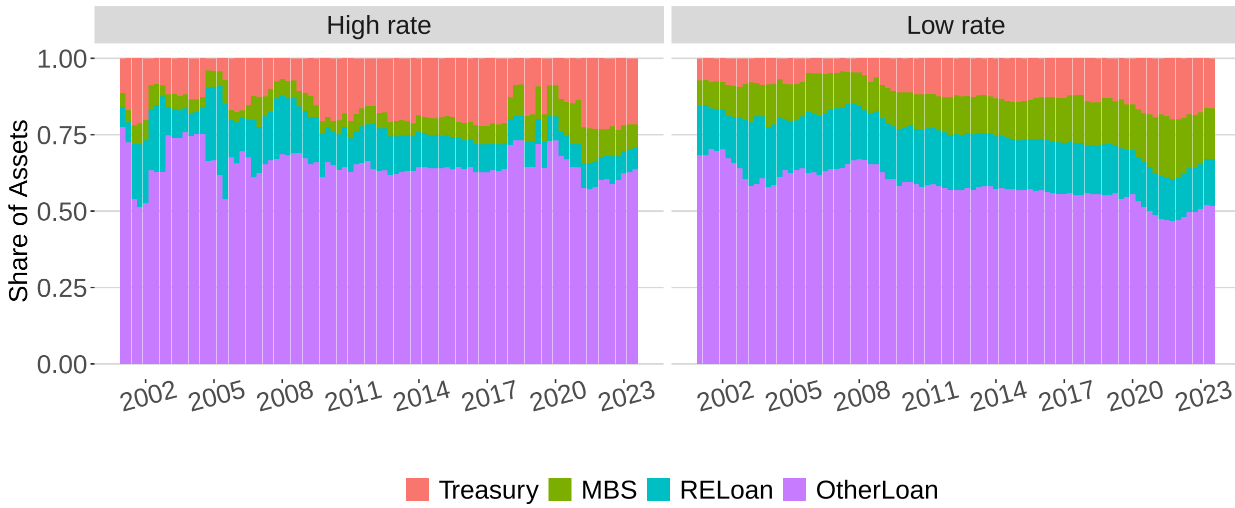
(b) Wholesale Funding Share



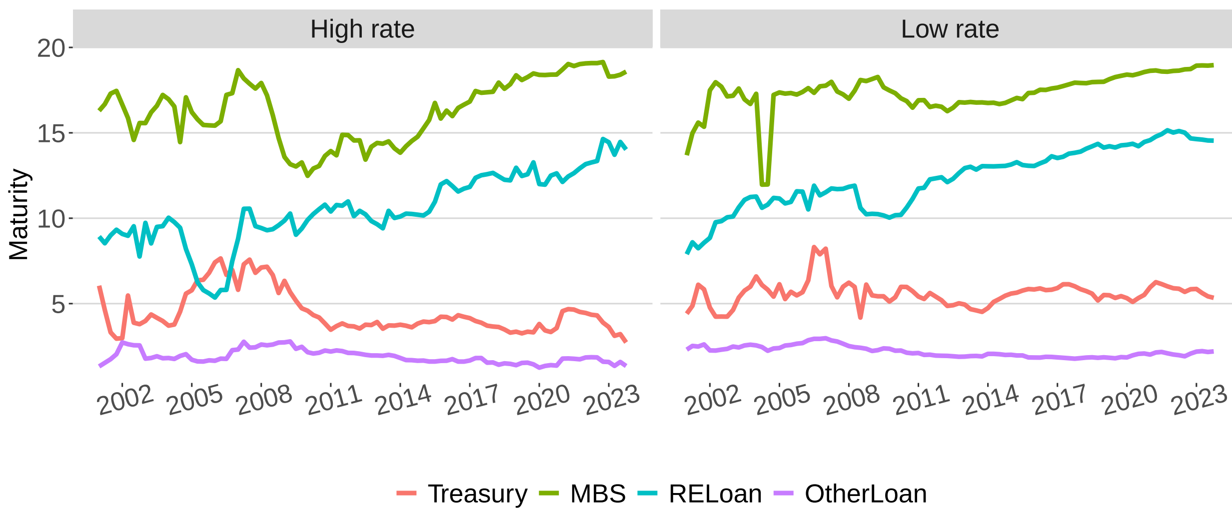
Notes: The figures plot the wholesale funding share (in panel A) and rate (in panel B) of high- and low-rate banks among the top 25 banks from 2001Q1 through 2023Q4. The wholesale funding includes federal funds purchased and repurchase agreements, subordinated debt, and other borrowed funds. See Appendix 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.7: Maturity Decomposition

