Large depositors, retail depositors, and the deposits channel of monetary policy

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Recent work documents widespread depositor stickiness, yet deposit flows respond strongly to monetary policy. Using data on U.S. commercial banks since 1975, I show that the deposits channel operates primarily through a small number of large, responsive depositors who account for a substantial share of bank funding. I document that rates on large deposits are significantly more sensitive to policy rates—with pass-through more than double that of small deposits. Still, large deposits flow out more strongly in response to monetary policy shocks and account for essentially all aggregate deposit outflows. These patterns are not explained by local deposit market concentration. I show that the outflows of large deposits lead to lower lending, particularly at small banks. My results suggest that as the share of large, responsive deposits rises, the deposits channel is likely to become stronger.

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How does monetary policy transmit through the banking system? One mechanism that has received a lot of attention in finance and macroeconomics is the deposits channel of monetary policy (Drechsler, Savov, and Schnabl 2017). It posits that when the Fed raises policy rates, banks use market power in deposit markets to keep deposit rates low relative to market rates. This widening spread between market rates and deposit rates prompts deposit outflows, constraining banks' funding and leading them to cut lending.

Recent work using transaction-level data argues that an important source of banks' market power in deposit markets is that depositors are inattentive, inert, and lack financial sophistication—forces I collectively refer to as "depositor stickiness" (Adams et al. 2021; Fleckenstein and Longstaff 2024; Cirelli and Olafsson 2025; Egan et al. 2025; Lu and Wu 2025). This literature shows that most depositors respond only weakly to changes in interest rates. But the deposits channel relies precisely on depositors moving funds in response to interest rates: flowing out when policy rates rise but deposit rates stay low, and flowing back in when policy rates fall. This poses a puzzle: if most depositors are sticky, why do we observe large deposit flows in response to monetary policy—both at the bank level and in the aggregate (e.g., Drechsler, Savov, and Schnabl 2017; Wang et al. 2022)?

In this paper, I resolve this puzzle by distinguishing between small and large depositors. The size split is promising *ex ante* to get at sticky vs. responsive depositors for two reasons. First, for large balances, dollar gains from shopping around for a better rate are larger and thus more likely to overcome fixed search or switching costs (Hortaçsu and Syverson 2004; Honka, Hortaçsu, and Vitorino 2017). Second, large deposits are more likely to be held by corporations, non-bank financial intermediaries (NBFIs), and high-net-worth individuals (see Section 2), who are typically seen as more financially sophisticated (Lusardi and Mitchell 2014, 2023; Graham 2022) and attentive (Gabaix 2019) than other households and small businesses who hold small deposits.

I show that small deposits are indeed sticky: they get low, policy-insensitive rates but stay with banks when monetary policy tightens. In contrast, large deposits flow in and out of banks in response to monetary policy, even though their rates are twice as sensitive to the policy rate. While large deposits constitute only about 1% of deposit accounts, they account for about 50% of total deposits as of 2024.[1] As a result, deposit flows—both at the bank level and in the aggregate—are driven primarily by a small set of large, responsive depositors, even as most depositors are sticky.

[1] Large deposits are defined as those above \$100,000 before 2009Q3 and above \$250,000 thereafter, reflecting the structure of banks' regulatory filings. This binary split is imposed by data availability; depositor responsiveness likely varies continuously or in tiers with deposit size rather than jumping at these thresholds. I also study large vs small *depositors* directly—using aggregate deposit data by holder sector and, for households, by the wealth and income distribution—and document similar patterns.

I first document that rates on large deposits are more sensitive to market rates than rates on small deposits. Because comprehensive data on deposit rates by balance size are not available, I employ an indirect empirical strategy. Using regulatory data on U.S. commercial banks ("Call Reports"), I find that banks' total deposit rate pass-through ("beta")—which is a weighted average of the beta on large and small deposits—increases with the share of large deposits in the cross-section of banks in every monetary policy cycle since 1975. I show that this pattern is not driven by local deposit market concentration or deposits' maturity structure, and holds for deposit subsets such as interest-bearing transaction deposits, savings deposits, and time deposits. Using Ratewatch offered rates, I show that the betas on *small retail* deposit products are similar across the distribution of the large-deposits share. These facts suggest that betas on large deposits are significantly higher than betas on small deposits. I regress deposit betas on the share of large deposits and recover the implied large- and small-deposit betas of about 0.7 and 0.3, respectively.

I then provide direct evidence that large deposits get better and more policy-rate-sensitive pricing. First, I use the sparse data on larger-denomination, "relationship" and "premium", and corporate deposit products in Ratewatch and show that these products are significantly more sensitive to market rates than the retail deposit products. Second, I bring in novel hand-collected data on banks' posted deposit rate schedules, gathered from banks' websites using the Internet Archive's Wayback Machine. I document that banks use balance-tiered deposit pricing—offering higher rates on larger deposit balances, especially when the policy rate is high. As a specific example, in December 2023, at the peak of the most recent tightening cycle, Wells Fargo (one of the three largest banks in the U.S.) offered a 0.25% annual percentage yield (APY) on savings deposits below $100,000, but 2.5% APY on deposits above $1,000,000; the effective federal funds rate (FFR) then was 5.33%. In February 2022, right before this tightening cycle started and with the FFR at 0.08%, Wells Fargo's offered rates on savings deposits were 0.02% APY on all balance tiers.

A key challenge in interpreting these results is that large deposits tightly overlap with uninsured deposits. As such, rates on large deposits may contain risk premia to compensate their holders for the risk of bank default. If the risk premia are large enough and positively co-move with policy rates, they can explain the higher rates on large deposits during monetary tightening even if the underlying, "risk-free" deposit betas are similar across large and small deposits. I show that risk cannot fully explain my results. First, I show that short rates and bond spreads are *negatively* correlated. Second, I show that changes in bank bond spreads over monetary policy cycles do not systematically co-move with the large deposits share. Third, I adapt the framework of Correia, Luck, and Verner (2025) to show that the share of large deposits does not predict an elevated probability of bank failures. Finally, I show that the 5 largest U.S. banks, which are commonly believed to be "too-big-to-fail" (O'Hara and Shaw 1990; Flannery 2010; Strahan 2013), have high shares of large deposits and high deposit rate betas across all monetary policy cycles since 1975. Taken together, these facts suggest that risk premia cannot be the main driver of the higher rates and betas on large deposits.

I then turn to deposit flows and show that, in aggregate, large deposits flow out (flow in) following monetary tightening (easing), while total small deposits do not change. Large deposits thus account for the *entire* aggregate total deposit response to monetary policy, which serves as the "first-stage" of the deposits channel. This does not mean that small deposits are completely unresponsive to rates: both large and small deposits rotate from lower-yielding non-time deposits (demand and savings) into higher-yielding time deposits when the Fed tightens. Large and small deposits' inflows into time deposits are similar, but large non-time deposits contract about twice as much as small non-time deposits. The rotation from non-time to time deposits then roughly cancels for small deposits, but yields an overall contraction for large deposits. This pattern holds when monetary policy is measured as raw changes in the federal funds rate, as well as for Romer and Romer (2004) monetary shocks and Bauer and Swanson (2023) high-frequency monetary shocks. Raw rate changes are endogenous and positively correlate with income, while identified monetary shocks predict income declines. The fact that large deposits flow out in response to both suggests the result is driven by depositors' sensitivity to interest rates rather than differential effects of monetary policy on income and savings across depositor types. Consistent with these aggregate patterns, banks with a higher share of large deposits experience significantly more deposit outflows following monetary tightening.

Together, these findings point to small deposits being significantly more sticky than large deposits. To get a sense of how important this differential stickiness is for deposit pricing quantitatively, I compare it against local deposit market concentration. Concentration has been prominent as a cross-sectional driver of deposit pricing in the literature (Berger and Hannan 1991; Neumark and Sharpe 1992; Drechsler, Savov, and Schnabl 2017; Li, Loutskina, and Strahan 2023; Li, Ma, and Zhao 2025). I show that the large deposits share is a much stronger predictor of deposit betas in the cross-section of banks than local deposit market concentration, explaining 15% of the variation in deposit betas compared to 2% for the local deposit market Herfindahl-Hirschman Index (HHI).

Finally, I show that the outflows of large deposits matter for bank lending, especially at small banks. In aggregate, small banks (bottom 99% by total assets) cut lending in response to tightening monetary shocks, while large banks (top 1%) do not. To disentangle effects on credit supply from contemporaneous changes in credit demand induced by monetary policy, I follow Drechsler, Savov, and Schnabl (2017) and study small business lending at the bank-county level. I compare small business lending by banks with high vs low shares of large deposits within the same county, controlling for county-level loan demand. I find that *small* banks with a high share of large deposits contract lending more strongly following monetary tightening. These results are consistent with deposit outflows (driven by large deposits) leading to a contraction in credit supply at small banks, while large banks substitute lost deposits with other funding and do not cut lending. Given that small banks account for about 33% of total lending (and lend to more financially constrained borrowers), these results are consistent with the deposits channel of monetary policy having important credit supply effects.

Overall, my findings point to a "two-tier" deposit market structure, where small deposits are indeed sticky and stay with banks despite getting low and insensitive rates, while large deposits flow in and out of banks in response to monetary policy and get significantly higher deposit rate pass-through. These findings imply that the strength of the deposits channel depends on the relative mix of responsive (large) and sticky (small) deposits. This mix has changed over time: the share of deposits held by the top 1% highest-income and highest-net-worth households has been on the rise since the 1980s. If these trends continue, the deposits channel will likely strengthen. As a back-of-the-envelope calculation, my estimates imply that a 10 percentage point increase in the large deposits share would increase the aggregate deposit beta by about 0.04 (8% of the average deposit beta of 0.5). At the same time, for a 1 percentage point monetary policy tightening, deposits would contract by an additional 1% at the 2-year horizon, prompting a further 0.80% lending cut at small banks.

I also document that banks with a high share of large deposits hold shorter-maturity assets that provide a natural hedge to the more interest-sensitive large deposits. As such, banks with more large deposits are able to maintain stable net interest margins (Drechsler, Savov, and Schnabl 2021). A shift towards the more interest-sensitive large deposits in the future may thus result in banks holding shorter-duration assets, reducing the maturity transformation capacity of the banking system.

My results also have a methodological implication for empirical work studying bank deposit pricing. A common practice in the literature is to focus on retail deposit rates from Ratewatch (e.g. Erel et al. 2024; Kundu, Muir, and Zhang 2024; Lu and Wu 2025; Egan et al. 2025). My results show that this practice is appropriate when studying retail depositors, but not when studying banks' overall deposit funding costs.

Related literature and contribution. This paper contributes to several strands of the literature.

