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 align deposit rate with market rates, hold shorter-term assets, and primarily earn spreads by taking more credit risk through personal and business loans; and low-rate banks, which offer low, interest-insensitive deposit rates, hold more long-term assets (e.g., MBSs), and make fewer loans. This divergence leads to a significant shift of deposits towards high-rate banks during monetary policy tightening, 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 focus on systemically important banks—the 25 largest banks as classified by the Federal Reserve's H.8 report—and categorize those ranked in the top tercile by deposit rates as high-rate banks.[1] High-rate banks operate with far fewer physical branches and engage far less in maturity transformation—they 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. These high-rate banks disproportionately channel incom-

[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 influence of the largest banks is disproportionately significant in shaping macroeconomic implications. Third, small banks are regulated very differently than large banks. Fourth, as shown by d'Avernas et al. (2023), small banks and large banks have different business models throughout the sample, while we show large banks behave very similar before 2009. We show our results are robust when extending the analysis to include the top 100 banks, which account for 85% of total bank assets.

ing deposits to riskier lending, such as personal and C&I loans. Thus, tightening monetary policy doesn't necessarily reduce credit supply to the real economy. Additionally, these banks tend to hold more shorter-maturity assets—on average three years shorter than low-rate banks—which reduces the extent of maturity transformation performed by the banking sector. Should deposits continue 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 75% greater reduction in the number of branches compared to low-rate banks, accompanied by a 64% decline in branch-to-deposit ratio. This trend coincides with the rapid growth of e-banking services, marked by a surge in Google searches for 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 80 basis points higher than that of low-rate banks. Additionally, charge-offs on loans and leases for high-rate banks have been three times those of low-rate banks during the same period.

While the 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 0.68, and this figure has fallen to around 0.15 for the recent two rate hiking cycles. That is, for every 100

[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.

basis point increase in the Federal funds rate, low-rate banks now pass along only 15 basis points to depositors, compared to 68 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. A possible explanation for this shift is that as some banks transition to online operations, low-rate banks that maintain physical branches end up retaining depositors who prefer or value in-person banking services, resulting in a stickier depositor base. This allows them to charge higher markups in the form of even lower deposit rates that are insensitive to fluctuations in market interest rates. Alternatively, as low-rate banks in our sample offer both online services and physical branches, they may incur higher marginal costs, which compels them to offer lower deposit rates. However, when examining non-interest expenses, we do not find evidence of higher costs.

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

This perspective also sheds light on why no substantial credit crunch has arisen despite sharp interest rate raises by the Federal Reserve since 2022. These increases were accompanied with annual deposit outflows surpassing 8%, the highest since 1973. Despite these outflows, credit availability has remained stable. This stability is due to the rate hikes disproportionately impacting low-rate banks, reducing their holdings of treasuries and agency MBSs, while high-rate banks experienced minimal deposit outflows, allowing their lending to households and businesses to continue almost unaffected.

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 8% higher credit risk. This redistribution not only affects the risk profile and hence the stability of the banking sector but also its fundamental ability to meet the maturity transformation needs of the economy.

Understanding this shift is 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. Last, we show that both the changing composition of top 25 banks and within-bank strategy adjustments contribute to the observed diverging patterns 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. 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 0.53 to 2.02.

While the distributions reveal a noticeable disparity in deposit rates across banks, a potential concern is whether the variability in rates signifies a systematic shift or is influenced by a few small banks offering exceptionally high-rates. We examine the allocation of bank assets corresponding to various measures of CD rates relative to the sample average: below 0.75 times the average, between 0.75 and 1.25 times the average, and above 1.25 times the average.

Figure 2 demonstrates a significant shift in the distribution of banks' asset shares. Before 2009, the majority of bank assets—more than 70%—were linked to rates offered close to the sample average. However, by 2023Q4, this landscape had changed dramatically: assets tied to banks offering rates between 0.75 and 1.25 times the average dropped to just 4%, while 74% of assets linked to rates below 0.75 times the average and 22% to rates above 1.25 times the average., according to the CD rate classification in panel (a). A similar trend is observed based on the DepRate classification in panel (b).[4] 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

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

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

illuminate the economic forces driving this bank divergence phenomenon.

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.[5]

3.1 Data

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

Deposit rates. We source weekly surveyed deposit rate data from the RateWatch database, provided by S&P Global, covering the period from 2001Q1 through 2023Q4.[6] 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.[7] 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

[5] 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.

[6] 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.

[7] 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.

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.[8]

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

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

3.2 Methodology

We aim to delineate the emergence of two distinct categories within systemically important banks and examines how this bifurcation influences broader macroeconomic dynamics. We categorize banks based on deposit rates into high and low-rate types and then examine how related factors such as branch operations, asset allocation, loan portfolio risk profiles, and monetary policy transmission have evolved for each group. It is crucial to emphasize that our use of deposit rates for classification does not imply causality with other operational decisions, all of which we recognize as endogenous choices made by banks. Indeed in the stylized model presented in Section 7, deposit rates and risk taking is an endogenous choice that is nevertheless useful for classifying banks. The primary reason for using deposit rates as our classification metric is their frequent updates and reliable empirical measurement, making them a timely and observable criterion for distinguishing between different banking models. In Section 6.1.1, we explore various potential drivers of this divergence, and show that the proliferation of e-banking likely serves as the primary catalyst.

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

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

here.[9] These BHCs are then classified into high-rate and low-rate types, with the classification methodology detailed in the subsequent section. We then aggregate and analyze time-series patterns on various characteristics for each bank type. To assess the significance of observed differences, we employ the following specification:

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

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

Since we are examining diverging patterns, both α and β are important for interpretation. The α coefficient represents the difference in $Y_{i,q}$ between high- and low-rate banks prior to 2009, while β measures the divergence relative to the pre-2009 period. Divergence is confirmed if α is insignificant and β is significant, or if both coefficients are significant with the same sign. Conversely, if both coefficients are significant but with opposite signs, it indicates divergence before 2009 and convergence thereafter. [10]

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 6.3, we thoroughly examine the robustness of our cutoff choices, and expand the analysis to include a broader set of banks and extend the sample period.

3.3 Classification of High- and Low-rate Banks

We aim to establish a consistent classification for each bank throughout the sample period to avoid biases due to time-varying misclassifications, which are more likely to occur before 2009 due to

[9] In identifying top 25 banks quarterly, we note fluctuations with banks momentarily reaching the top 25 and then dropping out. To enhance stability and consistency in our sample, we require a bank to remain in the top 25 for four consecutive quarters before inclusion. This year-long criterion ensures we focus on banks with sustained systemic significance.

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

the smaller dispersion in deposit rates, as shown in Figure 1.[11] This process involves three steps described subsequently.

First, we rely on both the CD and DepRate rates to mitigate the noise and limitations inherent in each individual measure. DepRate offers a direct and comprehensive measure of the deposit rates paid by banks, but it may adjust slowly. Conversely, the CD rate provides more immediate insight into banks' pricing strategies but is limited to a specific product category and may suffer from missing data due to potential self-reporting issues. To incorporate information from both rates, we use a weighted rank method. We first rank banks based on each rate, then standardize these ranks based on the number of banks, ensuring that the standardized ranks fall within the same range (0 to 1). We then average these standardized ranks. When the CD data is available, we equally weight both standardized ranks. Otherwise, we rely solely on the standardized DepRate ranking.[12]

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

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

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

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

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

4 Diverging Banking Sector

The diverging pattern in the banking sector is already observable through summary statistics, as delineated in Panel A of Table 2, showcasing key characteristics of high-rate and low-rate banks across two distinct periods: 2001-2007 and 2017-2023. During 2001-2007, high-rate banks generally had fewer branches and shorter asset maturities compared to low-rate banks, with no significant differences in asset size, insured deposit share, branch-deposit ratio, net interest margin (NIM), or charge-off rates. Post-2017, significant distinctions emerged across all metrics except size: high-rate banks exhibited significantly lower branch-deposit ratios, much fewer branches and shorter maturities, higher NIM rates, and charge-off rates. Notably, the divergence is primarily driven by shifts in low-rate banks, for example, the NIM rate of high-rate banks remained stable at around 300 basis points, while that of low-rate banks decreased from 280 to 230 basis points, with similar patterns observed in other statistics. Next, we examine the divergence in all metrics and discuss their implications.

4.1 Diverging Deposit Rates

We validate our classification over time by analyzing the rate behavior of high- and low-rate banks in Figure 3. Figure 3a presents the time series 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 500 basis points, 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 displays the cumulative branch growth of high- and low-rate banks, revealing two significant trends.[13] Initially, both types of banks expanded their branches until 2009. However, since then both categories have reduced their branch numbers, with high-rate banks experiencing a much more pronounced reduction—exceeding 60% from 2011 to 2023. This indicates that while branches were crucial for banking operations before 2009, high-rate banks have significantly decreased their reliance on branches for conducting business.

To address concerns that branch closures by high-rate banks might be driven by deposit withdrawals, we further analyze the logged ratio of branches to the real value of deposits (deposits normalized by the consumer price index). A higher branch-to-deposit ratio indicates a substantial physical branch presence, as it shows more branches per deposit. Conversely, a lower ratio suggests a decreased reliance on physical branches. Figure 4b illustrates that while the branch-to-deposit ratio has decreased for both high-rate and low-rate banks, the decline is markedly steeper among high-rate banks. This trend underscores high-rate banks' significant move away from traditional branch-based banking, potentially indicating a shift towards digital banking solutions.[14]

Moreover, the two types of banks cater to distinct demographics. A trend evident in Figure 4c shows high-rate banks increasingly focusing on areas approximately two years younger than those served by low-rate banks. We further analyze the target clientele of branch-based banks and mobile banks in Appendix Figure B.5 using 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.[15]

To determine the statistical significance of the observed divergences, we apply regression analysis based on Equation (1), with detailed results presented in Table 3. The findings confirm earlier trends: post-2009, high-rate banks exhibit a markedly greater reduction in branch numbers (75%), branch-to-deposit ratios (46%), and a 0.5-year additional decline in average customer age, in comparison to low-rate banks.[16] These magnitudes remain robust after incorporating quarter fixed effects to adjust for aggregate shocks, as shown in the even-numbered columns of the table.

These observations are consistent with the findings of Jiang, Yu and Zhang (2022): low-rate

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

[14] 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.

[15] 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.

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

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.

Despite a modest reduction in their branch networks, it may seem counterintuitive that low-rate banks have paradoxically increased the implicit costs for their depositors, evidenced by significantly lower deposit rates compared to the pre-2009 period. We highlight two potential explanations. One possibility is that the operational costs for low-rate banks have risen, partly due to their provision of both traditional in-person banking services and e-banking services. Another plausible explanation is that low-rate banks may 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 analyze the non-interest expense as a ratio of assets between the two types of banks, shown in Appendix Figure B.6. Our findings indicate a slight decline in the non-interest expense rate for low-rate banks over the sample period, contradicting the marginal cost-based hypothesis. We will later provide additional evidence that aligns with the markup explanation.

4.3 Divergence on Asset Composition

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

4.3.1 Net Interest Margin

We begin by examining banks' net interest margins. Figure 5a reveals that high-rate banks maintain a significantly higher net interest margin than low-rate banks post-2009, despite offering higher deposit rates. Since net interest margin represents the difference between interest earned and interest paid, this indicates that high-rate banks achieve higher yields on their assets. Supporting this, Figure 5b shows that although both bank types had similar interest income rates before 2009, high-rate banks obtained significantly higher income rates afterward. These findings suggest a portfolio shift by high-rate banks toward higher-yielding assets.[17]

4.3.2 Asset Reallocation

Banks can pursue higher yields through two primary strategies: increasing credit risk or investing in longer-maturity assets to capture the term premium. To understand their strategies, we examine the portfolio holdings of high-rate and low-rate banks. Loans are categorized into four segments: personal loans, commercial and industrial (C&I) loans, real estate loans, and other loans. Securities are divided into two categories: MBSs and other securities.[18]

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

Table 4 provides a detailed examination of asset allocation shifts. Post-2009, high-rate banks have notably increased their portfolio in personal loans by 6.4% and C&I loans by 2.7%, while reducing their MBS holdings by 2.5%, compared to low-rate banks. This marks a significant change from the pre-2009 period, where the differences in personal loans were 4.1%, in MBS holdings were -8.8%, and C&I loans showed minimal disparity. The most dramatic shift is in real estate loans, where high-rate banks transitioned from holding 6.4% *more* to 6.1% *less* than low-rate banks.

The final two rows of Table 4 show the charge-off rates and maturity for each asset category. The charge-off rate, which indicates the percentage of loans or credit accounts considered uncollectible and written off as losses, serves as a key measure of a bank's credit quality. Personal and C&I loans generally involve higher credit risk than other loan types and securities. Therefore, the increase in these loans by high-rate banks suggests a shift toward greater credit risk. Conversely,

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

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

real estate loans and MBSs have much longer maturities.[19] Hence, by reducing their holdings of real estate loans and MBSs, high-rate banks lower their exposure to interest rate risk.

These changes offer prima-facie evidence of a growing divergence in asset management strategies between high-rate and low-rate banks. Specifically, High-rate banks take on more credit risk by focusing on lending to firms and households. In contrast, low-rate banks are holding longer-term assets, engaging more in maturity transformation. The next two sections provide a deeper examination of these two aspects of risk.

4.3.3 Credit Risk

As discussed above, credit risk is primarily tied to loan portfolios, as securities like Treasuries and MBSs typically have government backing. As high-rate banks tilde towards personal and C&I loans, they expose themselves to higher credit risk.

To verify this, we examine the overall returns of loan portfolios. Figure 7a indicates a divergence in loan rates: both bank types reported similar rates before 2009, but a salient diverging pattern is observed post-2009. By the end of our sample, high-rate banks charge around 910 basis points, compared to 630 basis points for low-rate banks. Column 1 of Panel A in Table 5 further supports this divergence through regression analysis.

To isolate the credit risk premium, we subtract the equivalent maturity Treasury yield from the loan rate. Figure 7b illustrates the evolution of credit spreads for the two types of banks over time. Similar to loan rates, a significant divergence in credit spreads emerges post-2009, with high-rate banks showing an excess of 260 basis points by the sample period's end. Column 2 of Panel A in Table 5 confirms this, indicating a 80 basis point increase in credit spreads for high-rate banks compared to low-rate banks after 2009, which is 24% higher than the sample average credit spread of 320 basis points. This suggests high-rate banks are engaging in riskier lending to generate higher spreads.