(a) Share of Assets



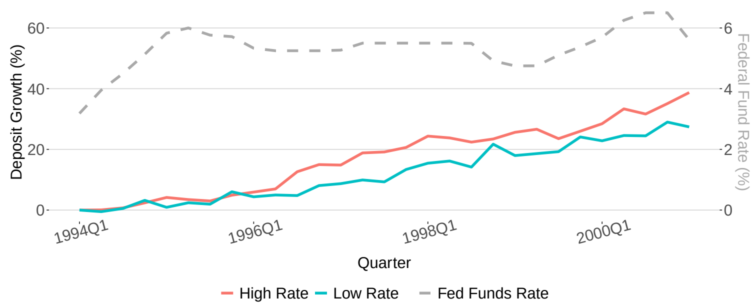
(b) Maturity



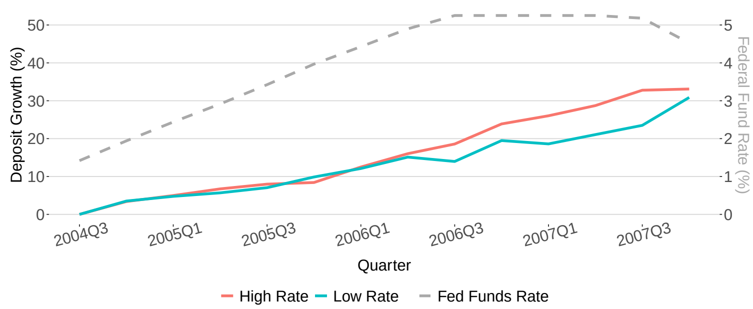
Notes: This figure compares the portfolio characteristics of high- and low-rate banks among the top 25 banks from 2001Q1 through 2023Q4. Figure B.7a examines the portfolio composition of high-rate and low-rate banks; share of treasuries (red), mortgage-backed securities (green), real estate loans (blue), and other loans (purple). Figure B.7b examines the maturity (years) of these asset classes for high-rate and low-rate banks. 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.8: Deposit Growth (Fixed Top 25 Banks)