First, this paper contributes to the literature on bank deposit pricing. Berger and Hannan (1989, 1991), Neumark and Sharpe (1992), Rosen (2002, 2007) document that banks do not fully pass through market rates into deposit rates, and that this imperfect pass-through is stronger in more concentrated deposit markets. This idea received renewed interest with the seminal work by Drechsler, Savov, and Schnabl (2017, 2021).[2] I study differences in deposit pricing between large and small deposits and document that rates on large deposits are much more sensitive to market rates, with banks using balance-tiered and "relationship" deposit pricing. In this, my paper closely relates to contemporaneous work by Dias and Schmidt-Eisenlohr (2026). They also find that banks with more uninsured deposits have higher deposit interest expense (particularly during monetary tightening), and argue, as I do, that this premium is not explained by risk. I complement their work by providing *direct* evidence that larger deposit balances get higher and more policy-sensitive rates using novel hand-collected data on banks' posted deposit rates, and extending the analysis to deposit *flows* and bank lending.[3] My paper also complements contemporaneous work by Argyle et al. (2026). Using detailed data on retail depositor accounts at a sample of U.S. credit unions, Argyle et al. (2026) show that low-balance retail depositors are more sensitive to interest rate changes than high-balance retail depositors. My paper complements this work by examining differences between *retail* and *large* deposits.

Second, this paper contributes to the literature on the deposits channel of monetary policy (Drechsler, Savov, and Schnabl 2017; Xiao 2020; Supera 2021; Wang et al. 2022; Choi and Rocheteau 2023; Li, Loutskina, and Strahan 2023; Drechsler et al. 2024a; Begenau and Stafford 2025; Wang 2025).[4] I connect this literature with the growing work showing that

[2] Other recent contributions include Granja and Paixao (2024) and Begenau and Stafford (2025), who show that deposit rates are set at the bank level, especially for the largest U.S. banks. Relatedly, d'Avernas et al. (2024) and Kundu, Muir, and Zhang (2024) document that deposit pricing differs between small and large banks. Erel et al. (2024), Koont (2023), Koont, Santos, and Zingales (2024), and Jiang, Yu, and Zhang (2025) show that deposit pricing strategies are affected by digital banking. Greenwald, Schulhofer-Wohl, and Younger (2023) and Emin, James, and Li (2025) show that deposit rate pass-through varies with the level of interest rates.

[3] Dias and Schmidt-Eisenlohr (2026) advocate "bargaining power" as the explanation for the higher rates that the large (uninsured) deposits get. The superior bargaining power of large depositors may come from, *inter alia*, lower effective market concentration for large deposits, cross-selling, or simply large depositors being less "sticky" (less inattentive (rationally or behaviorally), more financially sophisticated, etc.). By showing that large deposit flows are more responsive to monetary policy despite getting higher rate betas, this paper rules out the former two explanations and strongly suggests that large depositors are less "sticky".

[4] This strand of research is part of the vast literature on the bank lending channel of monetary policy.

depositors are generally "sticky"—inattentive, inert, or financially unsophisticated (Adams et al. 2021; Fleckenstein and Longstaff 2024; Yankov 2024; Egan et al. 2025; Lu and Wu 2025). Together, these two literatures are in some tension: if most depositors are sticky and do not respond to changes in interest rates, then why do we observe strong deposit flows in response to monetary policy as documented by Drechsler, Savov, and Schnabl (2017)? This paper resolves this tension by showing that it is small depositors (who constitute the vast majority of deposit *accounts*) who are sticky; large depositors, who constitute only about 1% of accounts but control about 50% of deposit balances as of 2024[5], are responsive to interest rates. Thus, I show that the deposits channel works primarily through large depositors. In this, my paper closely relates to and complements contemporaneous work by Cirelli and Olafsson (2025). They use transaction-level data from a major Icelandic bank for 2016-2024 and show that wealthier households are more responsive to deposit spreads, reallocating funds from low-rate checking accounts to high-rate savings accounts within the bank. I document the large vs. small deposits heterogeneity across all U.S. banks over five decades (1975-2024) and show that this heterogeneity fundamentally shapes the deposits channel—with large deposits accounting for the entire aggregate deposit response to monetary policy.

Third, this paper connects to the broader literature on how financial sophistication, inertia, search costs and related frictions affect pricing in financial markets. See Barber and Odean (2013), Lusardi and Mitchell (2014), Gabaix (2019), Lusardi and Mitchell (2023) for reviews. Most closely related is Brown et al. (2024), who build a quantitative dynamic model to study sources of market power in the index funds market. Like this paper, they contrast small retail and large institutional investors, and document that index fund managers price discriminate between the two. They show that this is driven by differences in financial sophistication and degree of inertia, as institutional investors adjust holdings more often, face less information friction, and exhibit higher elasticity of demand with respect to fund fees. Similarly, Hortaçsu and Syverson (2004) show that prices of institutional S&P 500 index funds are lower and less dispersed than prices of retail S&P 500 index funds, which they argue points to higher search intensity among institutional investors. In the market for environmental, social, and governance (ESG)-oriented index funds, Baker, Egan, and Sarkar (2024) document that demand from institutional investors is considerably more elastic than retail demand; Ben-David et al. (2023) document that institutional investors are less likely to participate in high-fee specialized ETFs, consistent with them being more

See, *inter alia*, Bernanke and Blinder (1988, 1992), Gertler and Gilchrist (1993), Bernanke and Gertler (1995), Kashyap and Stein (1995, 2000), Khwaja and Mian (2008), Jiménez et al. (2012, 2014), Gomez et al. (2021).

[5] Author's calculations, see Section 3 for details.

financially sophisticated; Liu, Makarov, and Schoar (2023) show that wealthy investors are more financially sophisticated in the context of crypto markets. I document similar patterns in the market for bank deposits, which is the largest source of bank funding.

Fourth, given the overlap between large deposits and uninsured deposits, this paper connects to the literature on the role of uninsured deposits in bank funding. Egan, Hortaçsu, and Matvos (2017) highlight the role of uninsured depositors in driving banks' fragility. Iyer et al. (2019) show that "too-big-to-fail" banks are able to attract and retain uninsured deposits at lower rates than other comparable banks. Relatedly, Martin, Puri, and Ufier (2022) show that insured deposits flow in and uninsured deposits flow out at banks in financial distress. The 2023 Regional Bank Crisis motivated a new literature on how interest rate risk, combined with uninsured deposit funding, can produce financial fragility (Benmelech, Yang, and Zator 2023; Metrick 2024; Drechsler et al. 2024b; Cipriani, Eisenbach, and Kovner 2024; Jiang et al. 2024; Begenau, Landvoigt, and Elenev 2025; Blickle et al. 2025; Chang, Cheng, and Hong 2025; Kim, Kundu, and Purnanandam 2025). I contribute to this strand of literature by showing that the higher sensitivity of large (uninsured) deposit flows to interest rate hikes is not limited to the 2023 Regional Bank Crisis, and is instead prevalent in the U.S. data since the 1970s. My work also shifts focus from the "uninsured" nature of large deposits—which implies risk as their differentiating characteristic—onto their size and the fact that large deposits are more likely to be held by less sticky agents such as corporations, NBFIs, and wealthy individuals. Here, this paper is also related to the nascent literature on corporate deposits (Altavilla et al. 2022; Pancost and Robatto 2023a,b; Cooperman et al. 2025). Most pertinent is Cooperman et al. (2025), who use confidential regulatory data and show that corporate deposit rates were very sensitive to market rates during the COVID-19 pandemic.[6] I document similarly high deposit betas for corporate cash sweep accounts using Ratewatch data.

Finally, this paper contributes to the literature on bank interest rate risk management and complementarities between bank assets and liabilities (e.g., Flannery 1981; Berlin and Mester 1999; Kashyap, Rajan, and Stein 2002; Purnanandam 2007; Hanson et al. 2015; Hoffmann et al. 2019; Di Tella and Kurlat 2021; Egan, Lewellen, and Sunderam 2022; DeMarzo, Krishnamurthy, and Nagel 2024; Basten and Juelsrud 2025; Begenau, Piazzesi, and Schneider 2025). I show that banks with a high share of large deposits have shorter-maturity assets. This provides a natural hedge to the more interest-sensitive large deposits, helping banks achieve stable net interest margins (Drechsler, Savov, and Schnabl 2021).

[6] See also European Central Bank (2023), showing that overnight and term deposit betas on deposits of nonfinancial corporations were higher than on household deposits in the Eurozone over the period from 2007 to 2021.

2. Conceptual framework

This section outlines a simple framework to illustrate how differences in depositor stickiness affect the deposits channel of monetary policy. A model based on Drechsler, Savov, and Schnabl (2017) is presented in Appendix A.

Consider two types of depositors: large depositors who are "responsive" and small depositors who are "sticky". I use "depositor stickiness" as a collective term for inattention (rational or behavioral), inertia, and low financial sophistication, shown to be important features of depositor behavior in recent literature (Adams et al. 2021; Fleckenstein and Longstaff 2024; Cirelli and Olafsson 2025; Egan et al. 2025; Lu and Wu 2025). Specifically, large depositors are more willing and able to substitute between bank deposits and market alternatives, such as Treasury securities or money market funds (which I will collectively call "bonds") than small depositors. The assumption that large depositors are less sticky is plausible *ex ante* for two main reasons. First, large balances imply that gains from optimizing liquid holdings between bank deposits and non-bank alternatives are large and likely outweigh (fixed) search or switching costs (Hortaçsu and Syverson 2004; Honka, Hortaçsu, and Vitorino 2017). Second, large depositors are more likely to be corporations, non-bank financial institutions such as insurance companies, or high-net-worth individuals.[7] These agents are commonly considered more financially sophisticated (Lusardi and Mitchell 2014, 2023; Graham 2022) and attentive (Gabaix 2019).

Banks offer deposits and have some market power in deposit markets. Local market power arises from a limited number of banks in a given area (concentration) and from imperfect substitutability of deposits supplied by differentiated banks. Banks set deposit rates to maximize profits, taking into account the sensitivity of depositors to changes in deposit rates. Banks can distinguish between large and small depositors and set different rates for each group.[8] Because of banks' market power, deposit rates are set below the market interest rate. But because large depositors are more willing to substitute towards bonds (more "responsive"), banks set a higher rate on large deposits than on small deposits.

[7]For example, the 2022 Survey of Consumer Finances (SCF) shows that top-1% of highest-earning households, on average, held about \$252,000 of checking deposits and \$400,000 of savings deposits, while the bottom 99% held, on average, \$14,500 and \$18,500 in checking and savings accounts, respectively (see Table A1). Similarly, Farrell and Wheat (2016) document that small firms held only \$12,100 in average daily cash balances in 2015; the cash holdings of large corporations are in the millions and even billions of dollars (see, e.g., Apple Inc.'s 2022 10-K).