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

Banks can manage credit risk not only by adjusting their portfolio allocations but also within each loan category. Panel B of Table 5 breaks down the post-2009 charge-off rates across different

[19] 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.

loan types. Except for the "other loans" category, there are no significant diverging patterns in charge-off rates among the other categories. This indicates that changes in portfolio allocation are the primary means by which banks shift their credit risk.

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

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

4.3.4 Maturity Transformation

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

Figure 8a shows a clear divergence in asset maturity between the two types of banks. Before 2009, low-rate banks had an average maturity of about 6 years, which was 50% longer than the 4-year maturity for high-rate banks. Post-2009, low-rate banks' asset maturity extends to nearly 8 years, while high-rate banks' maturity stays around 4-5 years. Consequently, by the end of 2023, low-rate banks' assets are almost twice as long in maturity. Similarly, Figure 8b shows that high-rate banks consistently maintain a higher share of short-term assets, ranging from 50-60% while low-rate banks see their short-term asset share decline from 55% to 40% by 2023. The divergence in asset maturity is further confirmed in Panel A of Table 6. The analysis indicates that post-2009, high-rate banks have assets with 0.5 years shorter maturity (around 8% lower than the sample average) and hold 4.4% more short-term assets compared to low-rate banks.

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

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

5 Macroeconomic Effects

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

5.1 Transmission of Monetary Policy

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

5.1.1 Rate Sensitivity to Federal Funds Rate Changes

We begin by analyzing the response of deposit rates from high-rate and low-rate banks to Federal Funds Target rate changes across three rate-hiking periods. Figure 9 illustrates the deposit rate sensitivity for CD rates, savings deposit rates, and DepRate across these periods, calculated as the ratio of the total change in deposit rates to adjustments in the Federal Funds Target rate. In the first rate-hiking cycle from 2004Q3 to 2007Q4, both types of banks showed similar sensitivity to Federal Funds rate changes. However, distinct patterns emerged in subsequent cycles despite stable average sensitivities overall. Low-rate banks demonstrated almost no response to rate hikes, with their sensitivities approaching zero. Conversely, high-rate banks significantly raised their deposit rates, exhibiting strongly positive sensitivities.

We test these relationships through the following regression:

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

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

The first three columns of Table 7 confirms a distinct divergence in deposit rate sensitivity between high-rate and low-rate banks after 2009. Taking CD rates as an example, post 2009, high-rate banks show an average deposit rate sensitivity of 0.56, starkly contrasting with the 0.15 of low-rate banks.[20] This marks a significant change from pre-2009, where sensitivities for both types of banks were similar: 0.68 for low-rate banks and 0.71 for high-rate banks. The divergence stems mainly from low-rate banks reducing their sensitivity, while high-rate banks slightly increase theirs. Similar patterns are observed for savings and interest expense rate sensitivities.

The heightened interest-rate sensitivity of high-rate banks does not imply a correspondingly increased interest rate risk. As shown in column 4 of Table 7, these banks enjoy higher interest income rates during rising rate periods post-2009, which balances out the impacts on their NIM. Indeed, the sensitivity of the net interest margin (NIM) detailed in column 5 is comparable between high- and low-rate banks, with figures at 0.12 and 0.16 respectively.[21] This is consistent with findings in Section 4.3 that high-rate banks predominantly invest in short-term, floating-rate assets, effectively mitigating their interest rate risk. For robustness, we include quarter fixed effects in Appendix Table B.5 to control for common macroeconomic factors, yielding consistent results.

5.1.2 Deposits Reallocation During Monetary Policy Cycles

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

Figure 10 contrasts the deposit growth of high-rate and low-rate banks across three rate-hiking

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

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

cycles.[22] During the first cycle from 2004Q3 to 2007Q4, both bank types showed similar growth rates. However, significant divergences appeared in the subsequent cycles, with high-rate banks demonstrating notably higher deposit growth. Particularly from 2022Q1 to 2023Q4, deposits in high-rate banks remained stable, while low-rate banks saw a 10% outflow.

We further quantify the magnitude of deposit reallocation using Equation (2). The first two columns of Table 8 corroborate that after 2009, high-rate banks attract more deposits during periods of interest rate hikes. Specifically, a 100 basis point increase in the Federal Funds rate is associated with a 1.64% increase in annual deposit growth for high-rate banks relative to their low-rate counterparts.[23] This is a significant shift from the pre-2009 trend, where interest rate hikes were associated with deposit *outflows* from high-rate banks, albeit the effect was statistically insignificant. This trend underscores the significant impact of monetary policy on deposit allocations between high-rate and low-rate banks.

5.1.3 Monetary Policy Transmission to Lending

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

We explore the growth trajectories of personal loans, C&I loans, real estate loans, and MBSs relative to monetary policy cycles, analyzing how annual changes in asset category shares correlate with Federal Funds Rate fluctuations. Notably, we focus on changes in asset share rather than volume growth. This approach is motivated by the observation that high-rate banks typically experience enhanced deposit growth following interest rate hikes, which would naturally lead to increased growth across their asset classes. By focusing on relative shares, we can discern whether these banks disproportionately allocate their expanded capital base towards specific asset categories that facilitate improved balance sheet alignment.[24]

[22] 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.

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

[24] 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

The results, detailed in Table 8, point to distinct asset allocation strategies between high-rate and low-rate banks in response to interest rate fluctuations. High-rate banks predominantly direct incoming deposits toward personal and C&I loans, during periods of monetary tightening. Specifically, in the post-2009 era, a 1 percentage point increase in the Federal Funds rate is associated with a 0.53% increase in the share of personal loans (column 3) and a 0.36% increase in the share of C&I loans (column 5) for high-rate banks.[25] Conversely, low-rate banks show a notable reduction in their MBS holdings in response to deposit outflows during interest rate hikes. Specifically, a 1 percentage point increase in the Federal Funds rate leads to a 0.56% decrease in the MBS share for low-rate banks, as shown in column 9.[26] The results remain robust after controlling for quarter fixed effects, as indicated in the even-numbered columns.

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

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

Overall, our findings reveal a stark contrast in how high-rate and low-rate banks react to shifts in monetary policy, with significant implications for credit allocation and the broader economy. In the subsequent section, we will delve deeper into the implications of these differences.

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.

[25] The magnitude for high-rate banks post-2009 is derived by aggregating four coefficients involving the term $\Delta \mathrm{FFar}_y$. For example, the effect size of personal loans is calculated as 1.046 - 0.825 + 0.313 - 0.003 = 0.531.

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

5.2 Aggregate Implications

Explaining the Absence of a Large Credit Crunch for Recent Rate Hikes The current rate-hiking cycle began with a sharp increase in interest rates, starting from roughly 0 basis points in early 2022 to around 525 basis points. Concurrently, aggregate deposit growth declined substantially as shown in Panel A of Figure 11.[27] The annual decline in aggregate deposit growth of 8% 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 to low-rate banks, high-rate banks prioritize personal lending. Hence, the growth rate of personal loans is negatively correlated with aggregate deposit growth, as shown in Panel C of Figure 11.[28]

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.[29] 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.

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

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

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

Aggregate Banking Sector Capacity for Maturity Transformation and Risk-Taking Given the distinct portfolio compositions of high-rate and low-rate banks, the banking sector's ability to undertake maturity transformation and originate higher-risk loans is significantly influenced by the distribution of deposits between these banks. If deposits continue to flow towards high-rate banks—whether due to prolonged periods of tight monetary policy or tech-savvy depositors favoring these banks—the sector as a whole is less likely to engage in maturity transformation and increasingly assume greater credit risk. According to our estimates, if 10% of deposits shift from low-rate to high-rate banks, the banking sector as a whole invests in assets with approximately 5% shorter maturities and assumes 8% higher credit risk.[30] 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. Although both risk types have the potential to precipitate bank runs, their underlying dynamics and economic contexts differ substantially. As shown by Jiang et al. (2023), interest rate risk becomes particularly salient during periods of monetary tightening, which typically coincide with robust economic conditions. Conversely, credit risk tends to escalate during economic downturns, often prompting monetary easing through reductions in the Federal Funds rate. This difference in risk exposure suggests a more complex interplay between monetary policy, economic cycles, and bank stability.

6 Mechanisms and Robustness

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

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

6.1 Mechanisms

Our results so far indicate that this divergence became pronounced in 2009, coinciding with the proliferation of e-banking services. The direct impact of technology on this observed divergence requires further investigation. This section presents additional evidence that corroborates the nexus between e-banking innovations and the observed divergence in banking strategies, and also explores alternative explanations for this divergence.

6.1.1 e-Banking and the Divergence

We begin by examining public interest in online and mobile banking. Prior to 2009, Google search intensity for terms like ”mobile banking” and ”online banking” remained relatively low and stable (Appendix Figure B.8a). However, a significant surge in search volume occurred around 2009, especially for mobile banking searches, indicating a growing interest in e-banking. For instance, mobile banking searches climbed from an index of 17 in 2009 to 75 in 2022 (out of 100).[31] This trend aligns with the emergence and growing popularity of mobile banking apps from major banks (e.g., Citi, JP Morgan Chase), as shown in Appendix Figure B.8b. Google search trends for these apps began in 2008 and have grown steadily afterward. Additionally, the widespread adoption of 3G technology, crucial for mobile banking activity, coincides with the surge in mobile banking interest.[32] These trends collectively indicate that e-banking began to gain significant popularity around 2009.

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

[31] 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.

[32] 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.

a significant driver of the observed divergence in banking strategies.

6.1.2 Alternative Explanations

The pivotal year of 2009 prompts investigation into whether the diverging patterns in the banking sector are linked to stringent regulations introduced after the financial crisis. This section explores alternative explanations for these trends, including regulatory changes, the impact of liquidity injections post-crisis, and differences in the distribution of insured versus uninsured deposits, as well as distributions in savings and CD account holdings between high-rate and low-rate banks.

Regulatory Changes Following the 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.[33]

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 6, 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.10, show no significant divergence in reserve shares over time between the bank types. This absence of disparity suggests that the divergences observed within the banking sector likely do not stem from differential impacts of QE on the reserve balances of high- and low-rate banks.

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

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 4 of Table 10, which shows that although high-rate banks have a higher share of uninsured deposits compared to low-rate banks post-2009, this is primarily because high rate banks had much lower uninsured deposit shares before 2009. Appendix Figure B.11 supports this, showing minimal differences in uninsured deposit shares between the two bank types after 2009. Additionally, our findings on diverging charge-off rates suggest that even advanced screening technology at high rate banks cannot completely mitigate the credit risks they are exposed to. Therefore, the divergence in screening technology and difference in uninsured deposit share do not 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.12, 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.13. The updated figure shows that the pre-2009 correlation between C&I lending and time deposit share disappears after 2009, suggesting that the dynamics of C&I loans are not primarily driven by the proportion of time deposits versus other liquid deposits in recent decades.

To further assess whether 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.7 suggest that, although time deposits might explain changes in personal before 2009 (see column 2), their influence diminishes post-2009, as indicated by the negative coefficients of the three-way interaction. Furthermore, following Table 13 in Supera (2021), we incorporate growth in time, savings, and demand deposits as controls in our specification of Appendix Table B.8.

This analysis shows that only the growth in savings deposits is correlated with increases in personal and C&I loans, challenging the hypothesis that banks primarily use time deposits to finance business loans after 2009. Importantly, our findings remain robust across both tables, highlighting the need to consider the diverse strategies of banks to fully understand the dynamics of investment behavior within the banking sector.

6.2 Decomposing the Divergence: Composition vs. Within Bank Changes

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

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

Composition of Systemically Important Banks Throughout our sample period, 51 BHCs entered the top 25, signaling considerable compositional changes. To see how this influences our results, we exclude banks that entered the top 25 post-2009 and focus on those within the top 25 before 2009, extending their data throughout the analysis period.[34] The results, shown in Row 2 of Panel B in Table 9, show qualitatively similar results in all 8 columns. Quantitatively all results are similar except the reduction in the branch-deposit ratio from -1.02 to -0.19, suggesting that much of the branch divergence is attributable to compositional changes post-2009.

To further corroborate above findings, we perform a test through simulations by randomly selecting 25 banks each quarter from the top 100 and conduct 10,000 simulations. If diverging patterns were solely due to composition effects, random composition would significantly alter economic magnitudes. However, consistent results across simulations, as shown in Row 3 of Panel B, demonstrate that the changing composition of the top 25 banks is not the sole driver of the observed divergences.

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

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

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

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

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

6.3 Robustness

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

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

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

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

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

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

In this section, we offer a simple framework to rationalize the divergence observed in the banking sector. Our static model is based on the frameworks established by Salop (1979), Allen and Gale (2004). A key aspect of our model is the integration of endogenous adoption of e-banking by banks, facilitated by technological advancements, as 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.[35] By operating a local branch, banks set the deposit rate r_j to attract depositors and also decide on the risk level associated with their loan portfolios, represented by a return L_j. Banks can generate value from both deposit-taking and extending loans.

Following Allen and Gale (2004), we model the return on a risky loan portfolio using a two-point distribution: it yields a return of $L_j = f + l_j$ with probability $p(l_j)$, and a default return of zero with a probability 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

[35] 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.

bank's exposure to the risk of default.[36]

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

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

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

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

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

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

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

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

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

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

assume depositors gain utility, represented as γ, from the convenience of e-banking services:[37]

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

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 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

[37] 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.

optimally choose riskier projects. Moreover, our results are robust when we model the quality of branch service, η, as a decision variable for each bank. Here, a higher η incurs higher costs but results in better branch quality, which attracts more depositors.