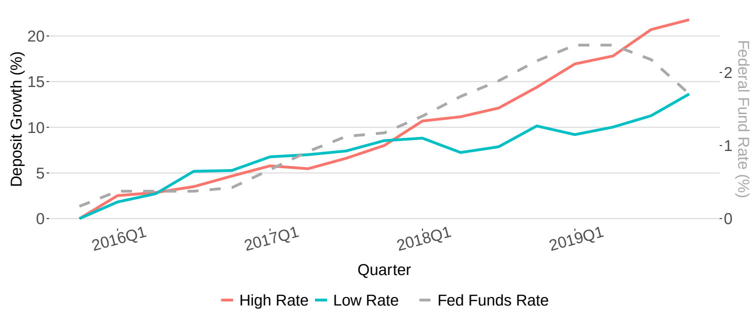
(a) 1994Q1-2001Q1



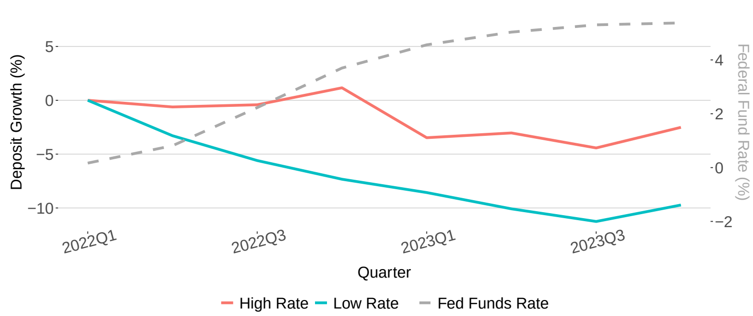
(b) 2004Q3-2007Q4



(c) 2015Q4-2019Q4



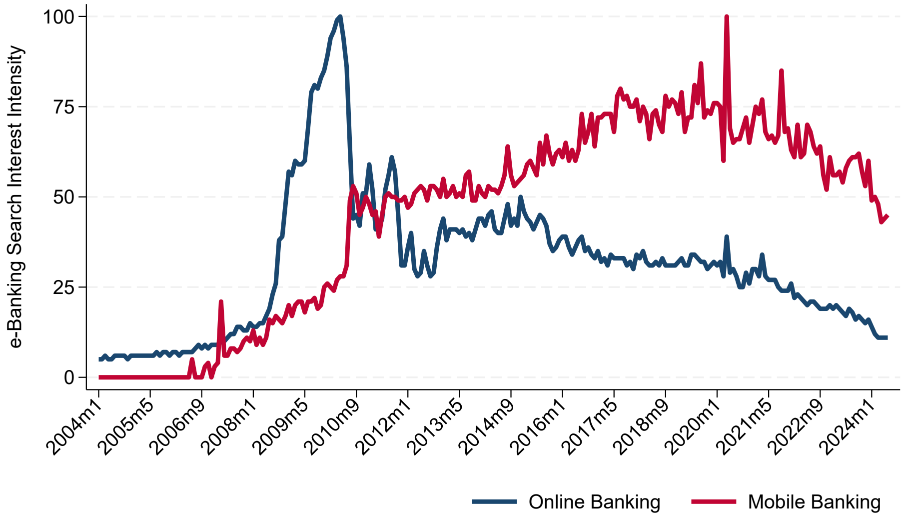
(d) 2022Q1-2023Q4



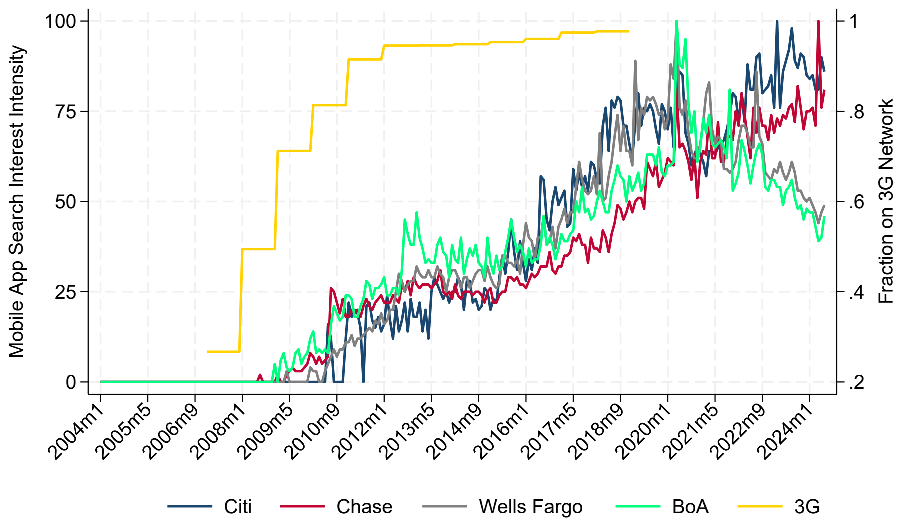
Notes: This figure compares the deposit growth of high- and low-rate banks among the top 25 banks over the four recent rate hiking cycles. The difference from Figure 10 is that in this exercise we fix the top 25 banks at the beginning of the cycle. Figures B.8a B.8b, B.8c, and B.8d compare the deposit growth experienced by high-rate banks to that of low-rate banks from 1994Q1 through 2001Q1, 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. 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 12MDC10K rate and deposit rate from the Call Report, falls within the top tercile.

Figure B.9: e-Banking Adoption 2004-2024

(a) Online and Mobile Banking



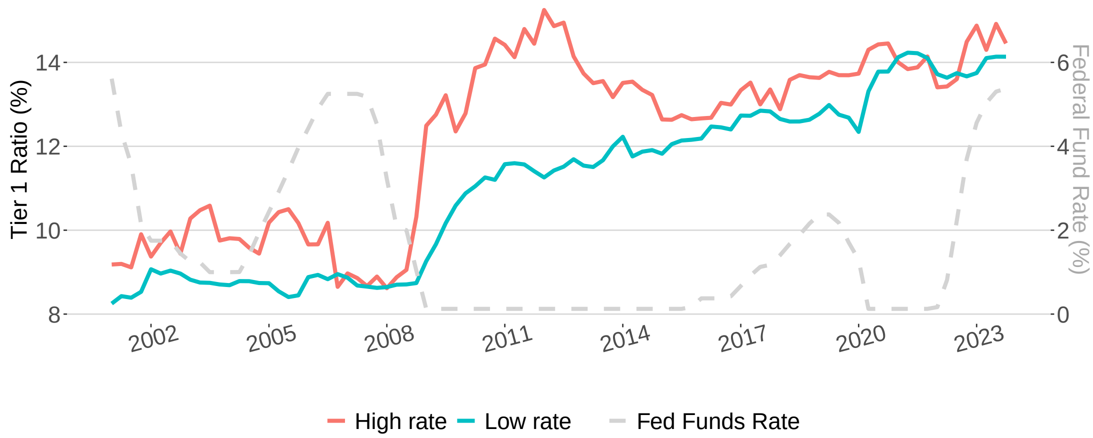
(b) 3G & Top 4 Banks: Mobile Apps



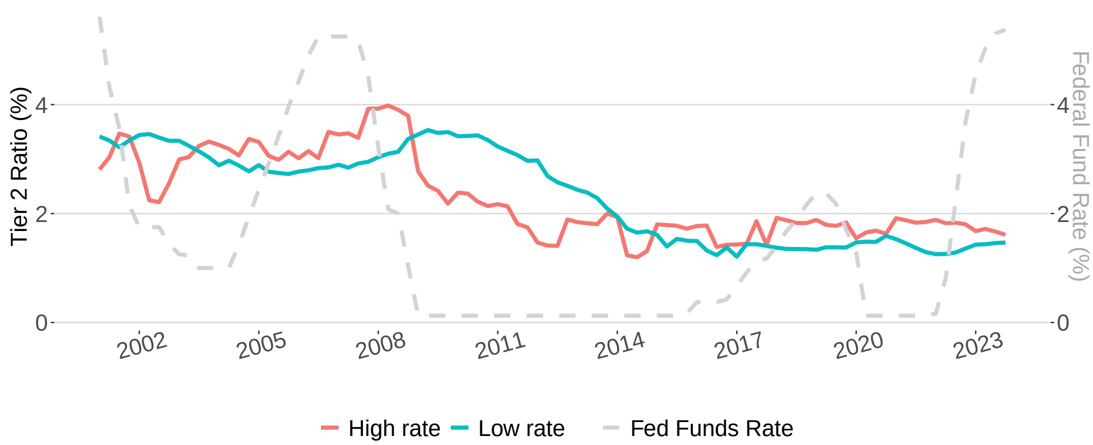
Notes: This figure plots the search interest intensity for online banking and mobile banking. Appendix Figure B.9a plots the search interest intensity for "online banking" (blue) and "mobile banking" (red) from 2004 through 2024. Figure B.9b plots the search interest intensity for "Citi App" (blue), "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.10: Tier 1 and Tier 2 Ratios