[8]This price discrimination can be conceptualized as second degree price discrimination (based on quantities). It can also be thought of as third degree price discrimination (based on depositor characteristics), since banks observe whether the depositor is a corporation, observe depositor's income when they open the account, etc. This paper is agnostic about the exact model of price discrimination. Appendix A assumes that banks know depositor types.

When the central bank raises the policy rate, banks increase deposit spreads (the difference between market rate and deposit rate) as in Drechsler, Savov, and Schnabl (2017). Equivalently, pass-through from market rates to deposit rates ("deposit beta") is below one. But because large depositors are more responsive, banks increase rates on large deposits more than on small deposits. Large deposits beta is therefore higher than small deposits beta. This is the first prediction of this framework:

Prediction 1: Deposit rate pass-through (beta) is higher for large deposits than for small deposits.

Yet, because large depositors are more willing to substitute towards bonds, they are more likely to leave banks when policy rates rise. To see this, consider the extreme case when small depositors are completely sticky and do not substitute into bonds at all. In this case, banks optimally set very low deposit betas on small deposits. Still, by assumption, small depositors do not withdraw money from banks when policy rates rise, in contrast to large depositors who do reduce their deposit holdings when the Fed raises rates. Appendix A, Proposition A2 shows this result more generally in the setting of Drechsler, Savov, and Schnabl (2017). This is the second prediction of this framework:

Prediction 2: Large deposits growth is lower (higher) than small deposits growth after a monetary policy tightening (easing) shock.

Differences in local deposit market concentration cannot generate such patterns. For concreteness, assume that large depositors face lower local market concentration and hence get higher deposit betas, consistent with prediction 1. But then large deposits would not flow out more than small deposits after monetary policy tightening: they would either flow out similarly (as in Appendix A) or large deposits would flow out *less* because they get better pricing. Differences in local market concentration cannot generate prediction 2.[9]

These two predictions have an important implication for the deposits channel of monetary policy: if large deposits flow out more when policy rates rise, they are more important for the "first stage" of the deposits channel (policy-induced deposit outflows that in turn prompt banks to cut lending). The composition of deposits between large and small depositors therefore matters for the strength of the deposits channel. I discuss this further in Section 7.

[9] Prediction 1 can also be generated by cross-selling of other bank products, such as loans and wealth management services, to large depositors. In this case, banks would want to keep large depositors by offering them higher deposit betas (i.e., not exploiting their local deposit market power fully). But in this case, large depositors should be *less* likely to leave banks after a monetary policy tightening, contrary to Prediction 2.

3. Data

This section describes the data sources used in my analysis and how key variables are constructed.

Bank accounting data. For bank balance sheet and income statement data I use the Federal Financial Institutions Examination Council's (FFIEC) Consolidated Reports of Condition and Income ("Call Reports"). Call Reports cover all U.S. depository institutions regulated by the Federal Reserve System, the Federal Deposit Insurance Corporation (FDIC), or the Office of the Comptroller of the Currency (OCC), at quarterly frequency (semi-annual for income statement data before 1983). My analysis focuses on commercial banks (federal- and state-chartered) for the period 1976Q1-2024Q1. The data are publicly available via the Chicago Fed and FFIEC websites.

The key variables used in the analysis are balance sheet quantities—deposits, wholesale funding, total liabilities, total assets, loans, cash and securities—as well as deposit expense rates which proxy for average interest rates that banks pay across all their deposit products. I compute the deposit expense rate as:

$$\text{Deposit expense rate}_{it} = \frac{\text{Deposit interest expense}_{it}}{0.5(\text{Deposit balance}_{i,t-1} + \text{Deposit balance}_{i,t})},$$

where Deposit interest expense$_{it}$ is total interest expense on deposits in domestic offices of a bank i over a reporting period t (quarter since 1983), and Deposit balance$_{i,t}$ is the interest-bearing deposits outstanding at bank i as of the end of the reporting period t.[10] The deposit expense rate is computed similarly for deposit subsets, namely savings deposits, interest-bearing transaction deposits, and time deposits. The resulting deposit expense rates are available quarterly starting in 1983Q1 and semi-annually for 1976Q1-1982Q4. For regression analyses, I use linear interpolation to estimate quarterly values for the 1976Q1-1982Q4 period.

Starting in 1982Q2, Call Reports also split deposits into accounts holding \$100,000 or less and accounts holding more than \$100,000 (≤ \$250,000 and > \$250,000 starting in 2009Q3). I call the deposits below the aforementioned thresholds "small", and the deposits above "large". I compute

$$\text{Large deposits share}_{it} = \frac{\text{Large deposits}_{it}}{\text{Large deposits}_{it} + \text{Small deposits}_{it}}.$$

[10]This is a common way of proxying bank-level deposit interest rates in the literature. See, e.g., Rice and Ors (2006); Drechsler, Savov, and Schnabl (2017, 2021); d'Avernas et al. (2024); Begenau and Stafford (2025).

This variable is reported only as of June 30 each year in 1982-1990, and quarterly afterwards. I interpolate the large deposits share linearly for the period 1982Q2-1990Q4.[11] In certain analyses (e.g., Figure 1), I extend the large deposits share back to 1975 by using the share of large time deposits as a proxy, which is available since 1973. Figure A1 plots the aggregate large deposits share over time. The share of large deposits in the U.S. banking system has been large throughout the sample (ranging from 35% to 60%) and increased over time.[12]

The key challenge in using long-run Call Reports data is that accounting definitions used in this reporting change over time. Whenever possible, I construct consistent series, and drop growth rates affected by breaks otherwise. Appendix B provides further details on the data construction.

Aggregate deposit distribution. I use the Financial Accounts of the United States ("From-Whom-to-Whom") data to get the aggregate composition of deposit claims on U.S.-chartered depository institutions by sector. The "From-Whom-to-Whom" (FWTW) data are quarterly, 1965Q2-2024Q4, and available from the Federal Reserve website. I can observe deposits of households, nonfinancial corporate and non-corporate businesses, other financial businesses, government, and the rest of the world.[13] Figure A2 Panel A plots the sectoral composition of deposits over time.

I supplement the FWTW data with the Distributional Financial Accounts of the United States (available here). This dataset has quarterly data on household deposits split by income and net worth distribution, 1989Q3-2024Q1. In my analysis, I use deposits held by bottom 50%, bottom 99%, middle 50-99%, and top 1% of households by net worth.

Concentration. I use the FDIC Summary of Deposits (SOD) data to compute local deposit market concentration. The SOD data record deposits at the branch level for all insured depository institutions in the United States, annually as of June 30. The data are publicly available since 1994. I extend this dataset back to 1975 via a Freedom of Information Act (FOIA) request to the FDIC. I use the branch-level deposit data to compute several measures

[11] I generally do not interpolate *levels* of large and small deposits for my analysis of deposit flows. Such interpolation introduces noise over the period when monetary policy shocks were large, thus reducing reliability of my estimates.

[12] Some of the increase in the large deposits share is mechanical, driven by economic growth and inflation pushing more deposits above the fixed $100,000 (or $250,000) threshold. However, as Figure A2 Panel C shows, the share of deposits held by non-household sectors and top-1% of highest-income households increased very similarly, from 30% in 1989 to 47% in 2025. The composition of deposits by balance has indeed shifted away from small retail household depositors.

[13] "Other financial businesses" sector definition used in this paper is broader than that in FWTW data and encompasses all non-depository financial institutions. Specifically, I sum up deposits held by money market funds, insurance companies, finance companies, pensions, mortgage REITs, and other financial businesses (as defined in FWTW).

of local deposit market concentration. First, following Drechsler, Savov, and Schnabl (2017) and the subsequent literature, I compute county-level Herfindahl-Hirschman index (HHI). Second, I redefine the market to be a metropolitan statistical area (MSA) if a county is part of an MSA and a county otherwise. I then compute the HHI for these markets as the measure of local deposit market concentration.[14] See Appendix B for additional details.

Offered deposit rates: Ratewatch. My first data source on offered deposit rates is Ratewatch. This is a commercial dataset with weekly offered (advertised) rates at the bank-branch-product level. The vintage I work with starts in July 2001 and ends in May 2024.

Ratewatch data are very prominent in the banking literature. In principle, it covers a large number of deposit products (e.g., money market accounts with a minimum balance of $10,000, with a minimum balance of $100,000, or $1 million, etc.) But in practice, coverage of different products is very uneven. Simple small-retail products are covered best. These are: interest checking accounts with $2,500 minimum balance, savings accounts with $2,500 minimum balance, money market accounts with $10,000 and $25,000 minimum balance, and 12-month certificates of deposit (CDs) with a minimum balance of $10,000. The literature using Ratewatch has focused exclusively on these products (Drechsler, Savov, and Schnabl 2017; d'Avernas et al. 2024; Kundu, Muir, and Zhang 2024; Begenau and Stafford 2025). I study these products, but also make use of the limited information available on other products, namely those with higher required balances, so-called "relationship" or "premium" accounts, as well as certain corporate deposit accounts.

For comparison with Call Reports, I aggregate Ratewatch data to the bank-product level by taking the average of the rates offered on a given product across all branches of a given bank at a given time. This is generally straightforward and does not result in much lost information, since banks typically have the same rate across all branches (the so-called uniform deposit pricing, see Granja and Paixao (2024), Begenau and Stafford (2025)).

Offered deposit rates: Hand-collected data. Ratewatch's coverage of accounts above the small-retail tier is sparse, so I cannot rely on Ratewatch alone to study posted rates on large or premium accounts directly. To fill this gap, I assemble a parallel hand-collected panel of posted deposit rate schedules at the 32 largest U.S. commercial banks: I scrape each bank's own website for current rates and query the Internet Archive's Wayback Machine for archived snapshots of historical rates. The resulting harmonized quarterly panel covers 2015Q1-2026Q1 and contains roughly 48,000 bank-product-tier-quarter observations across

[14] This is similar to the market definition used by regulators in bank merger reviews. See, for example, Federal Reserve FAQ on Competitive Effects in Bank Mergers and Acquisitions.

savings, money market, CD, and business MMDA products. Table A2 reports coverage of this newly-assembled dataset.