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

8 Conclusion

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

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

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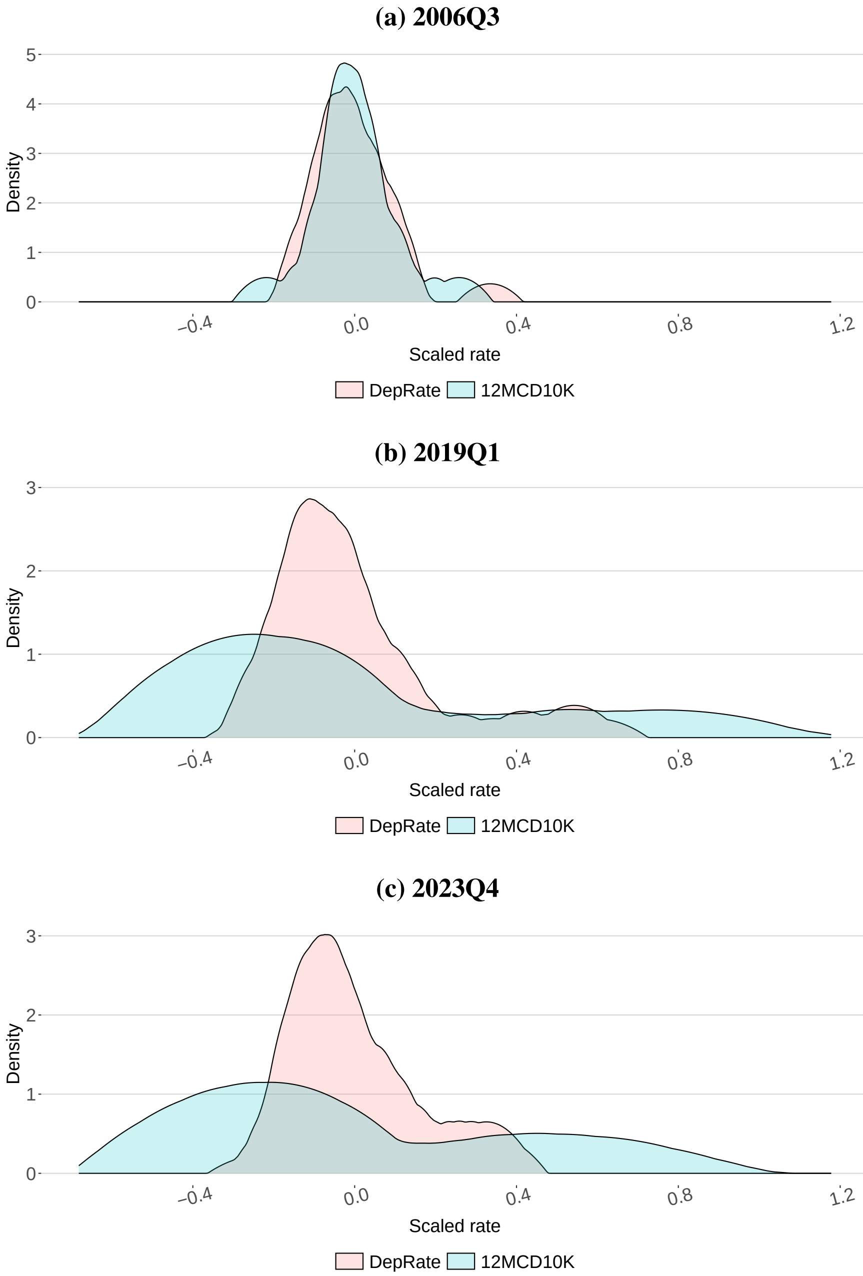
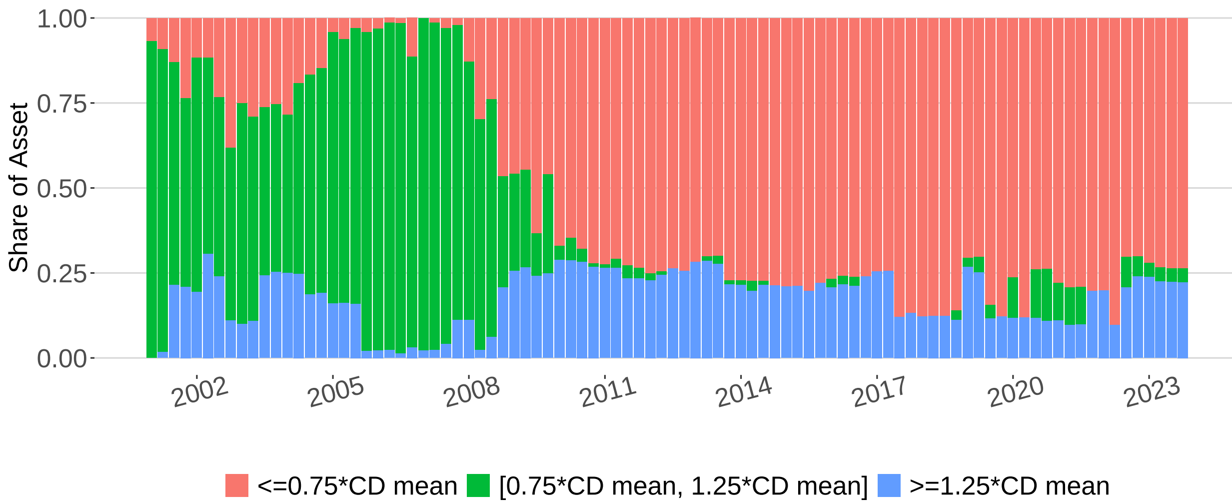
Figure 1: Dispersion of Deposit Rates for Top 25 Banks



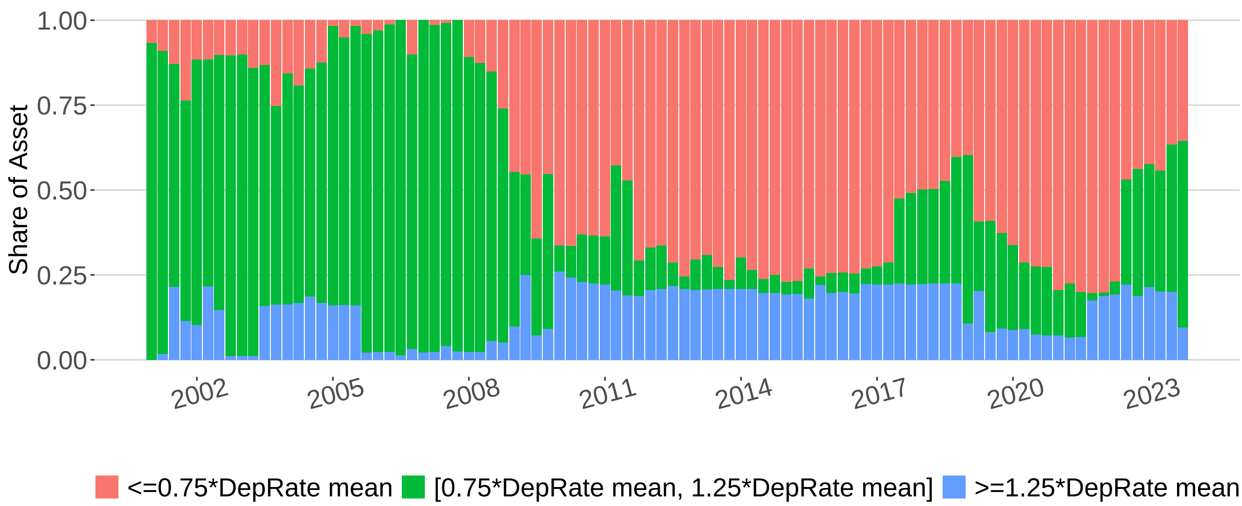
Notes: This figure depicts kernel density plots of the scaled and demeaned 12-month certificate of deposit rates of at least $10,000 (CD) and the scaled and demeaned deposit rates (DepRate) derived from Call Reports provided by the top 25 banks at 2006Q3, 2019Q1, and 2023Q4, representing the peak of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

Figure 2: Asset Distribution of Top 25 Banks

(a) Classification based on CD



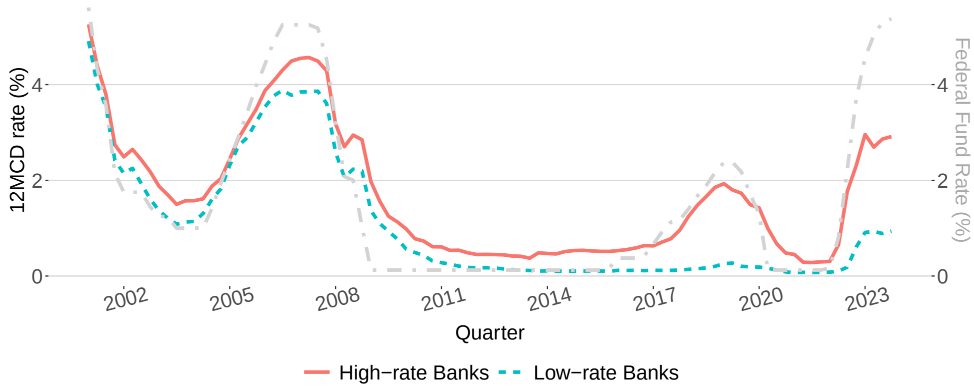
(b) Classification based on DepRate



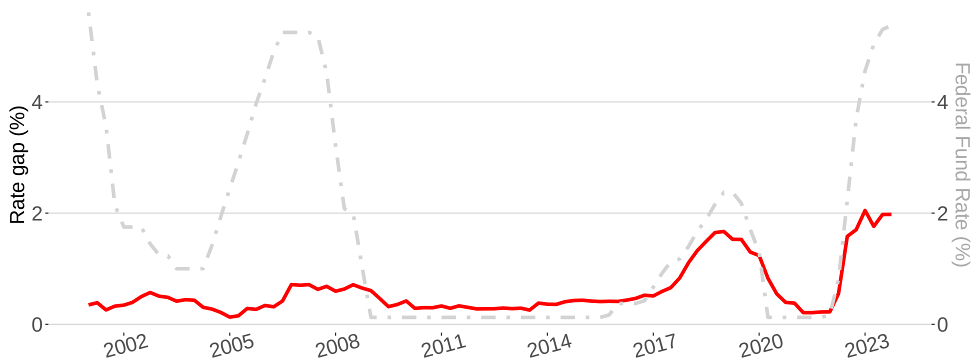
Notes: This figure illustrates the distribution of bank assets among three categories for the top 25 banks: banks with deposit rates below 0.75 times the sample average, banks with deposit rates within the range of 0.75 times to 1.25 times the sample average, and banks with deposit rates exceeding 1.25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

Figure 3: Dispersion of Bank Deposit Rates

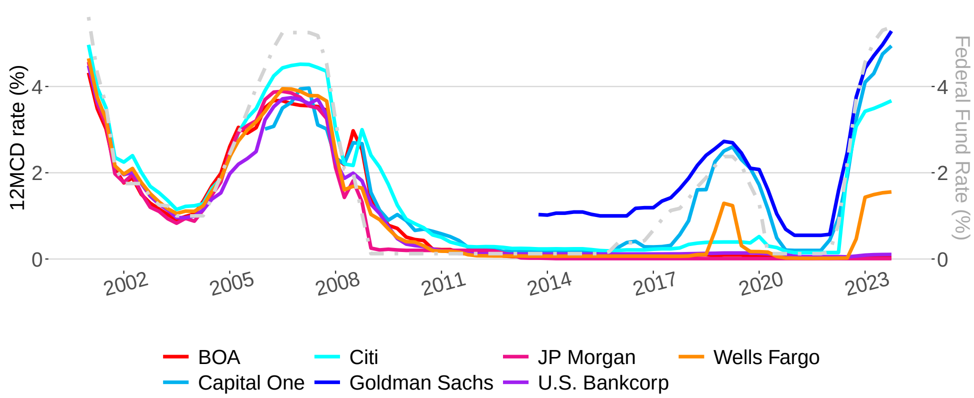
(a) CD Rate



(b) CD Rate Gap



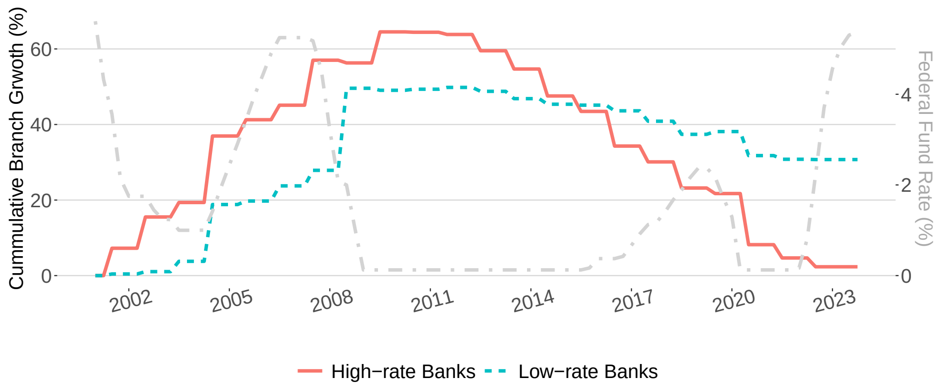
(c) CD Rate by Bank for Select Banks



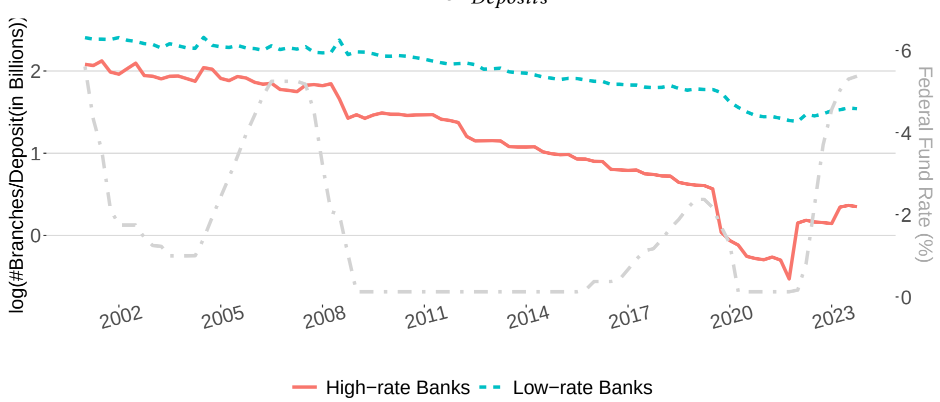
Notes: This figure depicts the dispersion in deposit rates among the top 25 banks, categorized by high and low rates from 2001Q1 to 2023Q4. Figure 3a shows a time-series of the asset-weighted average 12-month certificate deposit (CD) rates for high-rate (blue) and low-rate (red) banks. Figure 3b details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