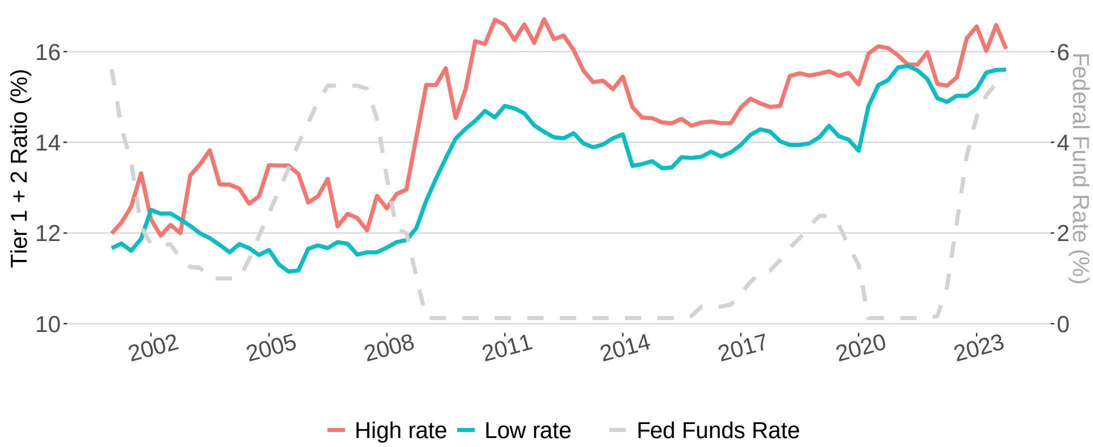
(a) Tier 1 Ratio



(b) Tier 2 Ratio

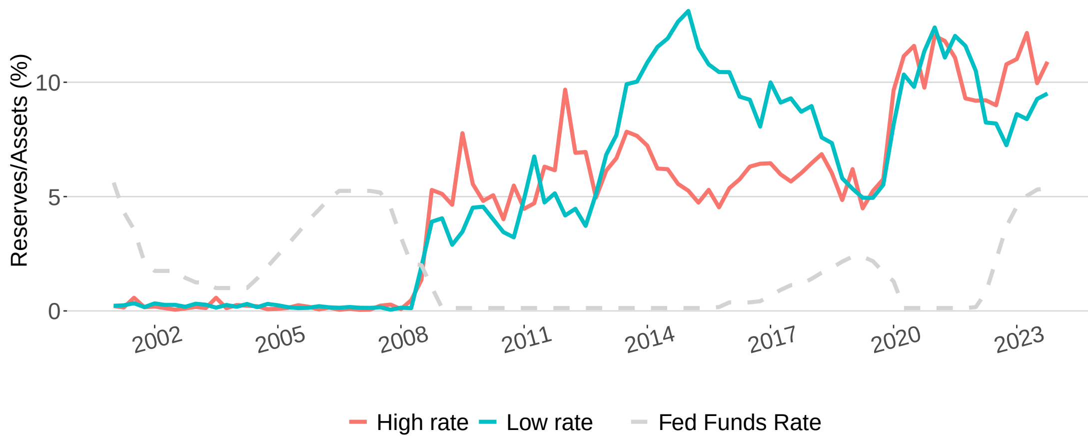


(c) Tier 1+2 Ratio



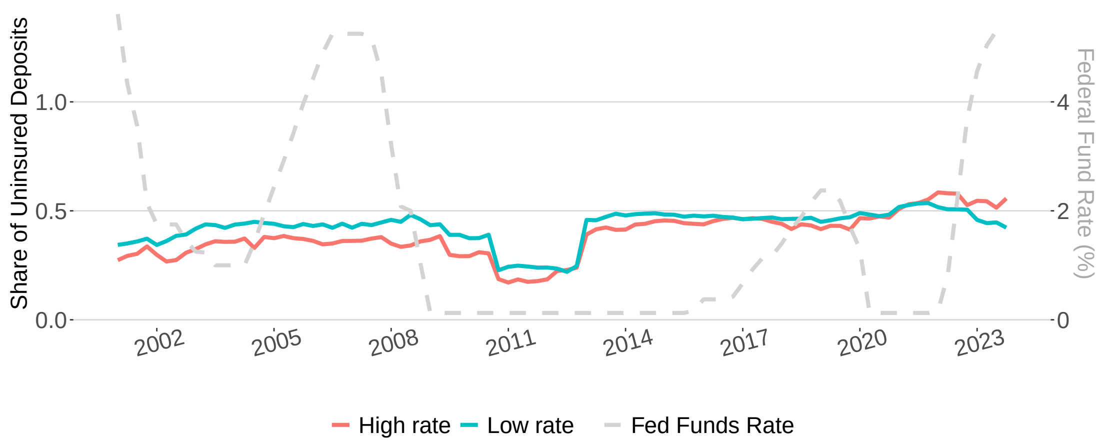
Notes: This figure compares the Tier 1/2 ratio of high- and low-rate banks among the top 25 banks from 2001Q1 through 2023Q4. See Appendix Table A.1 for more details on the construction of key variables. The left y-axis represents the quarterly average Federal Fund Target rate (FFTar). A bank is categorized 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.11: 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.