Despite spanning only the past decade, the panel is challenging to construct, for three reasons. First, the Wayback Machine does not make *regular* snapshots of banks' rate pages; coverage is therefore unavoidably irregular. This problem is compounded because several large banks deploy commercial bot-protection (e.g., hCaptcha, Akamai) that returns errors or infinite redirects to any non-interactive client. Most large banks also require users to input their ZIP-code before the webpage renders rates; the Wayback crawler never does this and therefore saves empty pages. Second, most rate pages built after 2017 fetch their numbers from a separate internal API after the page mounts, so the archived HTML is empty—Citibank's main rate page, for example, has 440 archived snapshots between 2011 and 2015, not one of which records a single rate. Third, even when an archived page does contain rates, the page itself may not have been updated for years, masking rate changes that survive only on separately posted, dated PDF rate sheets at URLs no longer reachable on the live site. Reconstructing each bank's continuous timeline therefore requires combining several source types—server-rendered HTML pages, dated PDF rate sheets, JSON or JSONP rate APIs, and in some cases embedded JavaScript variable files—and tracking down obsolete URL conventions across each bank's archival history. Appendix C describes the sources, scraping pipeline, and resulting panel in detail.

Other bank-level data. To study risk faced by bank depositors, I supplement the bank-level data described above with the FDIC's list of bank failures following Correia, Luck, and Verner (2025). I also collect data on banks' bond prices from LSEG Mergent Fixed Income Securities Database (FISD) and FINRA's TRACE dataset. Appendix B describes how these data are cleaned and merged in with the main bank data. I use Gürkaynak, Sack, and Wright (2007) estimated Treasury yield curve model to compute maturity-matched bond spreads.

Macroeconomic data. I obtain effective federal funds rate, 3-month T-Bill rate, 1-, 2- and 10-year Treasury yields, real GDP, consumer price index (CPI), unemployment rate, and Moody's seasoned Baa corporate bond spread relative to 10-year Treasury from the Federal Reserve Bank of St. Louis' FRED database. For robustness analyses, I also obtain aggregate banking sector statistics from the Federal Reserve's H8 release, as well as Historical Bank Data from the FDIC. Finally, I collect data on monetary policy shocks. I use Romer and Romer (2004) shocks, as extended to 2018 by Miguel Acosta. I also use Bauer and Swanson (2023) high-frequency monetary policy shocks, downloaded from the San Francisco Fed's website.

Table 1 reports summary statistics for the main bank-level variables used in the analysis, including deposit expense rates and offered rates on select retail deposit products from Ratewatch, large deposit share, growth rates of deposits and other bank balance sheet quantities, as well as local deposit market concentration measures. Table A3 reports correlations between the large deposit share and other bank-level variables. The share of large deposits is positively correlated with bank size; it is also positively correlated with bank book equity ratio and return on assets, especially since 2000. The large deposit share is negatively correlated with HHI and bank age. Table A4 shows that large deposit share is very persistent over time. Within 1 year (5 years), the probability of remaining in the top quintile is 0.81 (0.65), and the probability of remaining in the bottom quintile is 0.76 (0.58).

4. Pricing of large vs small deposits

In this section, I examine the pass-through from policy rates to deposit rates and how it differs by deposit balance size.

4.1. Deposit betas increase with the share of large deposits across every monetary policy cycle since 1975.

Given the lack of direct comprehensive data on deposit rates by deposit balance, I first employ an indirect approach and study how deposit expense rates and betas vary with the share of large deposits at the bank level. The idea is as follows. Consider total deposit expense beta, defined for a given bank i and a given period $[t_0, t_1]$ as:

$$\text{Deposit expense beta}_{i,t_0\to t_1} = \frac{\text{Dep. exp. rate}_{i,t_1} - \text{Dep. exp. rate}_{i,t_0}}{\text{Short rate}_{t_1} - \text{Short rate}_{t_0}},$$

where Dep. exp. $\text{rate}_{i,t}$ is defined in Section 3 and Short rate_t is the short rate in period t, chosen to be the effective federal funds rate.[15] Total deposit expense beta is a weighted average of the small and large deposit account betas:[16]

$$\text{Dep. exp. beta}_{i,t_0\to t_1} \approx (1-\alpha^{Large}_{i,t_0})\text{Dep. exp. beta}^{Small}_{i,t_0\to t_1} + \alpha^{Large}_{i,t_0}\text{Dep. exp. beta}^{Large}_{i,t_0\to t_1}.$$

[15]The results are unchanged if I use 3-month Treasury yield instead.

[16]There is also a third "covariance" term, $(\alpha^{Large}_{i,t_1} - \alpha^{Large}_{i,t_0})(\text{Dep. exp. rate}^{Large}_{i,t_1} - \text{Dep. exp. rate}^{Small}_{i,t_1})/\Delta_{t_0,t_1}\text{SR}$. This term is empirically small and is thus ignored for simplicity.

Assuming that small and large deposit betas are approximately equal across banks[17], we have that:

$$\text{Dep. exp. beta}_{i,t_0\to t_1} \approx \text{Dep. exp. beta}^{Small}_{t_0\to t_1} + \alpha^{Large}_{i,t_0}\left(\text{Dep. exp. beta}^{Large}_{t_0\to t_1} - \text{Dep. exp. beta}^{Small}_{t_0\to t_1}\right). \quad (1)$$

Thus, if large deposit betas are higher than those on small deposits, we should observe a positive relationship between total deposit expense beta and the share of large deposits across banks.

I test this hypothesis using Call Reports data for the period 1975Q1-2024Q1. In the first step, I identify tightening monetary policy cycles as periods when the federal funds rate increases from its local trough to local peak (e.g., the most recent tightening cycle 2022Q1-2024Q1), and easing cycles as periods when the federal funds rate declines from its local peak to local trough.[18] Equipped with the cycle dates, I compute total deposit expense betas for each bank over each cycle and plot these betas against the share of large deposits.

Figure 1 shows the results. It is a binscatter plot of total deposit expense betas over each monetary policy cycle against the share of large deposits at the beginning of the cycle. The figure shows a strong positive relationship between total deposit expense betas and the share of large deposits across banks in every tightening monetary policy cycle since 1975, consistent with the hypothesis that betas on large deposits are higher than betas on small deposits. This also holds for easing cycles, as shown in Figure A4. This result is not driven by local deposit market concentration (Figure A5); the results are also similar for deposit subtypes, namely savings (Figure A6) and time deposits (Figure A7). Figure A8 shows explicitly that banks with higher share of large deposits raise their deposit expense rates more during tightening cycles and end up with higher deposit expense rates at the end of tightening cycles; thus, the result in Figure 1 cannot be explained only by banks with a higher share of large deposits paying *lower* deposit rates and then catching up when market rates rise.

To examine the relationship between deposit betas and the share of large deposits more formally, I run panel local projections (Jordà 2005):

$$\Delta\text{Dep. exp. rate}_{i,t-1,t+h} = \alpha^h_t + \beta^h \Delta\text{FFR}_t \times \text{Lrg. dep. share}_{i,t-1} + \Gamma^h X_{i,t} + \varepsilon_{i,t+h}, \quad (2)$$

[17] The results below support this assumption. See Figure A12.

[18] Figure A3 plots the federal funds rate and highlights the identified tightening and easing cycles. Table A5 lists the start and end dates of each cycle, as well as their duration and the change in the federal funds rate during each cycle.

where ΔDep. exp. rate$_{i,t-1,t+h}$ is the change in deposit expense rate at bank i from $t-1$ to $t+h$, α_t^h is the time fixed effect, ΔFFR_t is the change in the federal funds rate from $t-1$ to t, and Lrg. dep. share$_{i,t-1}$ is the share of large deposits at bank i as of $t-1$. The vector $X_{i,t}$ includes 4 lags of the dependent variable and 4 lags of ΔFFR_t, all interacted with Lrg. dep. share$_{i,t-1}$, and interacted with controls—log of local deposit market HHI, log of bank age, share of bank's time and savings deposits that reprice within 3 months and between 3 and 12 months, book capitalization ratio, and share of liquid assets (cash and securities) in total assets, all measured as of $t-1$. I estimate this equation for horizons $h = 0, 1, \ldots, 8$ quarters ahead. The coefficient of interest is β^h, which captures how the response of deposit expense rates to changes in the short rate varies with the share of large deposits. The share of large deposits (and certain other controls interacted with the short rate change, e.g., HHI) is standardized such that a one-unit change in these variables corresponds to an increase from 25th to 75th percentile in their respective distributions within each quarter. I run these local projections both with raw changes in the short rate and instrumenting these changes with Romer and Romer (2004) and Bauer and Swanson (2023) monetary shocks in LP-IV specifications (Jordà and Taylor 2025).[19]

Figure 2 shows the results. Figure 2 Panel A plots the estimated impulse response function (IRF) of total deposit expense rates to a one percentage point increase in the short rate, *incremental* for banks at the 75th percentile vs 25th percentile of the share of large deposits. The figure shows that banks with a higher share of large deposits respond significantly more to increases in the short rate, with the difference in responses (deposit betas) between banks at the 75th and 25th percentiles of the share of large deposits reaching about 4 basis points (bps) for each 100 bps increase in the short rate after 4 quarters. This difference is economically significant and represents about 25% of the standard deviation in deposit expense betas across banks in a typical monetary policy cycle. The results are qualitatively similar (but quantitatively stronger) when using Romer and Romer (2004) or Bauer and Swanson (2023) monetary shocks as instruments for changes in the short rate (Panels B and C of Figure 2).

Table 2 and Table A6 report these results in tabular form, highlighting that the coefficient on the interaction between the change in the short rate and the share of large deposits is positive and statistically significant at all horizons. The results also carry over

[19] Given the persistence of changes in the short rate, the local projections with raw changes in the short rate do not represent the response to a one-time change. I address this issue by controlling for leads in the short rate and their interactions with the share of large deposits and other controls, as suggested by Alloza, Gonzalo, and Sanz (2025). Note that I do not control for leads in LP-IV specifications, as the shocks are less persistent. The results are reassuringly similar.

to deposit subtypes separately, namely savings and time deposits (Figure A9), and to the sample of the top-10% of banks by total assets (Figure A10).

Taken together, the results show that deposit betas are higher for banks with a higher share of large deposits across every monetary policy cycle since 1975, consistent with betas on large deposits being higher than betas on small deposits.

4.2. Betas on small retail deposit products are low and do not vary with the share of large deposits.

A concern with the results above is that banks that have more large deposits may be different in other ways. For example, if banks that have more large deposits face relatively stronger credit demand when monetary policy tightens, they may raise rates relatively more to attract deposits to meet this credit demand. I address this concern by comparing total deposit expense betas documented above to betas on *small retail* deposit products. This is a placebo test: rate betas on small deposits should not increase with the share of large deposits in the cross-section of banks.