Figure 4: Branches

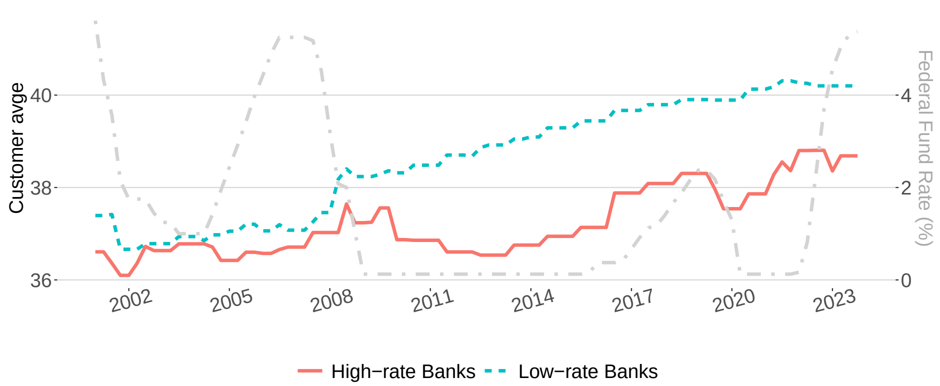
(a) Cumulative Growth of Branches



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



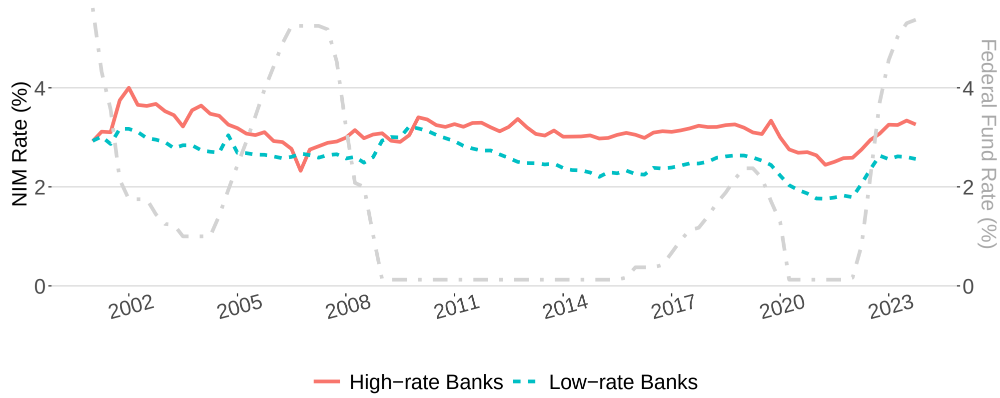
(c) Branch-weighted County Average Age



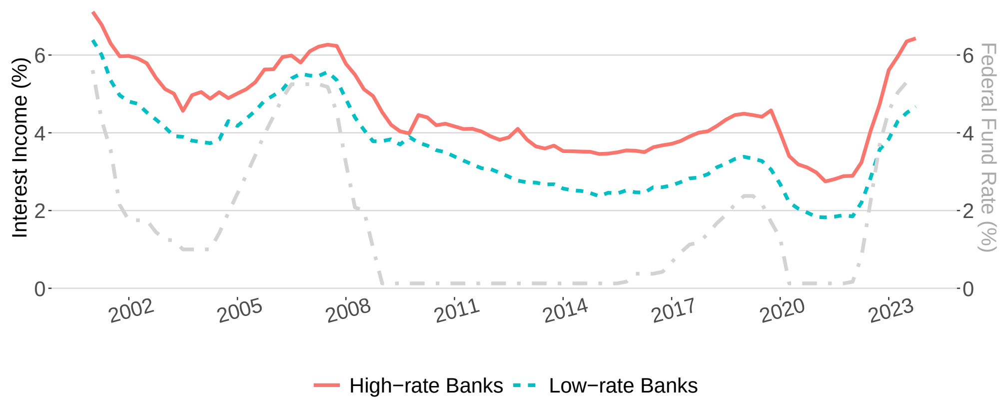
Notes: This figure compares branches operating by high- and low-rate banks among the top 25 banks from 2001Q1 through 2023Q4. Figure 4a presents the cumulative branch growth of high- and low-rate banks. Figure 4b presents the log-transformed ratio between branches and deposits (in Billions) of high-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

Figure 5: Net Interest Margin

(a) Net Interest Margin

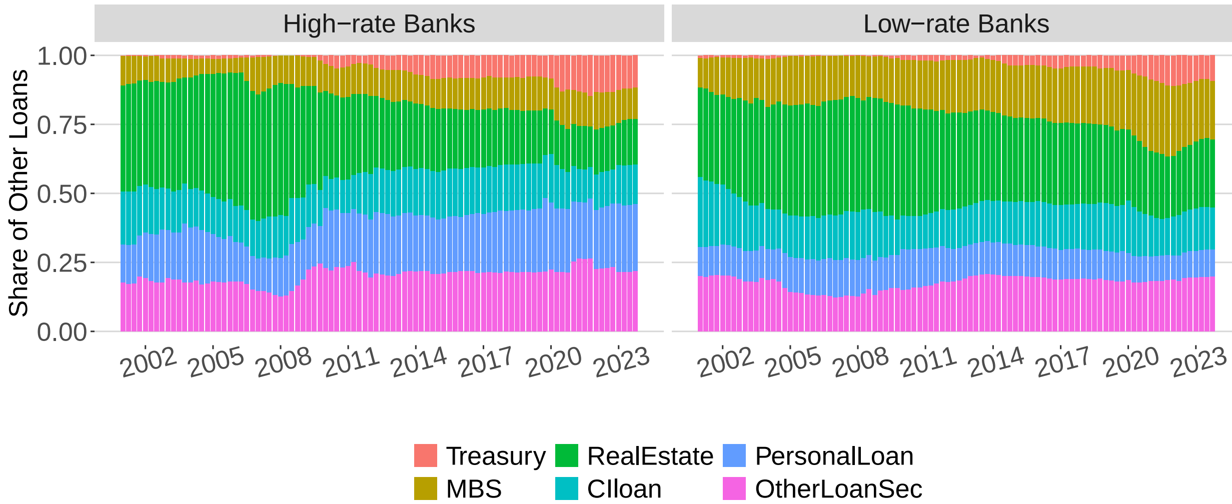


(b) Interest Income Rate



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

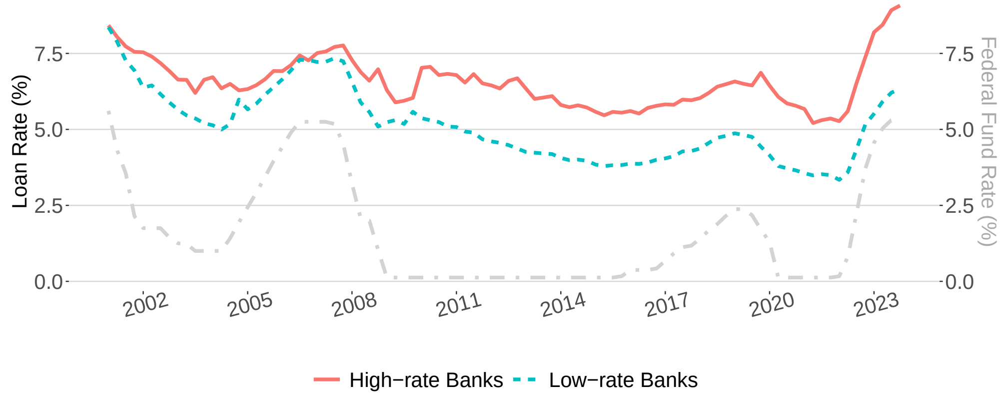
Figure 6: Portfolio Composition



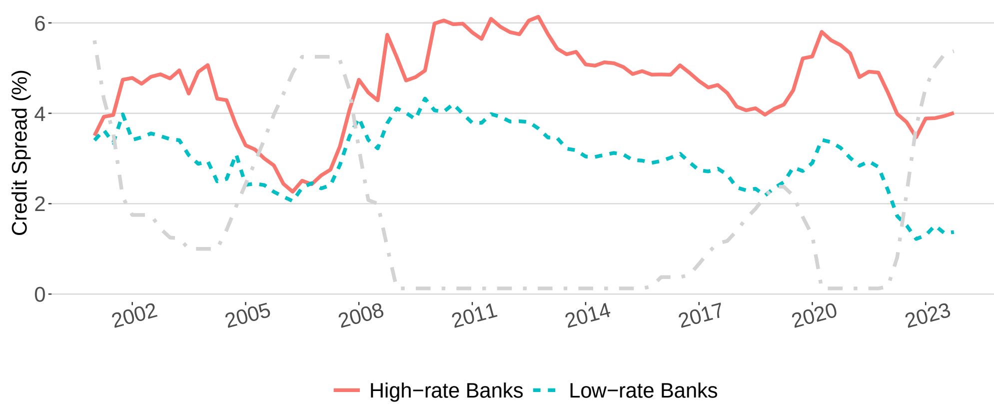
Notes: This figure compares the portfolio characteristics of high- and low-rate banks among the top 25 banks from 2001Q1 through 2023Q4. Figure examines the portfolio composition of high-rate and low-rate banks; share of treasuries, mortgage-backed securities, real estate loans, and C&I loans loans,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

Figure 7: Credit Risk

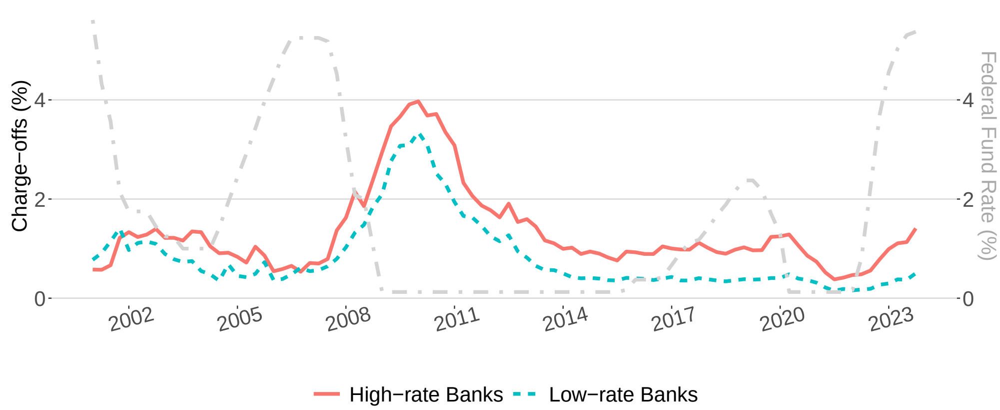
(a) Loan rate



(b) Credit spread



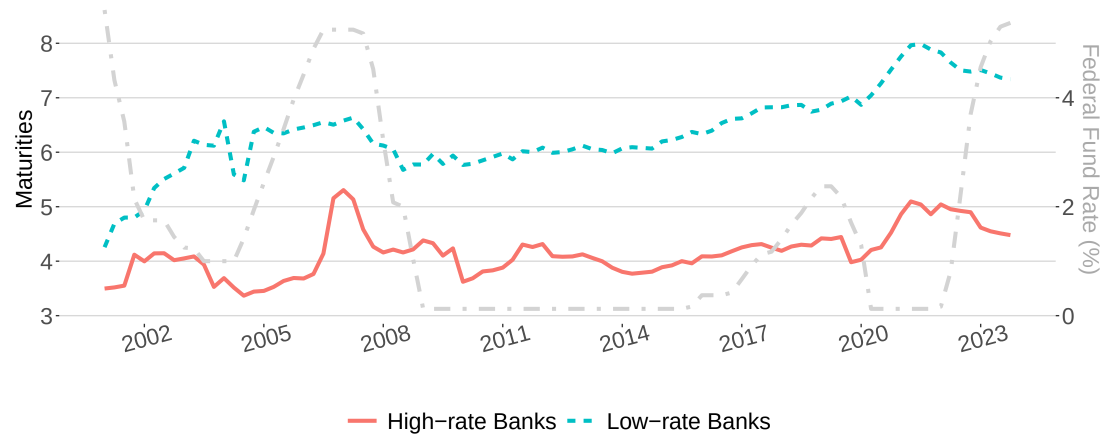
(c) Charge-offs



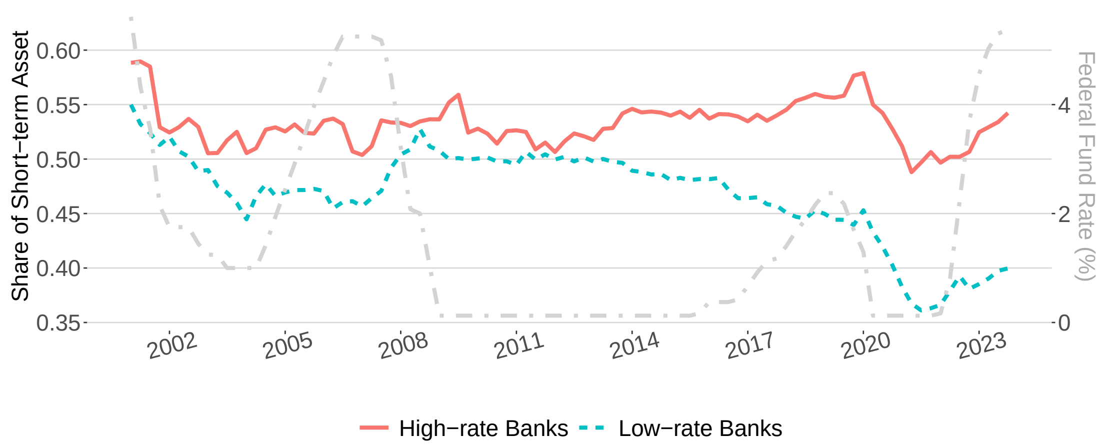
Notes: This figure compares the credit risk of high- and low-rate banks among the top 25 banks from 2001Q1 through 2023Q4. Figure 7a presents the loan rate (%) of high- and low-rate banks. Figure 7b presents the credit spread (%) of high- and low-rate banks. The credit spread is computed as the difference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