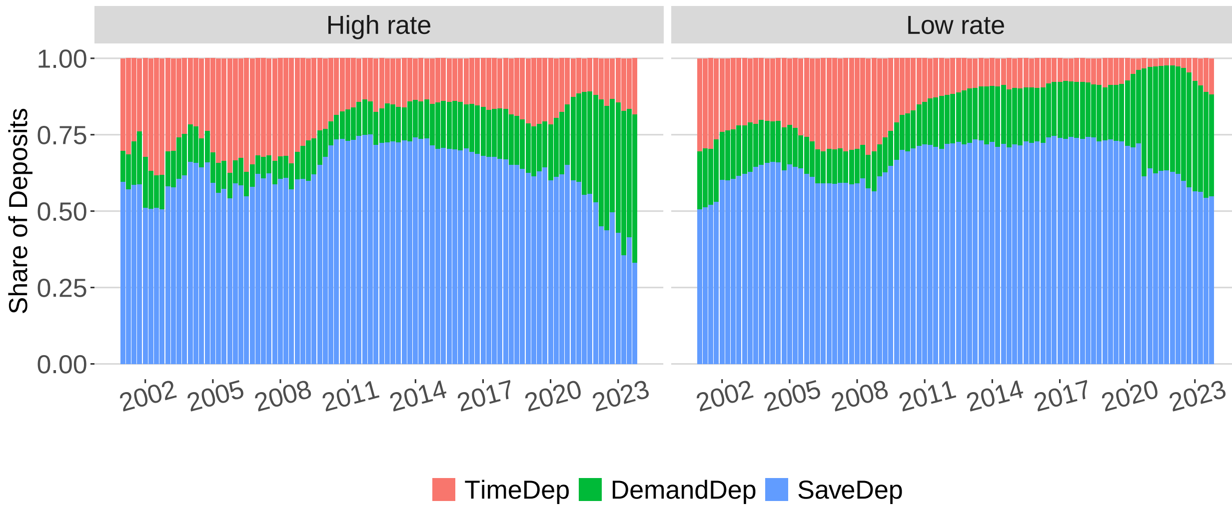
Figure B.12: Uninsured Deposit Share



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.13: Deposits Decomposition

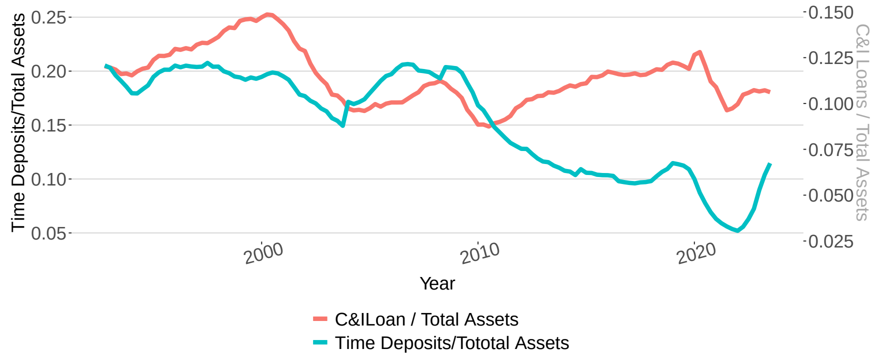
(a) Share of Deposits



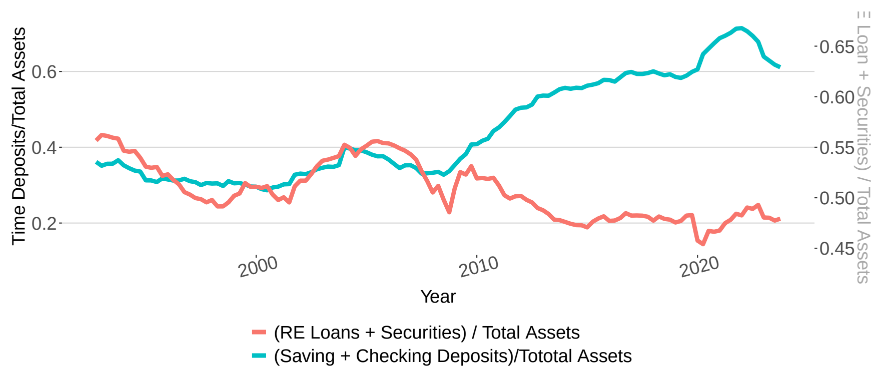
Notes: This figure compares the deposit composition of high- and low-rate banks among the top 25 banks from 2001Q1 through 2023Q4. See Appendix Table A.1 for more details on the construction of key variables. A bank is categorized as a *high-rate* bank if its average rank, calculated based on the CD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

Figure B.14: 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		
CD (%)	0.83	0.52	0.30***
DepRate (%)	0.90	0.46	0.45***
Insured Deposits Share	0.65	0.51	0.14***
log(# Branches)	776	1780	-1003***
$\log(\frac{\text{\# Branches}}{\text{Deposits}})$	0.10	0.98	-0.88***
NIM rate (%)	2.75	2.37	0.38***
Maturity (Years)	4.47	4.91	-0.44***
Charge-off Rate (%)	1.26	0.90	0.36***

Panel B: Correlation Matrix of Rates

	DepRate	SAV	CD	MM
DepRate	1.000	0.653	0.905	0.815
SAV	0.653	1.000	0.684	0.764
CD	0.905	0.684	1.000	0.840
MM	0.815	0.764	0.840	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 are reported separately for the two types of banks, as well as their difference. Standard errors 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. 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

Panel A: Classification at 2023Q4

High-rate banks	ALLY FINANCIAL, AMERICAN EXPRESS, BANK OF NEW YORK, CAPITAL ONE, CITI, GOLDMAN SACHS, HSBC, STATE STREET BANK
Low-rate banks	BANK OF MONTREAL, BOA, CHARLES SCHWAB, CITIZENS BANK, FIFTH THIRD BANK, FIRST CITIZENS BANCSHARES, HUNTINGTON, JP MORGAN, KEYBANK, M&T BANK, MORGAN STANLEY, PNC, REGIONS FINANCIAL, TD BANK, THUIST, U.S. BANKCORP, WELLS FARGO