I turn to Ratewatch data and focus on four well-covered small retail products (see Section 3 for additional discussion of Ratewatch data): interest checking accounts with $2,500 minimum balance, savings accounts with $2,500 minimum balance, money market accounts with $10,000 minimum balance, and 12-month certificates of deposit (CDs) with a minimum balance of $10,000. I compute product-level deposit betas for each bank over each monetary policy cycle in the same way as in the previous subsection, and plot these betas against the share of large deposits at the beginning of the cycle.

Figure 3 shows the results of this exercise. The figure plots binscatters of betas on savings accounts with $2,500 minimum balance against the share of large deposits at the beginning of the cycle, as well as the corresponding savings deposit expense betas computed from Call Reports, for all monetary policy cycles since 2001 (the start of Ratewatch data). Small savings accounts have very low deposit betas, 0.14 on average, and these betas do not vary with the share of large deposits across banks. In contrast, the corresponding Call Reports deposit expense betas are significantly higher and increase strongly with the share of large deposits. Similar findings hold for money market accounts with $10,000 minimum balance and interest-bearing checking accounts with $2,500 minimum balance (Figure A11): rates on these small retail deposit products exhibit low and insensitive betas that do not vary with the share of large deposits, while the corresponding Call Reports deposit expense betas are significantly higher and increase strongly with the share of large deposits.[20]

This result shows that banks with a higher share of large deposits do *not* pay higher and more sensitive rates on *all* deposit products. Banks with high and low shares of large deposits have similarly low and insensitive rates on small retail deposit products. Figure A12 shows that betas on large deposits (inferred from total deposit expense betas and small deposit betas using Equation 1) are also similar across banks with higher vs lower share of large deposits. Instead, as in Equation 1, the higher deposit expense betas at banks with a higher share of large deposits are driven by their different deposit composition between small (low-beta) and large (high-beta) deposits.

I exploit this idea further and estimate the following regression:

$$\text{Dep. exp. beta}_{i,c} = \gamma_{0,c} + \gamma_{1,c}\text{Lrg. dep. share}_{i,c} + \varepsilon_{i,c},$$

where Dep. exp. $\text{beta}_{i,c}$ is the deposit beta for bank i over cycle c and Lrg. dep. $\text{share}_{i,c}$ is the share of large deposits at bank i as of the beginning of the cycle c. I run this regression separately for each monetary policy cycle since 2001 using Call Reports deposit expense betas. $\gamma_{0,c}$ recovers an estimate of the average deposit beta at banks with no large deposits—i.e., an estimate of small deposit betas—while $\gamma_{1,c}$ recovers an estimate of the difference between large and small deposit betas. $\gamma_{0,c} + \gamma_{1,c}$ is then the average deposit beta at banks with only large deposits—i.e., an estimate of large deposit betas.

Figure 4 and Table 3 show the results for the monetary cycles after 2001, when Ratewatch data is available. Figure 4 plots the inferred small and large deposit betas for each cycle, while Table 3 reports these results in tabular form. Inferred betas on large deposits are much higher than those on small deposits in every cycle, with the difference being statistically significant for all cycles. The average inferred small deposit beta is 0.24, while the average inferred large deposit beta is 0.58, more than double that of small deposits. Note that the inferred small deposit betas are quite close to the actual betas on small retail deposit products, lending further credence to this exercise. The results are similar for savings and interest-bearing transaction deposits separately (Figure A13 and Table A7). They also hold further back in time, before Ratewatch data become available (Figure A14). In the full sample, the average inferred small deposit beta is 0.3, while the average inferred

[20] Figure A11 Panel C shows the binscatter for 12-month CDs with $10,000 minimum balance (12MCD10K) and the corresponding Call Reports deposit expense betas for *small* time deposits (<$100,000 before 2010Q1, <$250,000 thereafter). The pattern disappears: both Ratewatch and Call Report betas do not robustly increase with the share of large deposits. This is consistent with the main findings because small time deposits are (predominantly) retail deposit products. This "placebo" test further supports my hypothesis that large deposits are significantly more sensitive to market rates than small retail deposits.

large deposit beta is 0.7.

4.3. Banks use balance-tiered deposit pricing.

I now provide direct evidence that banks use balance-tiered pricing, with higher rates paid on larger deposit balances. I start with the Ratewatch data. In principle, Ratewatch covers many deposit products, including those with different minimum balance requirements. However, as discussed in Section 3, the coverage of different deposit products is highly uneven. Small retail deposit products (e.g., savings accounts with minimum balance $2,500, interest-checking accounts with minimum balance $2,500) are well covered, while large-balance deposit products (e.g., savings accounts with minimum balance $250,000 or above, interest-checking accounts with minimum balance $250,000 or above) are covered sporadically. Nevertheless, even these sparse data—ignored by previous research—help shed light on how deposit pricing varies by balance size.

Figure A15 plots rates on select deposit products with different minimum balance requirements at select large banks. Panel A plots money market deposit account (MMDA) rates with $10,000, $100,000, and $250,000 minimum balance, as well as rates on "premium" MMDA accounts with $100,000 minimum balance, with $250,000 minimum balance.[21] Panel B plots savings account rates with $2,500, $100,000, and $500,000 minimum balance as well as "relationship" accounts with $1 million minimum balance. Rates on the high-balance products are often missing in the Ratewatch data; but whenever they are available, they are significantly higher and more responsive to monetary policy than the rates on the simple retail products. For example, at Wells Fargo, the third-largest bank in the U.S., the rate on a savings account with a $1 million minimum balance rose from 1.1375% in September 2004 to 4.04% in December 2006 (beta of 0.8), while the rate on a savings account with a $2,500 minimum balance rose from 0.1725% to 0.4% over that same time period (beta of only 0.06). Similarly, at Bank of America, MMDA rates on premium $100,000 MMDA increased from 1% to 4.25% between July 2004 and September 2006 (beta of 0.81), while rates on $10,000 MMDA increased only a little, from 0.464% to 0.616% (beta of 0.04).

I supplement Ratewatch with hand-collected data on banks' posted rate schedules, gathered from banks' websites as described in Section 3 and Appendix C. Table 4 shows select examples of banks paying higher rates on larger deposit balances. Panel A shows pricing of savings deposits at Wells Fargo. A clear pattern emerges. When the monetary policy rate is low, Wells Fargo offered the same low rate on all savings deposits, *regardless of*

[21] "Premium" and "relationship" deposit products are effectively just high-balance deposit products; see Appendix D for additional discussion.

balance. But when the federal funds rate went up, Wells Fargo kept rates on small deposits low, and increased rates on large deposits. The same pattern holds for TD Bank (Panel B) and for Zions Bancorporation (Panel C).[22] Figure A16 shows how this balance-tiered deposit pricing looked on these banks' websites. For example, in May 2021, when the federal funds rate was at 6bps, Wells Fargo offered 2bps on all savings deposits, regardless of balance. But in December 2023, when the effective federal funds rate was at 5.33%, Wells Fargo offered 0.25% on balances ≤ $100,000, 1.01% on balances between $100,000 and $500,000, 2% on balances between $500,000 and $1 million, and 2.5% on balances above $1 million. The rate passthrough for the largest balance was thus 0.47 vs 0.04 on the lowest balance.[23]

Figure 5 summarizes the balance-tiered deposit pricing across monetary policy cycles in my hand-collected data. Panel A shows the share of banks in my sample that post tiered rates on savings and money market deposit accounts. The share strongly correlates with the federal funds rate—banks offer the same low rate to everyone when the policy rate is low, and offer tiered rates (higher rates for higher balances) when the Fed hikes. Panel B documents directly that the rates (APY) on the highest savings deposit balance tier are much more sensitive to changes in the policy rate than the rates on the bottom deposit tier. The average top-tier rate rises from 0.26% in 2022Q1 to 2.22% in 2024Q1, while the average bottom-tier rate rises from 0.16% to only 0.95% (betas of 0.4 vs 0.16). This divergence is even more pronounced for the median bank, for which the bottom-tier rates stay essentially flat close to 0%, while the top-tier rates increase similarly to the mean.

Finally, I also provide direct evidence that deposit pricing for large firms is more rate-sensitive than small-retail deposit pricing. Table A8 documents tiered pricing on *business* savings accounts. The pricing structure is very similar to that for individuals' deposits documented in Table 4 and discussed earlier in this section. Figure A15, Panel C also shows rates on corporate sweep accounts with minimum balance of $100,000 and $1 million. These accounts are used by corporations to "sweep" excess cash into interest-

[22]These three banks are chosen to represent different size bins in my hand-collected data. Wells Fargo is the third-largest bank in the U.S. as of 2023Q4. TD Bank is 10th, with only about 1/5 of the total assets of Wells Fargo. Zions Bancorporation is a "super-regional" bank, with 5% of total assets of Wells Fargo as of 2023Q1.

[23]The deposit rates studied here are *advertised* rates, and can be different from what depositors are actually *paid*. Ratewatch similarly posts advertised rates, and I confirmed that rates on small deposit accounts in my hand-collected data are consistent with the rates reported in Ratewatch. As shown in Figure 4 and Table 3, small deposit betas are similar whether inferred from Call Reports (and thus reflecting rates actually *paid*) or based on Ratewatch (advertised rates). It is harder to verify whether offered rates on large deposits reflect the rates these depositors are paid. Figure 4 and Table 3 suggest that the paid rate betas on large deposit accounts might be *higher* than their advertised rate betas. This could be explained by high-net-worth individuals and businesses getting even more favorable negotiated pricing than what is posted online.

bearing accounts overnight. The rates on these accounts are significantly higher and more sensitive to market rates than those on small retail savings deposit products. For example, at Bank of America, the rate on $100,000 corporate sweep account increased from 1.1% in July 2004 to 4.56% in September 2006, for a beta of 0.96.

Overall, the direct evidence from Ratewatch and posted rate schedules shows that banks use balance-tiered deposit pricing, with significantly higher and more policy-sensitive rates paid on larger deposit balances.

4.4. Differences in risk cannot explain the pricing patterns.

The core challenge in interpreting the results in this section is that large deposits tightly overlap with uninsured deposits, both conceptually and as a matter of definition. [24] As such, one prominent difference between large and small deposits is that the former have some uninsured component and thus are potentially riskier. If depositors demand compensation for this risk, and if these risk premia are large enough and positively correlated with market rates, then the higher betas on large deposits could be due to risk, not higher "base rate" betas.

I show that risk premia cannot explain the pricing differences between large and small deposits. First, Figure A18 plots monthly average Baa corporate bond spreads (Moody's Baa corporate bond yield minus 10-year Treasury yield) and average bank bond spreads (computed from TRACE data, maturity-matched spreads between bank bond yields and Treasury yields) over 1985-2024. The figure shows that bank bond spreads (and corporate bond spreads more generally) are *negatively* correlated with the federal funds rate, not positively, as would be needed to explain my results. Second, Figure A19 repeats the bin-scatter analysis as in Figure 1, swapping deposit betas for change in bank bond spreads over monetary policy cycles. The figure shows no relationship between changes in bank bond spreads and the share of large deposits across banks, suggesting that banks with a higher share of large deposits do not become riskier during tightening cycles (they are also not riskier per se, as shown in Figure A20).