Figure 8: Maturity

(a) Maturity



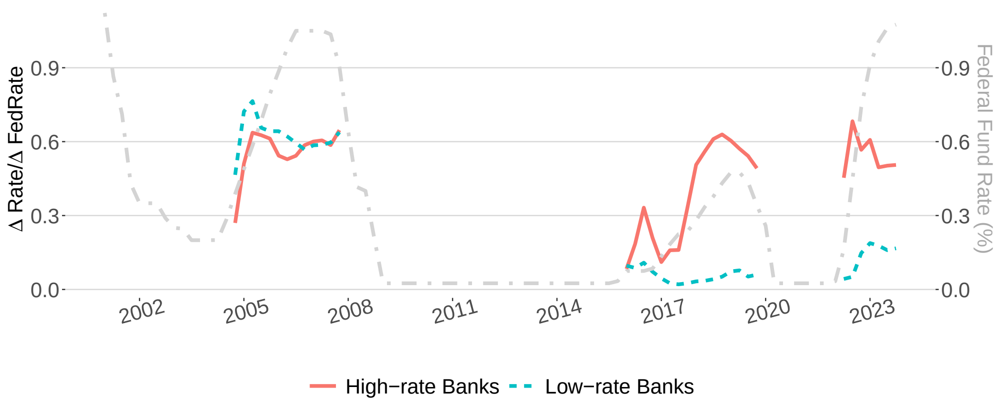
(b) Share of Short-Term Assets



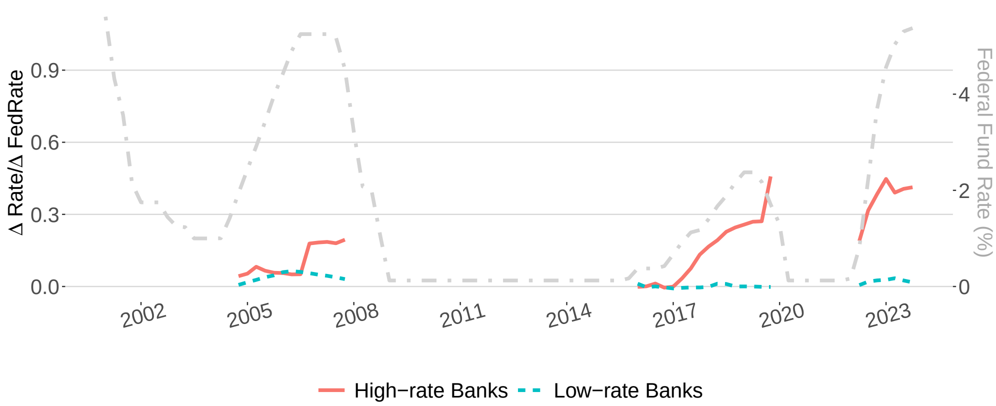
Notes: This figure compares the maturity risk of high- and low-rate banks among the top 25 banks from 2001Q1 through 2023Q4. Figure 8a presents the maturity (# of years) of high- and low-rate banks. Figure 8b presents the share of assets with less-than one-year maturity (short-term assets) for high-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

Figure 9: Deposit Rate Sensitivity

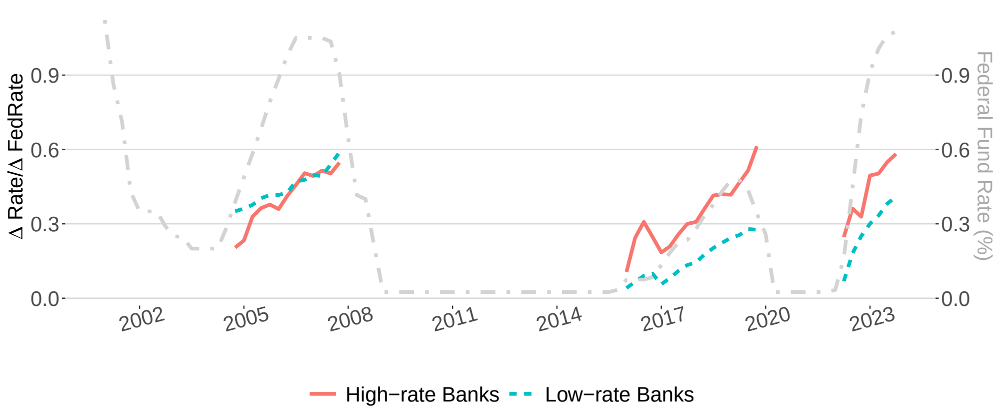
(a) CD



(b) SAV



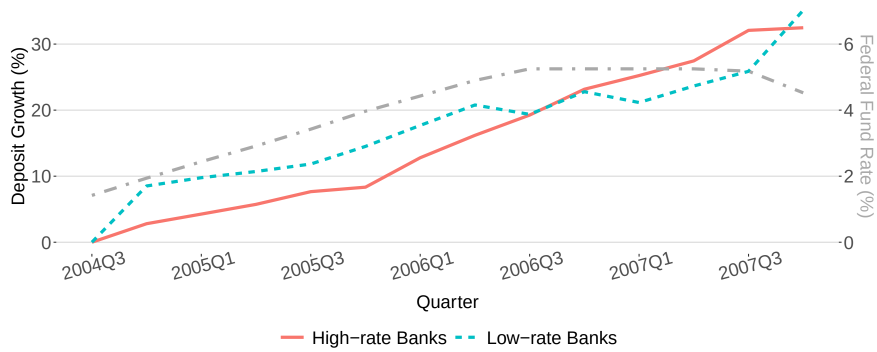
(c) DepRate



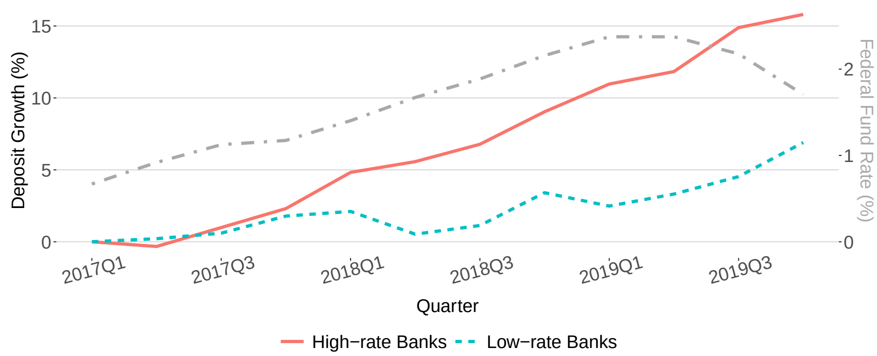
Notes: This figure compares the average deposit rate sensitivity of high- and low-rate banks among the top 25 banks over the three recent rate hiking cycles: 2004Q3 through 2007Q4, 2015Q4 through 2019Q4, and 2022Q1 through 2023Q4. Deposit rate sensitivity is defined as the ratio of the cumulative change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

Figure 10: Deposit Growth

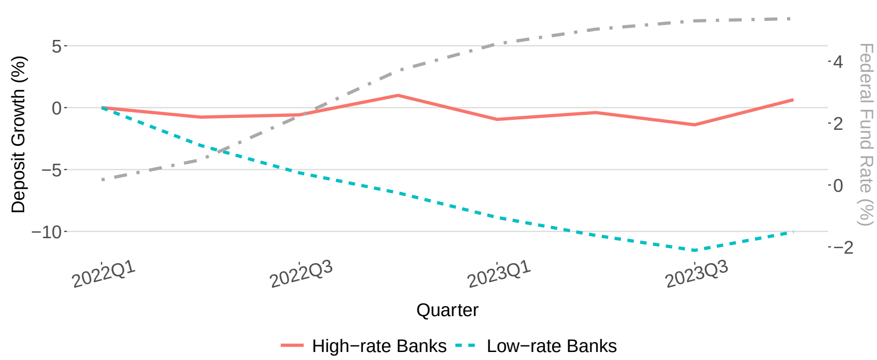
(a) 2004Q3-2007Q4



(b) 2015Q4-2019Q4



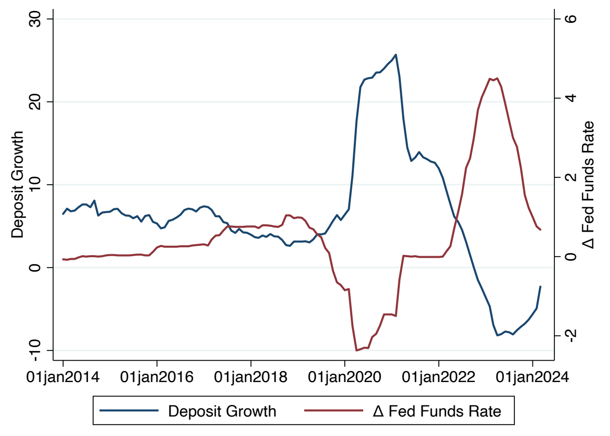
(c) 2022Q1-2023Q4



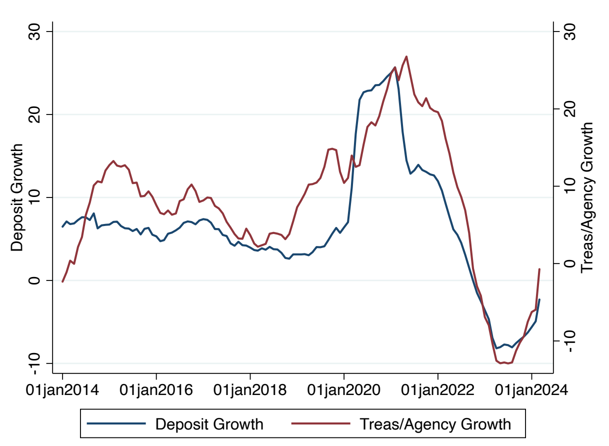
Notes: This figure compares the deposit growth of high- and low-rate banks among the top 25 banks over the three recent rate hiking cycles. Figures 10a, 10b, and 10c compare the deposit growth experienced by high-rate banks to that of low-rate banks from 2004Q3 through 2007Q4, from 2015Q4 through 2019Q4,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

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

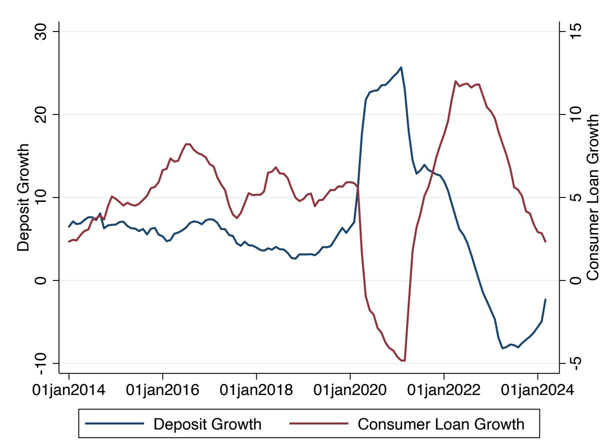
(a) Deposits and the Fed Funds



(b) Treasuries and MBSs



(c) Personal Loans



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

Table 1: Deposit Rates on Savings Accounts

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

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

Table 2: Summary Statistics

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

	2001-2007			2017-2023		
	High	Low	Diff	High	Low	Diff
CD (%)	2.97	2.63	0.35***	1.18	0.16	1.02***
DepRate (%)	2.43	1.93	0.51***	1.10	0.52	0.58***
Assets ($B)	231.21	233.86	-2.65	459.72	592.67	-132.95
Insured Deposits Share (%)	42.79	46.11	-3.32	39.80	46.32	-6.52***
#Branches	985	2488	-1503**	475	3375	-2900***
$\log \frac{\text{\# Branches}}{\text{Deposits (\$B)}}$	1.25	1.82	-0.57	-1.38	0.64	-2.02***
NIM rate (%)	3.22	2.81	0.41	3.01	2.35	0.66***
Maturity (Years)	3.80	5.84	-2.04**	4.30	7.09	-2.79***
Charge-off Rate (%)	0.99	0.74	0.25	0.88	0.32	0.56***

Panel B: Deposit Rate

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

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

Table 3: Bank Branches

	log(# Branches)		$\log(\frac{\text{Branches}}{\text{Deposit}})$		Branch-weighted County Average Age	
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(High Rate)×Post	-1.373***	-1.374***	-1.010***	-1.020***	-0.502***	-0.492***
	(0.192)	(0.193)	(0.177)	(0.176)	(0.071)	(0.086)
$\mathbb{1}$(High Rate)	-0.314***	-0.289**	-0.236***	-0.236***	-0.645***	-0.606***
	(0.112)	(0.113)	(0.090)	(0.087)	(0.049)	(0.060)
Post	1.360***	0.000	0.322***	0.000	1.999***	0.000
	(0.137)	(.)	(0.094)	(.)	(0.222)	(.)
Controls	✓	✓	✓	✓		
Quarter FE		✓		✓		
Adjusted R^2	0.297	0.300	0.396	0.355	0.364	0.242
Observations	2,300	2,300	2,300	2,300	1,799	1,799
Mean of Dep. Variable	7.042	7.042	0.759	0.759	38.805	38.805

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

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

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

Table 4: Asset Composition Shift

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

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

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

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

Table 5: Credit Risk

Panel A: Loans and Securities

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

Panel B: Charge-off Rates by Asset Class

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

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

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

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

Table 6: Maturity risk

Panel A: Loans and Securities

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

Panel B: Maturity by Asset Class

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Table 9: Channel Explorations and Robustness Tests

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

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

Table 10: Alternative Channels

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

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

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

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

Diverging Banking Sector: New Facts and Macro Implications
Internet Appendix

A Data Construction and Variable Definition

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

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

Additionally, in constructing growth variables, including deposit growth and various loan product growth rates, we account for mergers and acquisitions (M&As). We source M&A data from the Federal Financial Institutions Examination Council's (FFIEC) National Information Center[38] and incorporate statistics on target banks from the SDI or Call Reports.