Panel B: Persistence of Classification

High-rate banks (100%)	ALLY FINANCIAL, AMERICAN EXPRESS, BANCO BILBAO VIZCAYA ARGENTARIA, COUNTRYWIDE FINANCIAL, ING GROEP, MBNA CORPORATION, NORTH LAS VEGAS BRANCH, SOUTHTRUST CORPORATION
High-rate banks (≥90%)	Citi
Low-rate banks (100%)	ALLIED IRISH BANKS, BANK OF NEW YORK COMPANY, BOA, CHARLES SCHWAB, COMERICA INCORPORATED, FIRST CITIZENS BANCSHARES, FLEETBOSTON FINANCIAL CORPORATION, HUNTINGTON, JP MORGAN, MELLON FINANCIAL CORPORATION, NORTH FORK BANCORPORATION, SANTANDER BANK, SVB, U.S. BANKCORP, WACHOVIA CORPORATION, WELLS FARGO
Low-rate banks (≥90%)	BANK OF NEW YORK, KEYBANK, M&T BANK, NORTHERN TRUST, PNC, REGIONS FINANCIAL, STATE STREET BANK

Notes: Panel A of Table presents the classification for the top 25 banks at 2023Q4. Panel B lists banks that maintain a consistent classification throughout the entire sample period.

Table B.4: What Predicts the Bank Type?

	$\Pr(\text{High-rate}_{2009-2023})$ (1)	$\mathbb{1}(\text{High-rate}_{2009-2023})$ (2)
$\log(\frac{\text{Branches}}{\text{Deposit}})_{2001-2008}$	0.096***	0.134***
	(0.021)	(0.028)
Branch-weighted County Average $\text{Age}_{2001-2008}$	-0.036**	-0.039**
	(0.017)	(0.019)
$\log(\#\text{Branch})_{2001-2008}$	-0.070***	-0.102***
	(0.021)	(0.028)
$\text{Tier1/2}_{2001-2008}$	-0.001	-0.004
	(0.003)	(0.004)
Reserve $\text{share}_{2001-2008}$	7.447	7.498
	(7.275)	(7.613)
Insured $\text{dep}_{2001-2008}$	0.463***	0.383**
	(0.120)	(0.148)
$\Delta\text{Dep}_{2001-2008}$	0.001	0.000
	(0.003)	(0.003)
$\text{ROA}_{2001-2008}$	0.010	-0.001
	(0.014)	(0.015)
Constant	1.817***	2.117***
	(0.605)	(0.719)
Adjusted R^2	0.286	0.250
Observations	133	133

Notes: This table outlines how the characteristics of banks between 2001 and 2008 predict their classification from 2009 to 2023. The sample includes banks ever entering top 100 in the sample. The dependent variable of column 1 measures the average likelihood of a bank being classified as a high-rate bank after 2009. In column 2, the dependent variable indicates whether there is a greater than 50% likelihood of being classified as such. The independent variables represent the average characteristics of banks between 2001 and 2008. These include the log-normalized branch-to-deposit ratio, the branch-weighted average age of the counties they operate in, the log-normalized number of branches, the Tier 1/2 capital ratios, the reserve ratio, the share of insured deposits, the annual deposit growth rate, and the ROA, which are winsorized at the 1% and the 99% levels. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

Table B.5: Additional Results

	Noninterest Expense Rate (%) (1)	Noninterest Income Rate (%) (2)	Wholesale Share (%) (3)	Wholesale Rate (%) (4)
$\mathbb{1}$(High-rate)×Post	-0.141	-0.177	1.001***	-3.015**
	(0.148)	(0.159)	(0.255)	(1.413)
$\mathbb{1}$(High-rate)	0.335**	-0.015	-0.046	3.607**
	(0.136)	(0.124)	(0.114)	(1.390)
Quarter FE+Controls	✓	✓	✓	✓
Adjusted R^2	0.097	0.095	0.141	0.045
Observations	2300	2300	2262	2300
Mean of Dep. Variable	2.603	1.798	2.712	12.986

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

$$Y_{i,q} = \delta_q + \beta_1 \times \mathbb{1}(\text{High-rate}_{i,q}) \times \text{Post}_q + \beta_2 \times \mathbb{1}(\text{High-rate}_{i,q}) + \beta_3 \times Controls_{i,q-1} + \varepsilon_{i,q}$$

where i and q indicate the bank and quarter-year, respectively, $\mathbb{1}(\text{High-rate}_{i,q})$ denotes whether bank i is a high-rate bank at quarter q, $Post_t$ 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 non-interest expense, non-interest income, wholesale funding share and wholesale funding rate. 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 for the 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: Transmission of Monetary Policy (Robustness Check with Quarter FE)

	Liabilities			Assets	Assets - Liability
	ΔCD	SavRate	ΔInterest Expense	ΔInterest Income	ΔNIM
	(1)	(2)	(3)	(4)	(5)
ΔFed Funds$_q\times$ $\mathbb{1}$(High-rate) $\times$Post	0.368***	0.086***	0.122***	0.131***	0.011
	(0.100)	(0.016)	(0.028)	(0.044)	(0.048)
ΔFFTar× $\mathbb{1}$(High-rate)	-0.007	0.021**	-0.003	-0.019	-0.046
	(0.085)	(0.009)	(0.023)	(0.032)	(0.042)
$\mathbb{1}$(High-rate)×Post	0.002	0.019	-0.023*	-0.009	0.005
	(0.043)	(0.015)	(0.012)	(0.024)	(0.024)
$\mathbb{1}$(High-rate)	0.003	-0.011	0.016	0.014	0.004
	(0.039)	(0.012)	(0.011)	(0.022)	(0.023)
Controls+Quarter FE	✓	✓	✓	✓	✓
Adjusted R^2	0.507	0.143	0.629	0.434	0.102
Observations	1873	859	2300	2300	2300
Mean of Dep. Variable (level %)	0.860	0.218	0.919	3.538	2.622