Third, I follow Correia, Luck, and Verner (2025) and test whether banks with a higher share of large deposits are more likely to fail. I run the following regression:

$$\text{Fail}_{i,t+h} = \alpha + \beta \text{Lrg. dep. share}_{it} + \Gamma X_{it} + \varepsilon_{it}, \tag{3}$$

[24] Recall that I define large deposits in Call Reports data as deposits above $100,000 before 2009Q3 and above $250,000 thereafter, which roughly correspond to federal deposit insurance limits. The overlap is not perfect, as $250,000 became the effective insurance limit in 2008Q3 (with the Emergency Economic Stabilization Act of 2008, made permanent under The Dodd-Frank Act of 2010).

where $\text{Fail}_{i,t+h}$ is an indicator variable equal to 1 if bank i fails within h years of time t, and 0 otherwise; Lrg. dep. share_{it} is the share of large deposits of bank i at t; and X_{it} is a vector of control variables including log total assets, log bank age, dummies for quartiles of bank's past 3-year asset growth, and past 3-year GDP growth. Following Correia, Luck, and Verner (2025), I aggregate the data to the annual frequency (taking year-end values) and run this regression for horizons $h = 1, 3, 5$ years ahead. β captures whether banks with a higher share of large deposits are more likely to fail. The results, shown in Table A9, indicate that, if anything, banks with a higher share of large deposits are *less* likely to fail in the short run, although the estimates are only marginally statistically significant.

I also run the following predictive regression:

$$\text{Fail}_{i,t+h} = \alpha + \beta_1 \text{Lrg. dep. share}_{it} + \beta_2 \text{Lrg. dep. share}_{it} \times r_t + \Gamma X_{it} + \varepsilon_{it}, \tag{4}$$

where r_t is either change in the short rate or Romer and Romer (2004) shock at time t. In addition to controls included in Equation 3, X_{it} also includes four lags of r_t and various interactions: of lagged r_t with large deposits share, and r_t and its lags with log total assets and log bank age. The coefficient β_2 captures whether banks with a higher share of large deposits are more likely to fail when monetary policy tightens. The data used in this specification are quarterly, and I run this regression for horizons $h = 4, 12, 20$ quarters ahead (1, 3, 5 years ahead, respectively). Table A10 shows the results. β_2 is mostly negative—suggesting that, if anything, banks with a higher share of large deposits are *less* likely to fail when monetary policy tightens.

Finally, I exploit the fact that the largest banks in the U.S. are considered "too-big-to-fail"— they are thought to have a lower risk of failure due to implicit government support (O'Hara and Shaw 1990; Flannery 2010; Strahan 2013). If risk premia were driving the results, then the relationship between deposit betas and the share of large deposits should be much weaker among the largest banks. Figure A21 replicates the binscatter analysis in Figure 1 and Figure 3, splitting out the largest 5 banks by total assets at the beginning of each monetary policy cycle into their own bin. The figure shows that the relationship between deposit betas and the share of large deposits is similar among the largest banks and other banks. The largest "too-big-to-fail" banks have a high share of large deposits and high deposit betas, consistent with the main results.

This section documents that large deposits are priced much more competitively than small deposits. Large deposits exhibit consistently higher rate betas across all monetary policy cycles since 1975. These pricing patterns cannot be explained by risk premia.[25]

5. Deposit flows: Large vs small deposits

I now turn to testing prediction 2, which says that large deposits' growth is expected to be lower (higher) than small deposits growth after a monetary policy tightening (easing) shock.

I start by testing this on the aggregate U.S. data using Jordà (2005) local projections. I estimate the following specification:

$$\Delta_{t-1,t+h} \log Y = \alpha^h + \beta^h \text{MP shock}_t + \Gamma^h X_t + \varepsilon_{t+h}, \tag{5}$$

where $\Delta_{t-1,t+h} \log Y$ is log-change from $t-1$ to $t+h$ in Y_t which is either total deposits, large deposits, or small deposits, all deflated by CPI. MP shock$_t$ is a monetary policy shock, measured either as the simple quarter-on-quarter change in the effective federal funds rate, Romer and Romer (2004) monetary shock, or Bauer and Swanson (2023) high-frequency monetary shock. The latter two shocks are normalized so that the impulse responses correspond to a 100bps change in the FFR. X_t is a vector of controls, including 2 lags of the dependent variable, 2 lags of the monetary shocks, as well as controls for real GDP growth and inflation, their lags, and controls for quarters (to capture seasonality) and for zero lower bound (ZLB) period. I estimate these local projections for horizons $h = 0, 1, \ldots, 8$ quarters.

Figure 6 plots the resulting impulse response functions (IRFs). Panel A shows that total deposits growth declines following a tightening Romer and Romer (2004) shock, consistent with the deposits channel. Panels B and C show that this response is entirely driven by large deposits: large deposits decline sharply following the tightening shock, while small deposits, if anything, slightly increase. This is consistent with prediction 2. Figure A22 shows that this result is robust to using high-frequency monetary policy shocks as well as to using the simple ΔFFR directly. It also holds separately for large and small banks, as shown in Figure A23. This finding is also *not* driven by brokered deposits, which are typically thought of as wholesale funding (Figure A24).

To further establish robustness of this result, in particular across time periods,

[25] Dias and Schmidt-Eisenlohr (2026) calculate that the average loss on uninsured deposits has historically been too small to justify the sizeable rate premium on large (uninsured) deposits. They show that given the average bank failure rate since 1991 (0.3%) and the average loss rate for uninsured depositors at the failed banks (6%), the risk-neutral expected risk premium on large (uninsured) deposits is less than 2bps, which is an order of magnitude smaller than the rate premia documented in this section.

Figure A25 plots year-over-year real growth rates for total deposits against the year-over-year changes in the effective federal funds rate. The deposits data are aggregated from the Call Reports, representing total deposits held by U.S. commercial banks. As in Drechsler, Savov, and Schnabl (2017), the deposit growth is strongly negatively correlated with changes in the short rate, forming the basis of the deposits channel. I split total deposits into large and small deposits, and plot their growth rates in Figure A25 as well. The large deposits flows are strongly negatively correlated with changes in the short rate, while small deposits flows are much more muted. This suggests that *large* deposits are driving the aggregate deposit response to monetary policy, while small deposits appear much more sticky. This result holds throughout the whole period 1985-2024.

Does this mean that small deposits are completely unresponsive to monetary policy and market rates? No. I split both small and large deposits into non-time (demand and savings) and time deposits, and estimate Equation 5 for these dependent variables. Figure A26 shows that both large and small deposits *rotate* from lower-yielding non-time deposits to higher-yielding time deposits following a monetary tightening shock, but only large deposits decline overall.[26] This suggests that even small retail depositors are not completely inattentive to interest rates; they do respond to relative rates across different deposit products, but they do not leave banks altogether. This is consistent with the framework outlined in Section 2 and in Appendix A where the main difference between large and small depositors is that large depositors are better at or more willing to invest in non-deposit financial products such as bonds or money market funds. This is also consistent with prediction 2 — within deposits that decline following tightening monetary shocks (demand and savings), large deposits decline about twice as much at horizons ≥ 1 year.

I supplement this analysis of aggregate U.S. banking data (compiled from Call Reports) with analyses of aggregate deposit flows by sector and—for household deposits—by wealth distribution, using the Financial Accounts and the Distributional Financial Accounts of the United States (see Section 3). This serves two main purposes. First, it offers insight into which large depositors—wealthy households, non-financial corporations, or non-bank financial businesses—drive the outflows of large deposits following monetary tightening. Second, it helps alleviate concerns with measuring large deposits as those above the FDIC insurance limit.[27] I estimate local projections as in Equation 5, with the dependent

[26]The fact that time deposits flow *in* following monetary policy contractions is well-established in the literature. See Drechsler, Savov, and Schnabl (2017); Supera (2021); Drechsler et al. (2024a).

[27]For example, one could be concerned that any deposit slightly above the insurance limit (e.g., $251,000) could become a "small" deposit after the holder moves part of this deposit out of the banking system (e.g., moves $21,000 to money market funds, leaves $230,000 in the bank after monetary tightening). This can *mechanically* make the above-insurance-limit deposits decline more than the below-insurance-limit deposits

variable Y being, alternately, deposits of bottom-99% of households by net worth, deposits of top-1% of households by net worth, deposits of nonfinancial corporations, deposits of nonfinancial noncorporate businesses, and deposits of other (non-depository) financial businesses, all deflated by CPI.

Figure A27 plots the resulting IRFs. As expected from my previous results, I see that it is deposits of the top-1% of wealthiest households that decline following tightening monetary policy shocks; deposits of the bottom-99% of households by net worth, if anything, slightly increase.[28] But—perhaps surprisingly—nonfinancial corporate and non-corporate businesses' deposits do not decline on tightening monetary shocks. One possible explanation for this is that nonfinancial businesses maintain deposits for mostly operational reasons and thus do not move around to maximize rates quite as much as, e.g., wealthy households.[29] Deposits of non-depository financial businesses, on the other hand, clearly decline following monetary tightening.

I now turn to bank-level analysis. Specifically, if large deposits flow out more when the Fed tightens policy, I expect total deposits to decline more at banks with a higher share of large deposits before the tightening. However, it is unclear whether this response is symmetric across tightening and easing cycles, even if aggregate deposit flows are. When the Fed lowers rates, large depositors increase their deposit holdings, but they do not necessarily return their funds to the bank from which they withdrew in the previous tightening cycle. Therefore, I estimate the following flexible local projections:

$$\begin{aligned}\Delta \log \text{Deposits}_{i,t-1,t+h} = \alpha_t^h + \beta^{h,+} \Delta \text{MP shock}_t^+ \times \text{Lrg. dep. share}_{i,t-1} \\ + \beta^{h,-} \Delta \text{MP shock}_t^- \times \text{Lrg. dep. share}_{i,t-1} + \Gamma^h X_{i,t} + \varepsilon_{i,t+h}, \qquad (6)\end{aligned}$$

where $\Delta \log \text{Deposits}_{i,t-1,t+h}$ is the change in log real deposits at bank i from $t-1$ to $t+h$. MP shock_t^s is monetary policy shock in t, split separately into positive shock $\text{MP shock}_t^+ = \max\{\text{MP shock}_t, 0\}$ and negative shock $\text{MP shock}_t^- = \min\{\text{MP shock}_t, 0\}$. $\text{Lrg. dep. share}_{i,t-1}$ is the share of large deposits at bank i as of $t-1$. α_t^h is the time fixed effect, and the vector $X_{i,t}$ includes 4 lags of the dependent variable and 4 lags of the monetary shock, all interacted with $\text{Lrg. dep. share}_{i,t-1}$, and interacted with controls—log

following monetary tightening, even if true "large" and "small" deposits are similarly responsive to monetary policy.