We calculate the quarterly growth of a variable Y as:

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

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

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

Table A.1: Construction of Key Variables

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

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

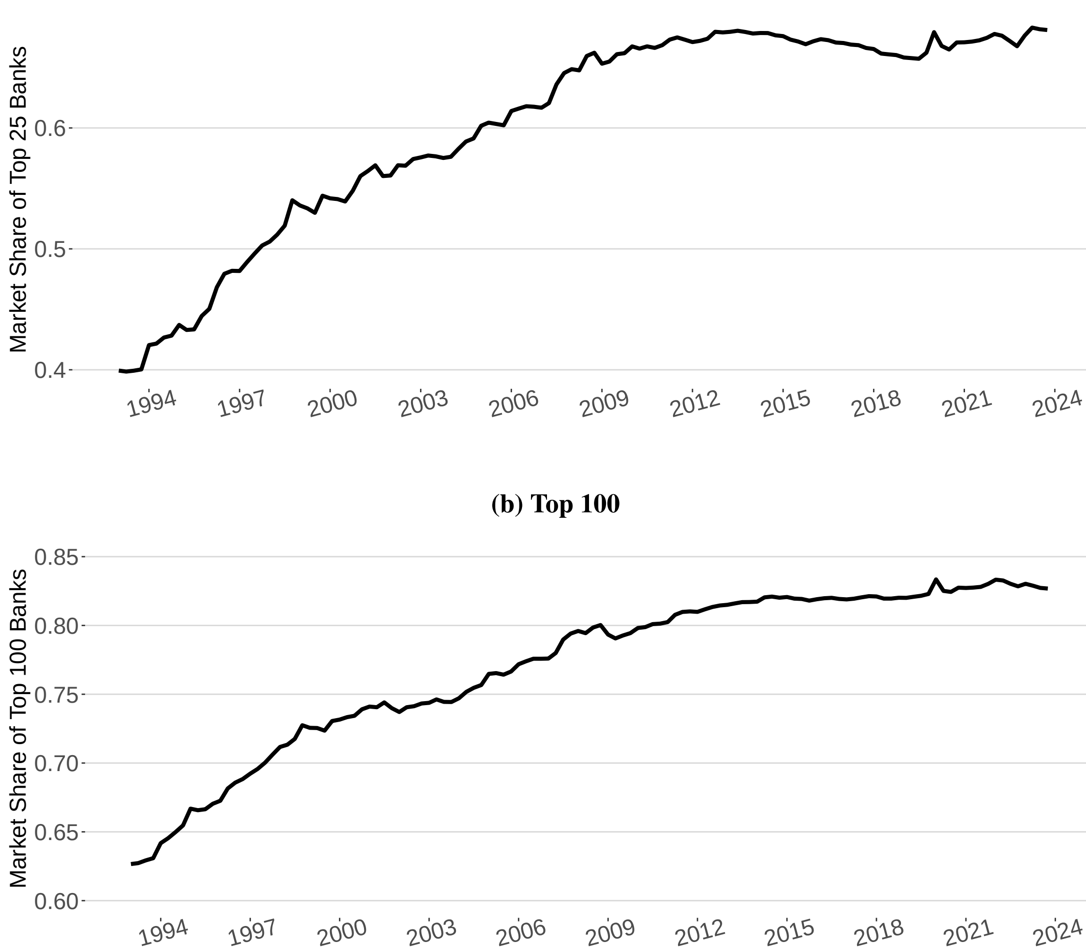
Notes: We follow the variable definitions from the FDIC's Statistics on Depository Institutions. See SDI.

B Additional Figures and Tables: Supporting Evidence and Alternative Channels

B.1 Figures

Figure B.1: Market Share of Top Banks

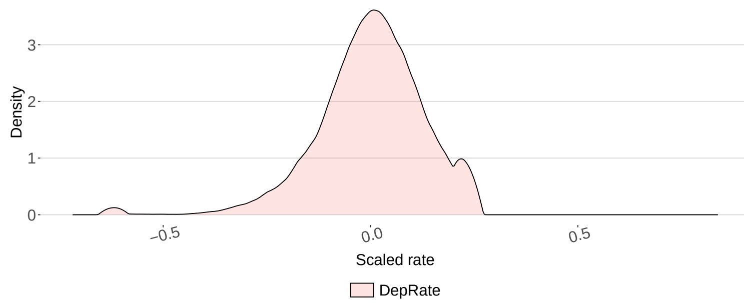
(a) Top 25



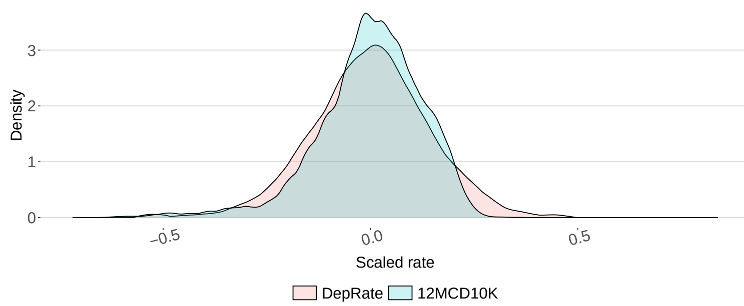
Notes: This figure presents the market share of the top 25 banks (in panel a) and top 100 banks (in panel b) from 2001Q1 through 2023Q4. Market share is measured by total assets. The top 25 (top 100) banks are defined according to bank size in each quarter. The data used to construct this figure comes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

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

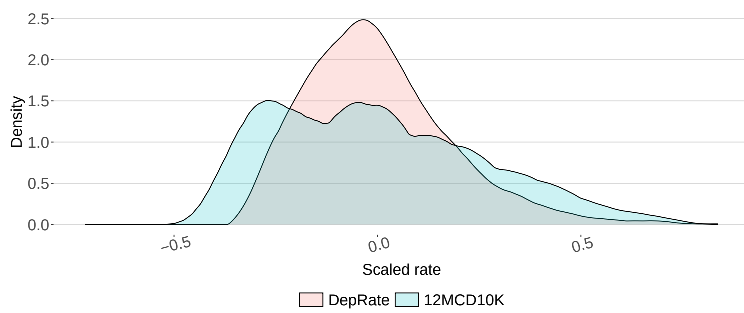
(a) 1995Q2



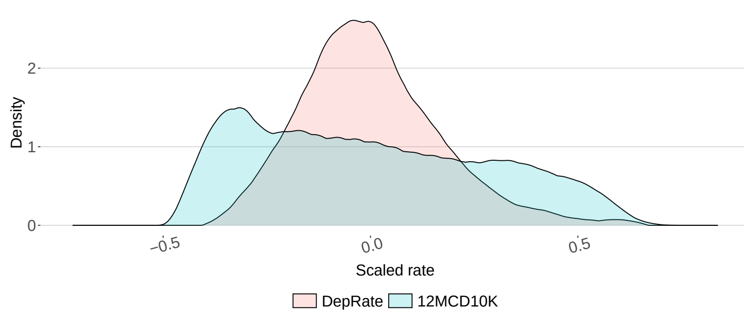
(b) 2006Q3



(c) 2019Q1



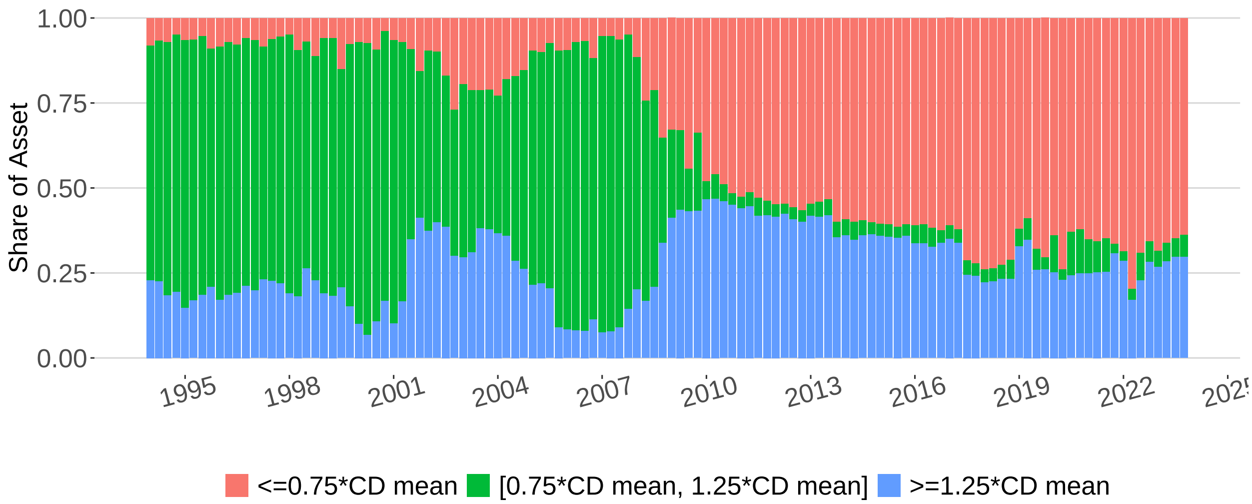
(d) 2023Q4



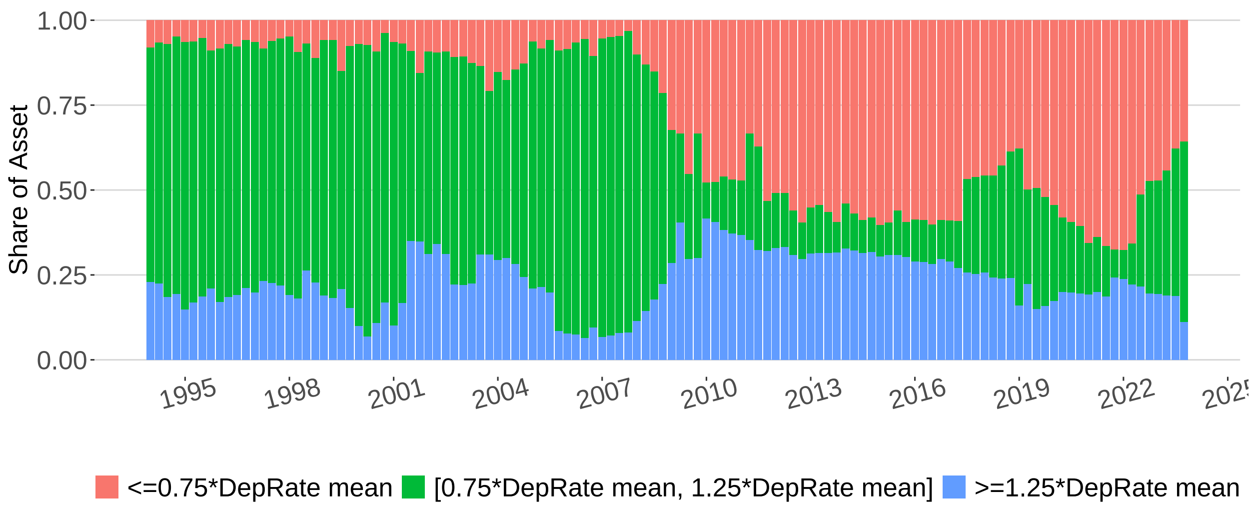
Notes: This figure depicts kernel density plots of the scaled and demeaned 12-month certificate of deposit rates of at least \$10,000 (CD) and the scaled and demeaned deposit rates (DepRate) derived from Call Reports provided by all banks at 1995Q2, 2006Q3, 2019Q1, and 2023Q4, representing the peak of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

Figure B.3: Asset Distribution of All Banks

(a) Classification based on CD



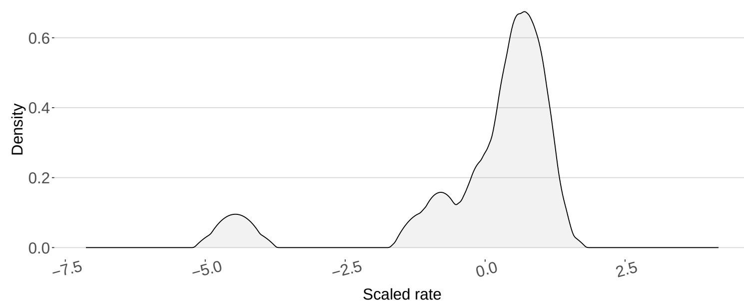
(b) Classification based on DepRate



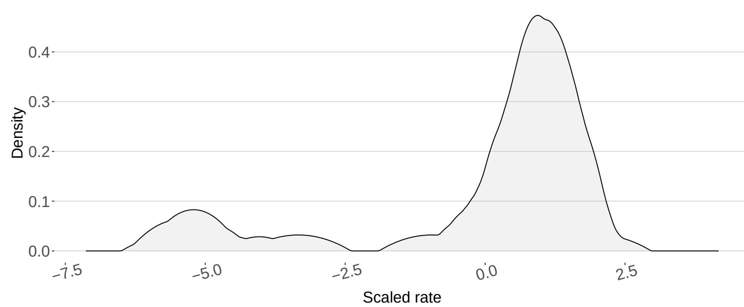
Notes: This figure illustrates the distribution of bank assets among three categories for all banks: banks with deposit rates below 0.75 times the sample average, banks with deposit rates within the range of 0.75 times to 1.25 times the sample average, and banks with deposit rates exceeding 1.25 times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