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

$$\Delta Y_{i,q} = \alpha_q + \beta_1 \times \Delta\text{Fed Funds}_q \times \mathbb{1}(\text{High-rate}_{i,q}) \times \text{Post}_q + \beta_2 \times \Delta\text{Fed Funds}_q \times \mathbb{1}(\text{High-rate}_{i,q})$$
$$+ \beta_3 \times \mathbb{1}(\text{High-rate}_{i,q}) \times \text{Post}_q + \beta_4 \times \mathbb{1}(\text{High-rate}_{i,q}) + \beta_5 \times Controls_{i,q-1} + \varepsilon_{i,q},$$

where i and q indicate the bank and quarter-year, respectively, ΔFed Funds$_q$ denotes the change in the Federal Funds Target Rate, $\mathbb{1}(\text{High-rate}_{i,q})$ denotes whether bank i is a high-rate bank at quarter q, $Post_t$ denotes the post-2009 period. 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, $\Delta Y_{i,q}$ is the 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 for the 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: Changes in Lending Rates During Monetary Policy Cycles

	ΔPersonal Loan Rate$_{i,y}$		ΔCreditCard Rate$_{i,y}$		ΔNon CreditCard Personal Loan Rate$_{i,y}$		ΔC&I Loan Rate$_{i,y}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔFed Funds$_y\times$ $\mathbb{1}$(High-rate) $\times$Post	0.147	0.226	-0.023	0.026	0.095	0.129	-0.010	-0.027
	(0.176)	(0.175)	(0.226)	(0.223)	(0.103)	(0.133)	(0.071)	(0.082)
ΔFed funds$_y\times$ $\mathbb{1}$(High-rate)	-0.099	-0.177	0.130	0.079	-0.096	-0.129	-0.023	-0.008
	(0.167)	(0.166)	(0.215)	(0.211)	(0.086)	(0.122)	(0.067)	(0.078)
ΔFed funds$_y$	0.505***		0.356***		0.536***		0.426***	
	(0.094)		(0.138)		(0.108)		(0.040)	
ΔFed funds$_y\times$Post	0.015		0.058		-0.098		0.143**	
	(0.101)		(0.145)		(0.113)		(0.059)	
$\mathbb{1}$(High-rate)$\times$Post	1.014**	0.958**	0.835**	0.883**	0.179	0.124	-0.037	-0.001
	(0.417)	(0.405)	(0.380)	(0.349)	(0.198)	(0.238)	(0.134)	(0.150)
$\mathbb{1}$(High-rate)	-0.606	-0.572	-0.386	-0.453*	-0.036	0.001	0.059	0.034
	(0.396)	(0.380)	(0.305)	(0.262)	(0.192)	(0.234)	(0.128)	(0.143)
Post	-0.154		-0.190		-0.165		0.003	
	(0.210)		(0.312)		(0.271)		(0.092)	
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Quarter FE		✓		✓		✓		✓
Adjusted R^2	0.373	0.049	0.105	0.008	0.381	0.018	0.536	0.006
Observations	2032	2032	1441	1441	2028	2028	2121	2121
Mean of Dep. Variable (level %)	7.655	7.655	11.525	11.525	4.596	4.596	3.832	3.832

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

$$\Delta Y_{i,y} = \delta_q + \beta_1 \times \Delta\text{Fed Funds}_y \times \mathbb{1}(\text{High-rate}_{i,q}) \times \text{Post}_q + \beta_2 \times \Delta\text{Fed Funds}_y \times \mathbb{1}(\text{High-rate}_{i,q})$$
$$+ \beta_3 \times \Delta\text{Fed Funds}_y \times \text{Post}_q + \beta_4 \times \mathbb{1}(\text{High-rate}_{i,q}) \times \text{Post}_q + \beta_5 \times \Delta\text{Fed Funds}_y + \beta_6 \times \mathbb{1}(\text{High-rate}_{i,q})$$
$$+ \beta_7 \times \Delta\text{Fed Funds}_y \times \mathbb{1}(\text{High-rate}_{i,q}) \times \text{Crisis} + \beta_8 \times Controls_{i,q-1} + \varepsilon_{i,q},$$