[28]Note that the deposit flow sensitivity to monetary policy seems to increase monotonically over the net-worth percentiles. Figure A28 shows that the deposits of the bottom 50% of depositors by net worth robustly *increase* following monetary tightening shocks. Deposits of the middle 50-99% do not respond. And the deposits of the top-1% of households sharply *contract* following tightening monetary shocks.

[29]The higher deposit rates that (large) nonfinancial businesses still seem to get, as shown in Section 4, may then stem from cross-selling (Basten and Juelsrud 2025).

of bank age, log HHI, and log of total assets, all measured as of $t-1$. I estimate this equation for horizons $h = 0, 1, \ldots, 8$ quarters ahead. The coefficients of interest are $\beta^{h,+}$ and $\beta^{h,-}$, which capture how the response of deposits to tightening and easing monetary policy varies with the share of large deposits. The share of large deposits is standardized such that a one-unit change corresponds to an increase from 25th to 75th percentile in the distribution of this variable within each quarter. As before, I use, alternately, changes in the federal funds rate, Romer and Romer (2004) shocks, and Bauer and Swanson (2023) high-frequency shocks as MP shock$_t$. The latter two are scaled so that they represent a 100bps change in the federal funds rate.

Table 5 shows the results. Consistent with the aggregate finding that large deposits flow out more following tightening monetary policy than small deposits, banks with a higher share of large deposits see larger total deposit outflows following federal fund rate hikes. The impulse response is statistically and economically significant: banks at the 75th percentile of the distribution of large deposits share see 1.2% (2%) lower total deposits at the 1-year (2-year) horizon. However, as hypothesized above, the effect is asymmetric between policy tightenings and easings. Following rate cuts, banks with more large deposits see lower deposit inflow; this effect is much smaller and mostly not statistically different from zero.[30] Table A12 shows that this result is similar when using Romer and Romer (2004) and Bauer and Swanson (2023) monetary policy shocks.

I briefly comment on potential endogeneity of the results in this subsection. Even if monetary policy shocks are exogenous to economic conditions, differential deposit response from large and small deposits may be driven not by different rate sensitivity of their holders, but by them being affected differently by the shocks in other ways. For example, if large depositors' income is more sensitive to monetary policy shocks, this may drive their deposits response. However, Favara, Loria, and Zakrajšek (2025) show that it is low-income households who are more sensitive to monetary policy shocks. For firms, Gertler and Gilchrist (1994) and Crouzet and Mehrotra (2020) show that large firms are less responsive to monetary shocks; relatedly, Greenwald, Krainer, and Paul (2025) show that large firms are able to draw on pre-arranged credit lines to smooth their cash holdings. Together, these findings suggest that if anything, small depositors should be more sensitive to monetary policy shocks, which is the opposite of what I find. Furthermore, the fact that the deposit rate and flow results are similar when using raw changes in the policy rate and

[30] Note from Table 5 that the total deposits response by HHI—albeit much weaker than the response by large deposits share, see also Section 6—is also asymmetric, with negative response to rate hikes and positive response to rate cuts. Table A11 shows the results of estimating local projections as in Equation 6 but not splitting ΔFFR into positive and negative parts.

identified monetary policy shocks (Romer and Romer (2004) or Bauer and Swanson (2023)) also suggests that the differential large vs small deposits response is due to different *rate pass-through* and not due to other channels through which monetary policy may affect depositors.[31]

Overall, the evidence in this section strongly supports prediction 2: large deposits respond strongly to monetary policy shocks, while small deposits are much more sticky. I find that, in aggregate, large deposits account for the *entire* total deposits' response to monetary policy shocks. Small deposits reallocate from demand and savings to time deposits, but do not contract overall. In the cross-section, banks that rely more on large deposits face higher deposit outflows when the Fed tightens monetary policy.

6. Comparison with local deposit market concentration

The previous section shows that small deposits are sticky and do not leave the banks following monetary policy tightening shocks, despite receiving low and rate-insensitive deposit rates, while large deposits flow in and out of banks in response to monetary policy. In this section, I gauge the quantitative importance of this heterogeneity in explaining deposit pricing. To this end, I compare it with *local deposit market concentration*, which has been prominent as a cross-sectional driver of deposit pricing in the literature (Berger and Hannan 1991; Neumark and Sharpe 1992; Drechsler, Savov, and Schnabl 2017; Li, Loutskina, and Strahan 2023; Li, Ma, and Zhao 2025).

I revisit Equation 2 and plot impulse response functions of total deposit expense rates to Romer and Romer (2004) monetary policy shocks *both* by the share of large deposits and by local deposit market HHI.[32] Both large deposits share and local deposit market HHI are standardized so that a unit increase corresponds to moving from the 25th to the 75th percentile of their respective distributions within each quarter. The IRFs are thus comparable in magnitude across the two variables and plotted on the same scale. Figure A31 shows that banks with a higher share of large deposits increase their deposit expense rates significantly more following a monetary policy tightening shock, as shown in Section 4. In contrast, local deposit market HHI is not a robust predictor of deposit

[31] Figure A29 shows that ΔFFR and identified monetary shocks predict opposite impulse responses for real GDP. The real GDP IRFs are positive in response to FFR hikes, because of the endogeneity of monetary policy—the Federal Reserve raises rates when the economy is strong. The real GDP IRFs to Romer and Romer (2004) and Bauer and Swanson (2023) high-frequency monetary shocks are negative, reflecting contractionary effects of tighter monetary policy.

[32] The choice of the shock is not important here. Table A6 and Table 2 show that the results are similar if I measure monetary policy using raw changes in the federal funds rate or Bauer and Swanson (2023) high-frequency shocks.

expense rate sensitivity to monetary policy shocks (see also Table A6). Not only are the IRFs on log HHI statistically insignificant at all horizons, they are also smaller in magnitude than the IRFs on the share of large deposits and the initial decline in deposit expense rates for banks with higher HHI reverses within a few quarters.

I then compare the explanatory power of local deposit market HHI and large deposits share for deposit expense betas and retail deposit betas across banks. I use the same definition of monetary cycles and the same procedure for calculating deposit expense betas and retail deposit betas as in Section 4. I regress the resulting betas on either local deposit market HHI or large deposits share as of the start of the cycle and compare the resulting R^2. Figure 7 Panel A shows that local deposit market HHI explains very little of the cross-sectional variation in total deposit expense betas, with R^2 below 5% in all monetary cycles and about 2% on average. In contrast, large deposits share explains about 15% of the variation in deposit betas across banks on average. Figure A32 shows similar results for savings deposits.

One might think that concentration (especially as measured by local deposit market HHI) is more important for pricing of *retail* deposit products. Large depositors may have access to much broader geographical markets (e.g., a high net-worth individual in Augusta, ME may easily bank with a bank in Boston, MA; this may be less true for ordinary households there). To address this concern, Figure 7 Panel B shows that local deposit market HHI similarly explains very little of the cross-sectional variation in retail deposit betas. In fact, the explanatory power of HHI for retail deposit betas is even lower than for total deposit expense betas, with R^2 below 1% in all monetary cycles.[33]

Overall, this section confirms that the heterogeneous pricing between large and small deposits is quantitatively important. The differences in rate betas on large and small deposits are larger and more persistent than those between banks operating in more vs less concentrated deposit markets.

7. Implications and discussion

7.1. Bank lending

I now provide evidence that the monetary-policy-driven outflows of large deposits documented in Section 5 propagate into bank lending. First, I run local projections similar

[33] The retail deposit betas are computed from Ratewatch data and aggregated from bank-deposit product level to bank level using savings, time and interest-bearing transaction deposit shares from Call Reports as weights. Figure A33 plots R^2 for these retail deposit products separately.

to Equation 5 with the dependent variable being total deposits, wholesale funding, total liabilities, total assets, loans, and liquid assets. All variables are expressed as contributions to total asset growth (i.e., $(Y_{i,t+h} - Y_{i,t-1})/\text{Total assets}_{i,t-1}$). This makes magnitudes of all balance sheet impulse response functions comparable. The data are aggregated across all commercial banks.

Figure 8 Panel A plots the resulting IRFs to Romer and Romer (2004) monetary shocks. The results confirm that deposits decline following monetary tightening shocks, as in Figure 6 (and Figure 6 shows that this decline is driven entirely by large deposits). However, the decline in deposits is *not* accompanied by declines in total liabilities, total assets, or loans. Instead, the decline in deposits is fully offset by an increase in wholesale funding. Thus, in aggregate, lending does not contract following monetary tightening shocks, as shown also by Gertler and Gilchrist (1993), Den Haan, Sumner, and Yamashiro (2007), and Greenwald, Krainer, and Paul (2025), among others.

I split the aggregate by bank size into top 1% of banks ("large") and bottom 99% ("small") of banks by total assets. Figure 8 Panel B shows that the deposit response is similar across both groups, with deposits declining both for large and small banks following monetary tightening shocks, with very similar magnitudes (Figure A23 shows that this decline is driven entirely by large deposits for both groups). However, the responses of other balance sheet variables are very different. Large banks do not cut total liabilities and total assets and *increase* lending following monetary tightening shocks, while small banks cut total liabilities, assets, and loans. Large banks balance the decline in deposits with an increase in wholesale funding, while small banks do not. This is consistent with the idea that large banks have better access to wholesale funding and use it to substitute lost deposits, while small banks do not, echoing the results in Kashyap and Stein (1995, 2000). The results are similar when using high-frequency monetary shocks (Figure A34).