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

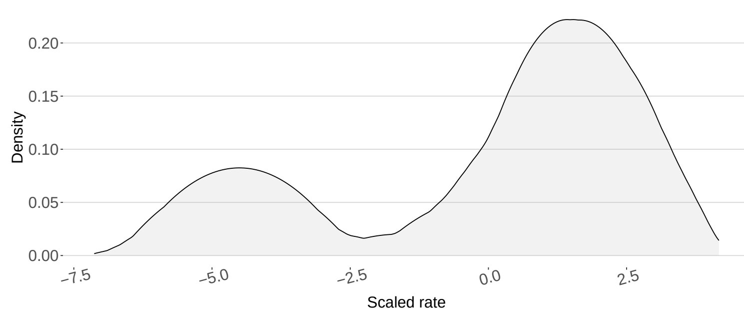
(a) 1995Q2



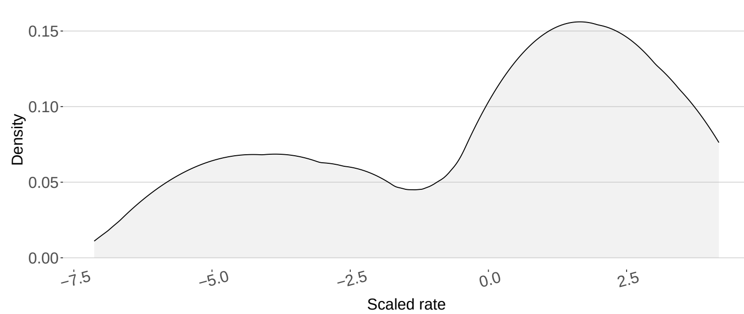
(b) 2006Q3



(c) 2019Q1



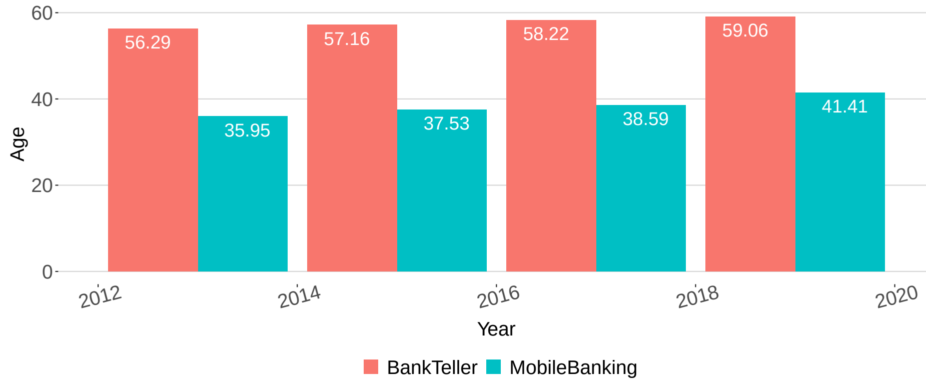
(d) 2023Q4



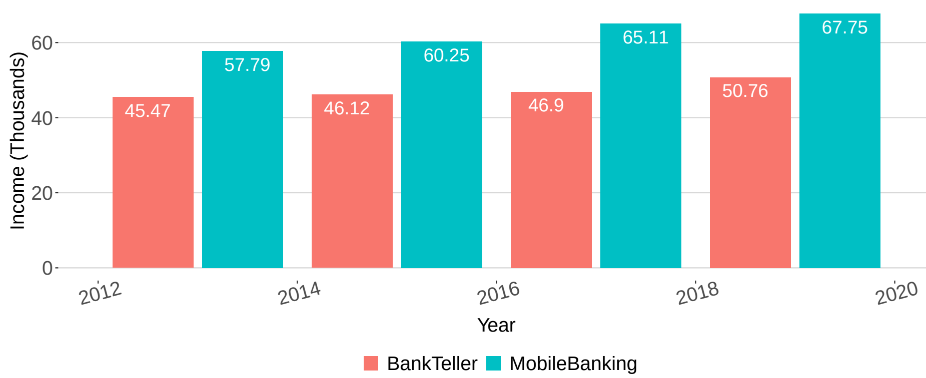
Notes: This figure displays kernel density plots of the demeaned logarithm of branch deposits by the top 25 banks at the peak of each interest rate hiking cycle. Figures a, b, c and d illustrate the kernel density at the following quarters: 1995Q2, 2006Q3, 2019Q1, and 2023Q4, respectively. The top 25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

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

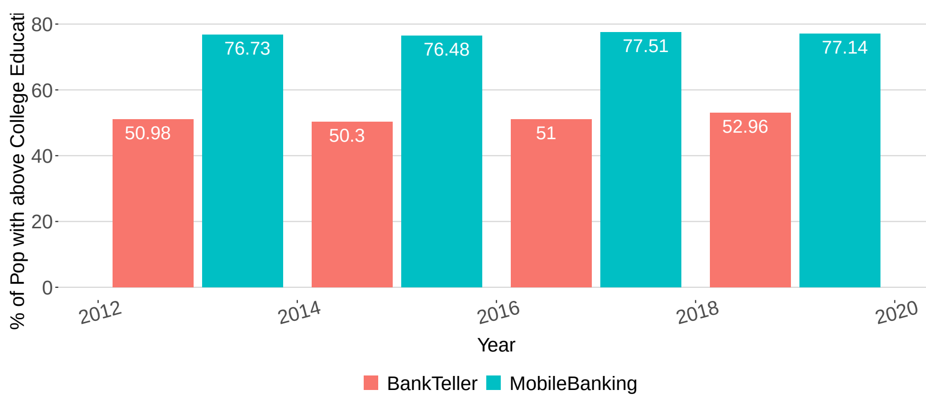
(a) Age



(b) Income



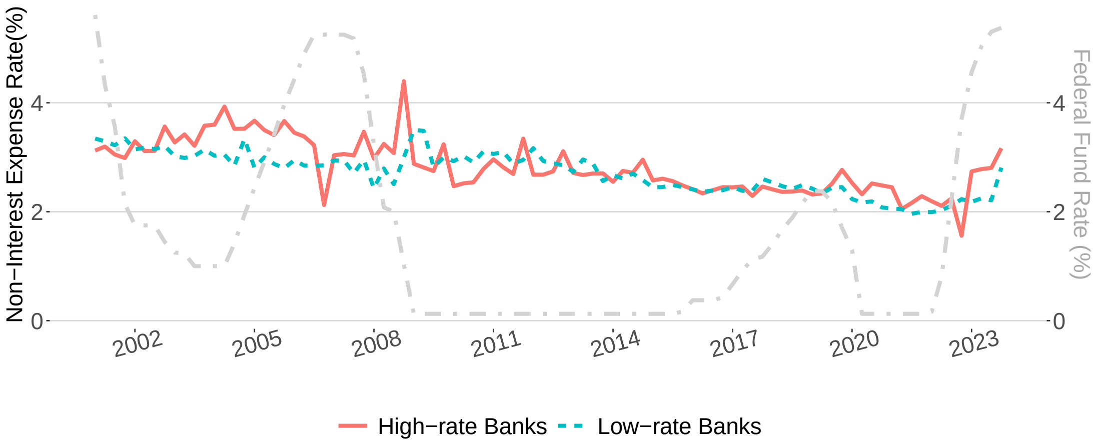
(c) Education



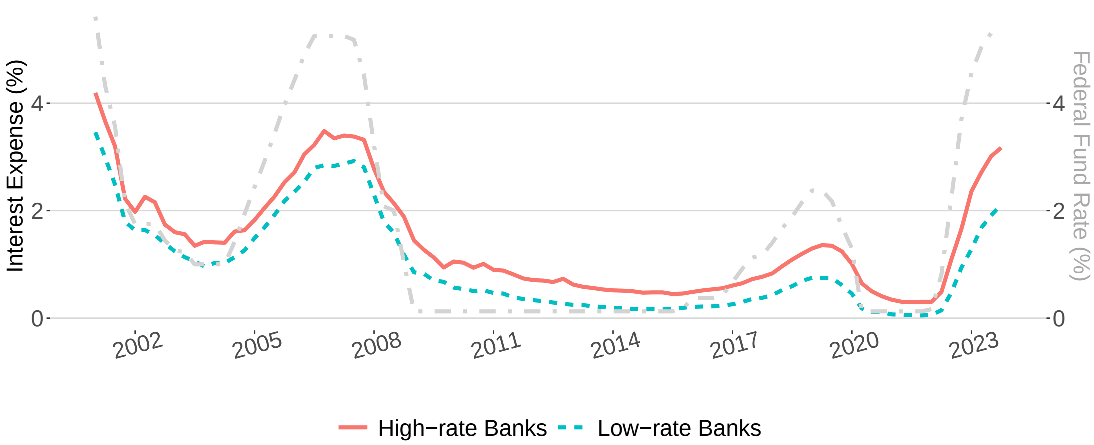
Notes: These figures present the characteristics of households utilizing bank tellers versus mobile banking as their primary means of accessing banking services. The data is derived from the FDIC Survey of Consumer Use of Banking and Financial Services. Respondents were asked to specify their most common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

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

(a) Non-interest Expense Rate



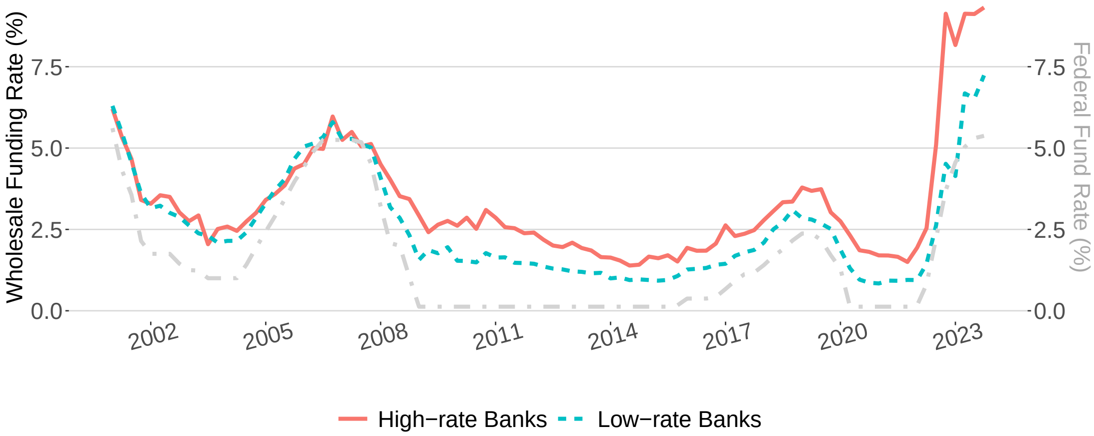
(b) Interest Expense Rate



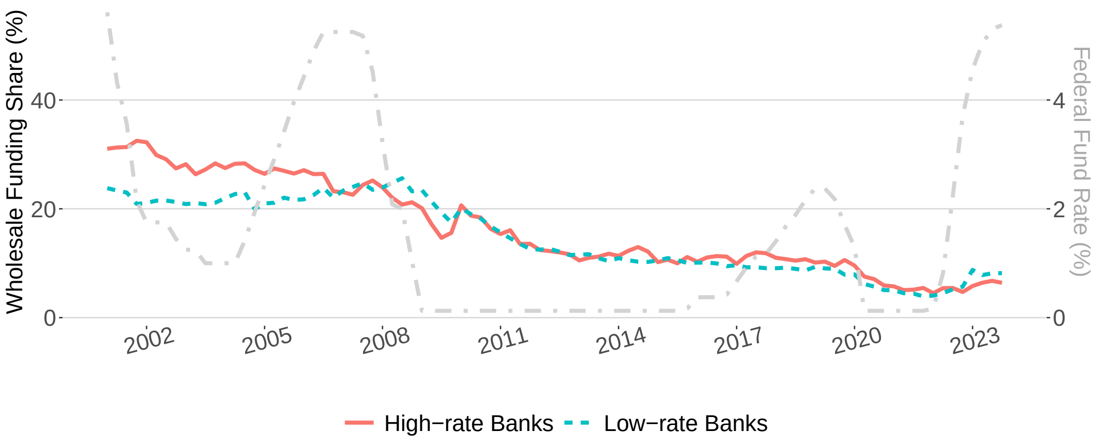
Notes: The figures plot the non-interest expense rate and interest expense rate of high- and low-rate banks among the top 25 banks from 2001Q1 through 2023Q4. See Appendix Table A.1 for more details on the construction of key variables. A bank is categorized as a *high-rate* bank if its average rank,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

Figure B.7: Wholesale Funding

(a) Wholesale Funding Rate



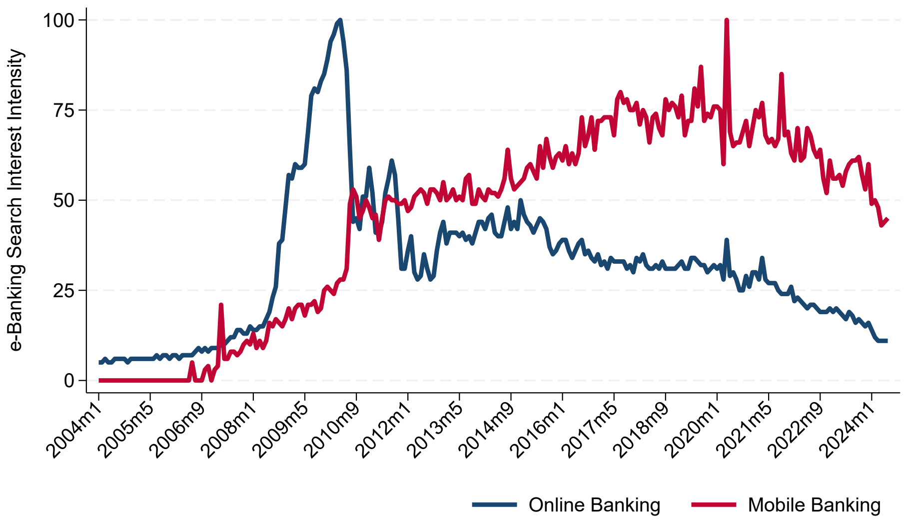
(b) Wholesale Funding Share



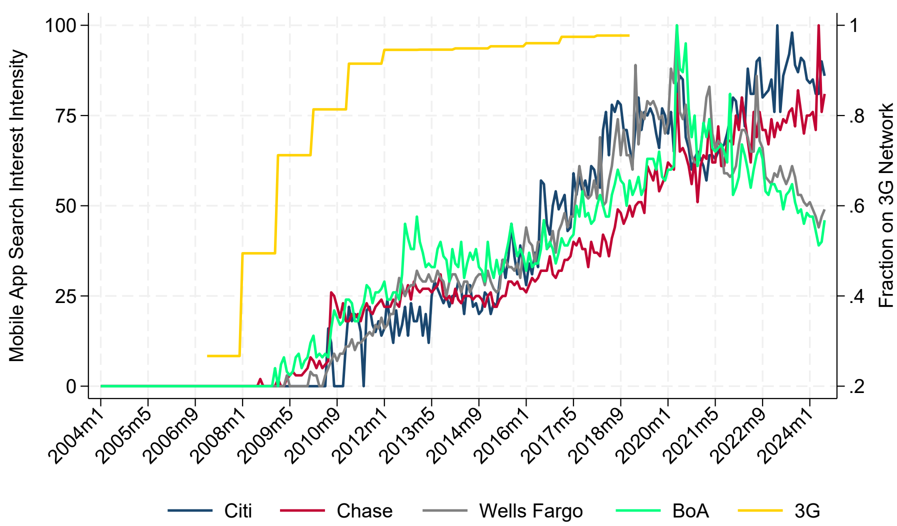
Notes: The figures plot the wholesale funding share (in panel A) and rate (in panel B) of high- and low-rate banks among the top 25 banks from 2001Q1 through 2023Q4. The wholesale funding includes federal funds purchased and repurchase agreements, subordinated debt, and other borrowed funds. See Appendix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