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$_{i,q}$) denotes whether bank i is a high-rate bank at quarter q, 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, ΔY$_{i,y}$ is the one-year growth of the total deposit, loans to individuals, C&I loans, treasury securities and MBS 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 for the 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 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	2.566***	0.678***	0.897***	0.377**	-0.092	0.004	-3.349**	-0.314
	(0.721)	(0.238)	(0.245)	(0.163)	(0.472)	(0.308)	(1.407)	(0.408)
ΔFFTar$_y\times$ $\mathbb{1}$(High-rate)	-2.358***	-0.424**	-0.973***	-0.344***	-0.364*	-0.212	1.861*	0.473
	(0.709)	(0.213)	(0.220)	(0.113)	(0.187)	(0.231)	(0.966)	(0.392)
ΔFed Funds$_y\times$ $\frac{\text{TimeDep}_{i,q-1}}{\text{Asset}_{i,q-1}}\times$Post	2.136	-3.241**	0.720	-1.438	5.591**	-4.395***	35.932**	8.567***
	(4.698)	(1.293)	(2.613)	(1.508)	(2.226)	(1.533)	(13.664)	(2.782)
ΔFFTar$_y\times$ $\frac{\text{TimeDep}_{i,q-1}}{\text{Asset}_{i,q-1}}$	-4.474	1.933**	-0.274	-0.279	-2.836**	2.168**	-31.004**	-5.727**
	(4.479)	(0.882)	(2.618)	(0.933)	(1.215)	(0.953)	(13.044)	(2.519)
Quarter FE+Controls	✓	✓	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.021	0.092	0.014	0.013	0.045	0.021	0.053	0.021
Observations	2300	2300	2300	2300	2300	2300	2300	2300
Mean of Dep. Variable (level)	13.399	13.399	15.119	15.119	29.878	29.878	16.893	16.893

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

$$\begin{aligned}\Delta Y_{i,y} = {} & \delta_q + \beta_1 \times \Delta\text{Fed Funds}_y \times \mathbb{1}(\text{High-rate}_{i,q}) \times \text{Post}_q + \beta_2 \times \Delta\text{Fed Funds}_y \times \mathbb{1}(\text{High-rate}_{i,q}) \\ & + \beta_3 \times \Delta\text{Fed Funds}_y \times \text{Post}_q + \beta_4 \times \mathbb{1}(\text{High-rate}_{i,q}) \times \text{Post}_q + \beta_5 \times \Delta\text{Fed Funds}_y + \beta_6 \times \mathbb{1}(\text{High-rate}_{i,q}) \\ & + \beta_7 \times \Delta\text{Fed Funds}_y \times \mathbb{1}(\text{High-rate}_{i,q}) \times \text{Crisis} + \beta_8 \times Controls_{i,q-1} \\ & \beta_9 \times \Delta\text{Fed Funds}_y \times \frac{\text{TimeDep}_{i,q-1}}{\text{Asset}_{i,q-1}} \times \text{Post}_q + \beta_{10} \times \Delta\text{Fed Funds}_y \times \frac{\text{TimeDep}_{i,q-1}}{\text{Asset}_{i,q-1}} + \varepsilon_{i,q},\end{aligned}$$

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 for the 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: 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	2.127***	0.598**	0.599*	0.183	-0.240	0.022	-1.834*	-0.227
	(0.682)	(0.257)	(0.322)	(0.175)	(0.441)	(0.265)	(0.993)	(0.444)
ΔFFTar$_y\times$ $\mathbb{1}$(High-rate)	-2.068***	-0.389	-0.709***	-0.236*	-0.159	-0.303	0.761	0.515
	(0.648)	(0.239)	(0.258)	(0.128)	(0.312)	(0.225)	(1.115)	(0.439)
log(Time Dep.$_{\cdot i,y}$)	-0.063	-0.014	0.084*	-0.013	0.018	0.013	0.088	-0.020
	(0.077)	(0.013)	(0.050)	(0.012)	(0.069)	(0.026)	(0.115)	(0.016)
log(Sav Dep.$_{\cdot i,y}$)	0.169***	0.023	0.128***	0.051***	0.131**	-0.043	-0.672*	-0.031
	(0.056)	(0.018)	(0.045)	(0.017)	(0.056)	(0.041)	(0.372)	(0.029)
log(Demand Dep.$_{\cdot i,y}$)	0.115**	0.002	0.060**	0.022*	0.096***	-0.026	-0.198	-0.023*
	(0.051)	(0.005)	(0.029)	(0.012)	(0.032)	(0.017)	(0.175)	(0.013)
Quarter FE+Controls	✓	✓	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.067	0.069	0.074	0.030	0.100	0.021	0.088	0.011
Observations	2300	2300	2300	2300	2300	2300	2300	2300
Mean of Dep. Variable (level)	13.399	13.399	15.119	15.119	29.878	29.878	16.893	16.893

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

$$\begin{aligned}\Delta Y_{i,y} = {} & \delta_q + \beta_1 \times \Delta\text{Fed Funds}_y \times \mathbb{1}(\text{High-rate}_{i,q}) \times \text{Post}_q + \beta_2 \times \Delta\text{Fed Funds}_y \times \mathbb{1}(\text{High-rate}_{i,q}) \\ & + \beta_3 \times \Delta\text{Fed Funds}_y \times \text{Post}_q + \beta_4 \times \mathbb{1}(\text{High-rate}_{i,q}) \times \text{Post}_q + \beta_5 \times \Delta\text{Fed Funds}_y + \beta_6 \times \mathbb{1}(\text{High-rate}_{i,q}) \\ & + \beta_7 \times \Delta\text{Fed Funds}_y \times \mathbb{1}(\text{High-rate}_{i,q}) \times \text{Crisis} + \beta_8 \times Controls_{i,q-1} \\ & \beta_9 \times \log(\text{Time Dep.}_{\cdot i,y}) + \beta_{10} \times \log(\text{Sav Dep.}_{\cdot i,y}) + \beta_{11} \times \log(\text{Demand Dep.}_{\cdot i,y}) + \varepsilon_{i,q},\end{aligned}$$

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 for the 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.

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.