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

(a) Online and Mobile Banking



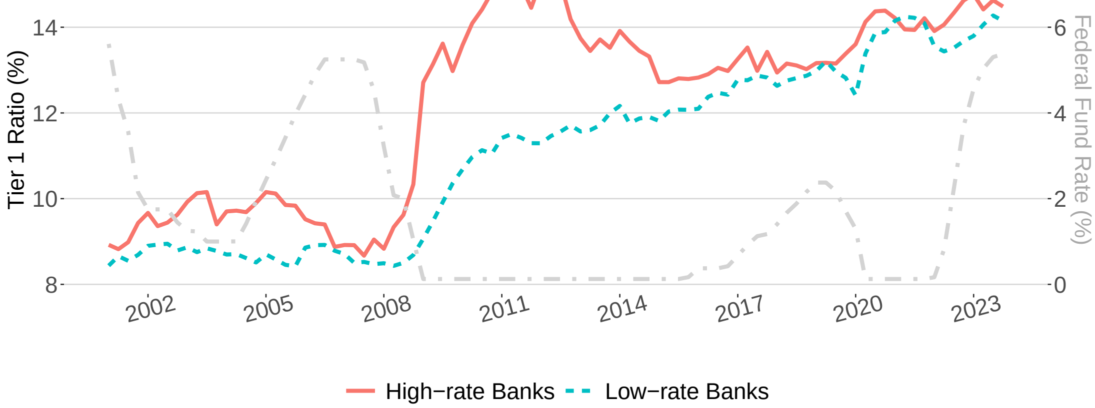
(b) 3G & Top 4 Banks: Mobile Apps



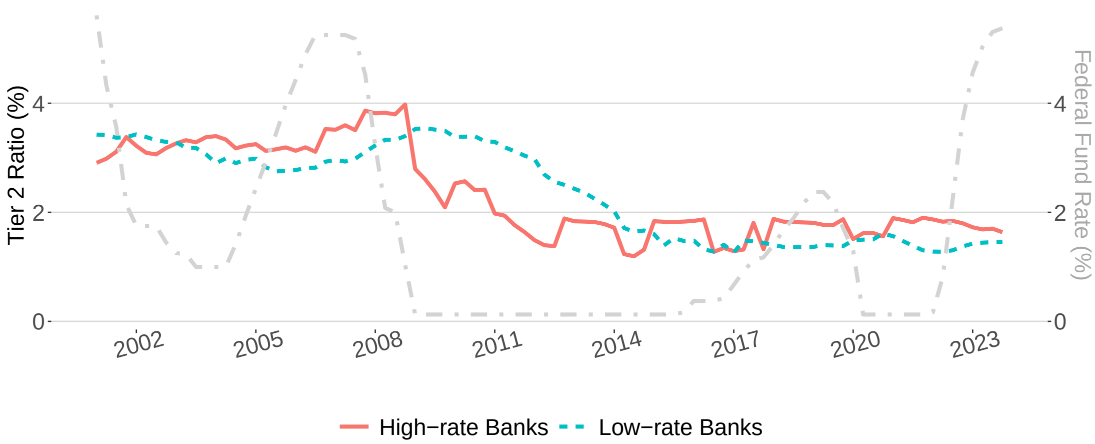
Notes: This figure plots the search interest intensity for online banking and mobile banking. Appendix Figure B.8a plots the search interest intensity for "online banking" (blue) and "mobile banking" (red) from 2004 through 2024. Figure B.8b plots the search interest intensity for "Citi App" (blue),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

Figure B.9: Tier 1 and Tier 2 Ratios

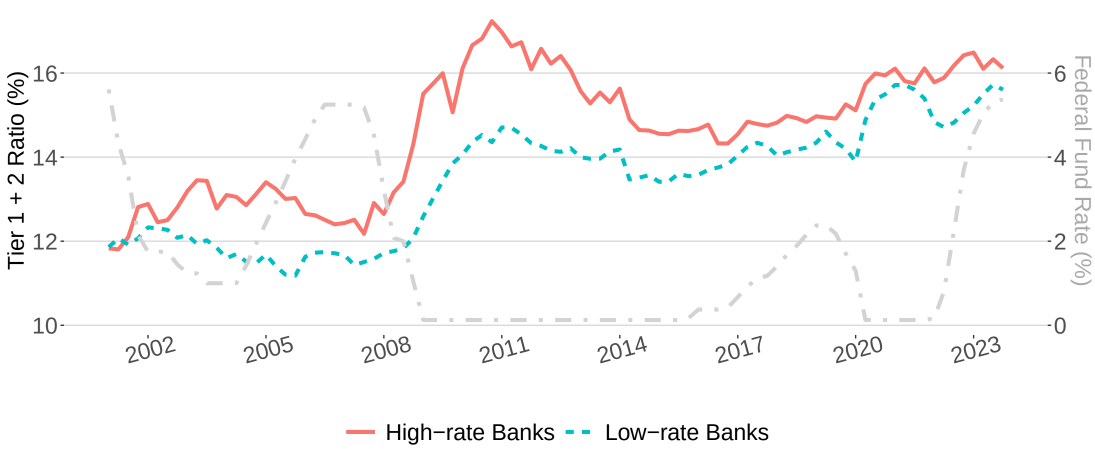
(a) Tier 1 Ratio



(b) Tier 2 Ratio

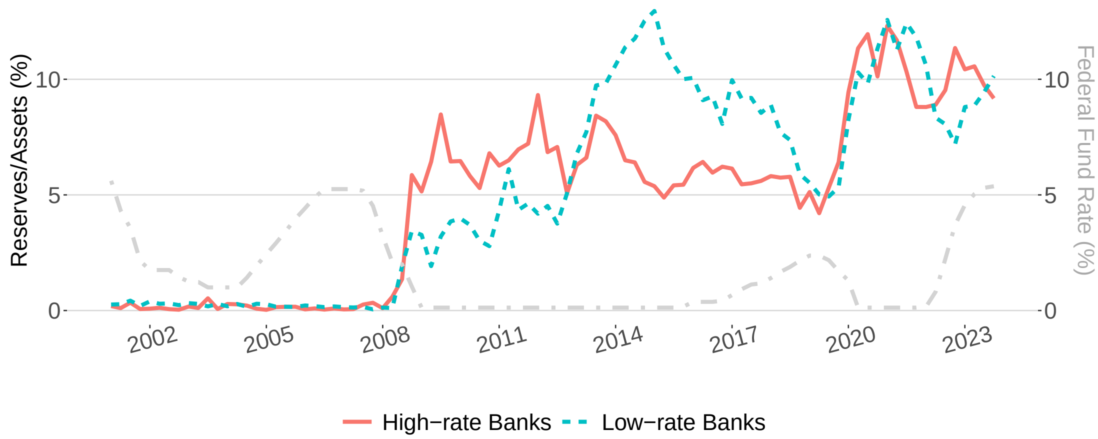


(c) Tier 1+2 Ratio



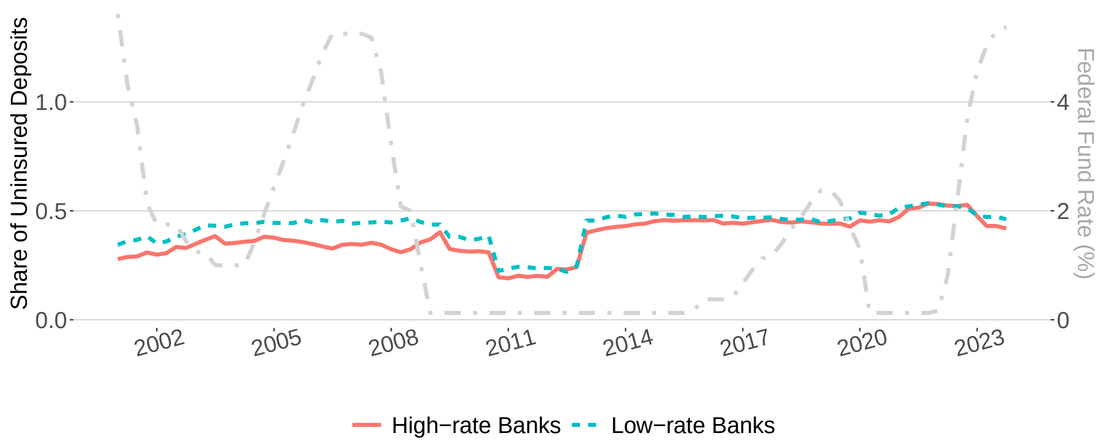
Notes: This figure compares the Tier 1/2 ratio of high- and low-rate banks among the top 25 banks from 2001Q1 through 2023Q4. See Appendix Table A.1 for more details on the construction of key variables. The left y-axis represents the quarterly average Federal Fund Target rate (FFTar). A bank is categorized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

Figure B.10: Reserves



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

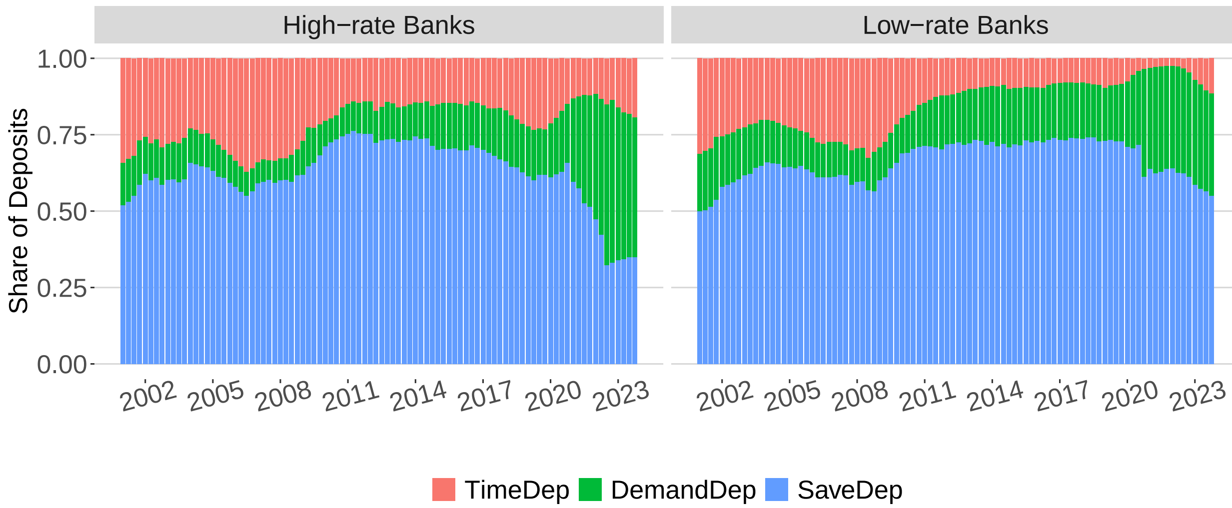
Figure B.11: Uninsured Deposit Share



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

Figure B.12: Deposits Decomposition

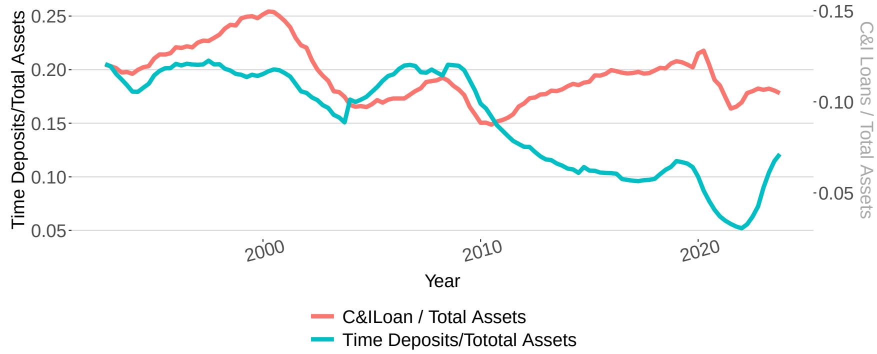
(a) Share of Deposits



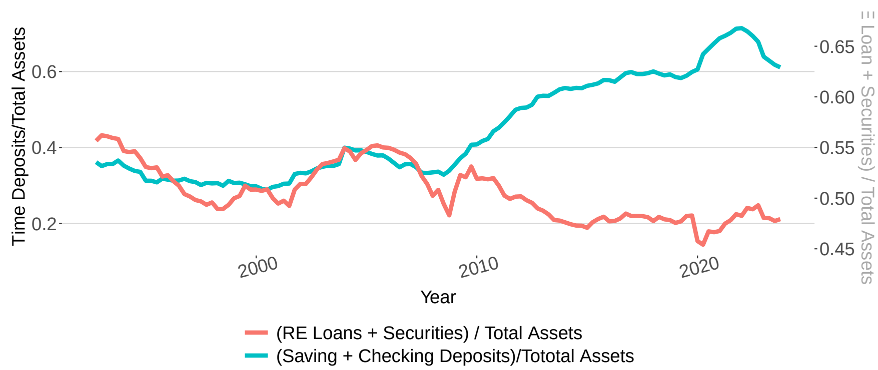
Notes: This figure compares the deposit composition of high- and low-rate banks among the top 25 banks from 2001Q1 through 2023Q4. See Appendix Table A.1 for more details on the construction of key variables. A bank is categorized as a *high-rate* bank if its average rank, calculated based on the CD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

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

(a) C&I Loans vs. Time Deposits



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



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

B.2 Tables

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

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

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

Table B.2: Summary Statistics

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

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

Panel B: Correlation Matrix of Rates

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

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

Table B.3: Classification of Banks

Classification of Banks

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

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

Table B.4: What Predicts the Bank Type?

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

where i and q indicate the bank and quarter-year, respectively, $\Delta\text{Fed Funds Rate}_y$ 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 $\text{ROA}_{i,q-1}$ 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 $\Delta\text{Fed Funds Rate}_y$ and Post$q$. We analyze two forms of dependent variables: 1) $\Delta\log(Q_{i,y})$, representing the logarithmic change in quantity, and 2) $\Delta\text{Share}_{i,q}$, denoting the change in share. A bank is categorized as a *high-rate* bank if its average rank, calculated based on the CD rate and deposit rate from the Call Report, falls within the top tercile. Each observation is weighted by its asset size from the previous quarter. Standard errors (in parentheses) are clustered at the quarter-year levels and are accounted for autocorrelation consistent errors using Driscoll-Kraay with 4-quarter lags. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

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

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

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

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

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

Table B.9: Composition of Top25 Banks

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

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

C Proofs

C.1 Solving the Model without Remote Banking Services

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

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

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

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

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

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

Based on the first two questions, we have

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

This gives

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

If $l_A > l_B$, the left side of the equation becomes negative, owing to the condition $p'(\cdot) < 0$. In contrast, the right side remains positive because of $p''(\cdot) \le 0$. Such a scenario is not feasible, leading to the conclusion that $l_A \le l_B$. Applying the same reasoning, we can also deduce that $l_A \ge l_B$. 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.