The aggregate results, however, may be driven by loan demand rather than supply (Bernanke and Gertler 1995). For example, small firms' loan demand may decline in response to monetary tightening shocks, while large firms' loan demand may increase (Gertler and Gilchrist 1994; Crouzet and Mehrotra 2020). As small banks are more likely to lend to small firms, while large banks are more likely to lend to large firms, this could explain the differential lending response across bank types. The aggregate results are thus inconclusive: they are consistent both with no credit supply effects from deposit outflows, and with reduced credit supply at both small and large banks. To make progress on this question, I follow Drechsler, Savov, and Schnabl (2017) and study the response of small business lending to monetary policy shocks at the bank-county level.[34] The idea is that if outflows of large deposits lead banks to reduce credit supply, then banks with more large deposits should cut their small business lending more following monetary tightening shocks even *within the same county* (where loan demand is presumably similar for banks with different large vs. small deposit composition). I estimate the following regression:

$$\log(\text{Small bus. lending}_{i,c,t}) = \alpha_{ic} + \delta_{ct} + \beta^{+}\text{MP}_t^{+} \times \text{Lrg. dep. share}_{i,t-1} \\ + \beta^{-}\text{MP}_t^{-} \times \text{Lrg. dep. share}_{i,t-1} + \Gamma X_{i,t} + \epsilon_{i,c,t}, \quad (7)$$

where the dependent variable is the log of small business lending by bank i in county c in year t, α_{ic} are bank-county fixed effects, δ_{ct} are county-time fixed effects. The main independent variable of interest is the interaction of monetary policy with the share of large deposits in total deposits. Given the asymmetric response of total deposits to tightening vs easing monetary policy by large deposits share documented in Section 5, I allow for different effects for tightening ($\text{MP}_t^{+} = \max\{\text{MP}_t, 0\}$) and easing monetary policy ($\text{MP}_t^{-} = \min\{\text{MP}_t, 0\}$). MP_t can be either change in the federal funds rate or one of the identified monetary shocks (Romer and Romer (2004) or Bauer and Swanson (2023)). Vector $X_{i,t}$ includes the share of large deposits (not interacted with the shock), as well as, in certain specification, additional controls for bank size and bank HHI. The controls for bank size and HHI also include interactions with MP_t^{s}, $s \in \{-, +\}$. Following DSS (2017), the sample includes all bank-county pairs with small business lending above $100,000 in 2010 dollars, from 1997 to 2013. I split the sample into top 1% of banks ("large") and bottom 99% of banks ("small") by total assets and run the regression separately for each group. The advantage of this specification is that county-time fixed effects absorb county-level loan demand differences that may be correlated with banks' large-deposit shares, so identification comes from differences between banks with more vs less large deposits within the same county-year.

Table 6 reports the results. The coefficients of interest are β^{+} and β^{-}, which capture how the response of small business lending to monetary policy—tightening and easing, respectively—varies with the share of large deposits. The results show that *small* banks that have a higher share of large deposits (and are thus more exposed to deposit outflows, as shown in Section 5) cut their small business lending more following monetary policy tightening. This is not driven by bank size or the average concentration of deposit markets

[34] The small business lending data are available under the Community Reinvestment Act (CRA) of 1977. Note that very small banks are not required to report under the CRA. As of 2024 the reporting threshold is $1,609 million in total assets for the previous two year-ends. In practice this means that only about 8% of banks are subject to CRA reporting requirements.

in which the bank operates, as the results are robust to controlling for these variables. The estimated effect is economically meaningful: moving from the 25th to the 75th percentile of large deposits share is associated with about 8% lower small business lending following a 100bps monetary tightening shock. But, following monetary rate cuts, small banks with a higher share of large deposits do not increase small business lending relatively more than those with a lower large deposits share. This makes sense, since I find that banks which rely more on large deposits do not experience stronger deposit inflows after monetary rate cuts (see Section 5). For large banks, both differential responses are not statistically different from zero.[35]

I note that this analysis cannot control for *within-county* differences in loan demand across bank types. For example, even within counties, borrowers served by banks with a higher share of large deposits may be more rate-sensitive and thus reduce their loan demand more following monetary tightening shocks. This would then drive the observed differential lending responses across banks with more vs less large deposits at small banks. It is not clear, however, why a similar dynamic would not be present across *large* banks with different shares of large deposits. Furthermore, it is likely that banks with more large deposits (even conditional on bank size) lend to larger firms and wealthier households (see evidence on cross-selling in Basten and Juelsrud (2023)). But these borrowers are likely to be *less* rate-sensitive (Favara, Loria, and Zakrajšek 2025; Crouzet and Mehrotra 2020), which would work *against* finding a negative relationship between large deposits share and lending response to monetary policy shocks.[36]

Overall, the results in this subsection are consistent with deposit outflows (driven by large, responsive depositors) leading to lending cuts at small banks. Large banks are able to substitute lost deposits with other funding sources and avoid cutting lending. Still, given that small banks accounted for about 33% of total lending over 1985-2024 (and they also lend to more financially constrained borrowers, e.g., small businesses), the deposits channel likely has important credit supply effects.

[35] These results are robust to using changes in the federal funds rate or high-frequency monetary shocks as the measure of monetary policy shocks (Table A15).

[36] Figure A35 reports panel impulse responses similar to those in Table 5. Overall, the evidence suggests that banks with a higher share of large deposits see stronger deposit outflows following monetary tightening, which translates into lower assets and lower loans, particularly C&I loans, relative to the banks with a lower share of large deposits. There is little differential behavior in response to monetary easings. This bank-level panel evidence is consistent with the aggregate and within-county analyses presented in this section.

7.2. Maturity transformation

Section 4 shows that banks with more large deposits have more rate-sensitive deposit rates. Does this mean that income of banks with more large deposits goes down more following monetary tightening shocks, since their deposit expense rises more? In this section, I show that this is not the case. Banks with more large deposits match their more rate-sensitive deposit rates with more rate-sensitive assets, thereby stabilizing their net interest margins following monetary policy shocks (Drechsler, Savov, and Schnabl 2021).

First, I show that banks' net interest margin (NIM) response to monetary policy does not vary with the share of large deposits. I estimate panel local projections similar to Equation 2:

$$\Delta Y_{i,t-1,t+h} = \alpha_t^h + \beta^h \text{MP}_t \times \text{Lrg. dep. share}_{i,t-1} + \Gamma^h X_{i,t} + \varepsilon_{i,t+h},$$

where $\Delta Y_{i,t-1,t+h}$ is change in either the interest expense rate, interest income rate, or NIM for bank i over the horizon h, and MP_t is the monetary policy measure at time t (either change in short rate or one of the monetary policy shocks). Interest expense rate is defined as total interest expense over a given period (quarter) divided by average total assets outstanding at the beginning and end of that quarter; interest income is defined similarly. NIM is the difference between interest income and interest expense rates. Other variables are as in Equation 2. The coefficients of interest are β^h which capture how the response of the outcome variable to monetary policy varies with the share of large deposits.

Figure A36 plots the estimated impulse response functions. Panel A shows that banks with more large deposits increase their interest expense rates more following monetary policy tightening, indicating that the higher deposit betas documented in Section 4 translate into higher overall interest expense sensitivity. However, Panel B shows that banks with more large deposits also increase their interest income rates more following monetary tightening. As a result, Panel C shows that NIMs do not respond differentially to monetary policy based on the share of large deposits. Figure A37 shows that this matching holds for Romer and Romer (2004) monetary policy shocks as well. Thus, banks with more large deposits appear to match their more rate-sensitive deposits with more rate-sensitive assets, stabilizing their NIMs following monetary policy shocks.

How are higher expense rates on large deposits matched with interest income when the policy rates rise? Figure A38 shows that banks with a higher share of large deposits hold shorter-maturity assets.[37] Table A16 confirms this relationship in a regression framework

[37] I approximate maturity of bank assets from Call Report data following English, Van den Heuvel, and

for select years between 1985 and 2023, and shows that the negative relationship between large deposits share and assets' repricing maturity holds also controlling for bank size, local deposit market concentration, bank age, and capitalization ratio.

One way to achieve shorter-maturity assets is to hold more commercial and industrial (C&I) loans, which tend to have floating interest rates or short maturities relative to other types of bank loans. Indeed, I find that banks with more large deposits hold more C&I loans. Figure A39 plots the relationship between banks' share of large deposits and their share of C&I loans in total loans. There is a clear positive relationship: banks with higher share of large deposits tend to have higher share of C&I loans. Table A17 presents the results in a tabular format. The positive relationship between large deposits share and C&I loan share is economically meaningful and statistically significant in all years. Furthermore, the explanatory power of the large deposits share is substantial, with R^2 between 5% and 20% across years.[38]

Overall, the results in this subsection suggest that banks with more large deposits engage in *less* maturity transformation by holding more rate-sensitive assets to match their rate-sensitive large deposits. This helps banks achieve more stable net interest margins over monetary policy cycles.

7.3. Implications for the deposits channel of monetary policy

The results in this paper suggest that large, responsive depositors drive the deposits channel of monetary policy. This has important implications for the strength of the deposits channel over time. Figure A2 Panel B shows that the share of deposits held by top 1% of highest-income and highest-net-worth households has been rising since the 1980s, consistent with the growing income and wealth inequality in the U.S. documented in the literature (Piketty, Saez, and Zucman 2018; Saez and Zucman 2020; Smith, Zidar, and Zwick 2023).[39] If these trends continue, large depositors are likely to account for an increasing share of total deposits over time. Given that my results show that large deposits are much more responsive to monetary policy, this compositional shift implies that the deposits channel is likely to strengthen over time.

Zakrajšek (2018) and Drechsler, Savov, and Schnabl (2021).

[38] The match between large deposits on the liability side of the banks' balance sheet and C&I loans on the asset side is also consistent with (some) of the large deposits coming from corporations and the importance of banking relationships for lending (Petersen and Rajan 1994; Berger and Udell 1995; Bolton et al. 2016). This also echoes the findings on cross-selling in Basten and Juelsrud (2023).

[39] Catherine, Miller, and Sarin (2025) show that wealth inequality in the U.S. has not increased if social security is properly accounted for as additional asset in households' wealth. The argument in this section, however, is about *financial* wealth only.

As a back-of-the-envelope calculation, I estimate that a 100bps monetary tightening is associated with about 750bps decline in *large* deposits over two years, based on Figure 6. For small deposits, I estimate a slightly positive response at 240bps over the same horizon. As shown in Appendix A, the total deposits response is a weighted average of large and small deposits responses. If the share of large, responsive deposits increases by 10 percentage points (e.g., from the current 50% to 60%), this would increase the total deposits response to a 100bps monetary tightening by about 100bps over two years. My estimates also imply that this would lead to an additional 80bps contraction in lending by small banks at the 2-year horizon in response to a 100bps monetary tightening shock.[40] This is an economically meaningful increase in the strength of the deposits channel of monetary policy.

Similarly, the results in the previous subsection indicate that banks match the more rate-sensitive large deposits with more rate-sensitive assets, thereby stabilizing their net interest margins following monetary policy shocks. This implies that as the share of large deposits rises, banks may tilt their asset composition towards shorter-duration assets such as C&I loans and away from real estate loans and mortgage-backed securities. Thus, as the share of large deposits rises, the maturity transformation capacity of the banking sector may decline.

8. Conclusion

Recent work shows that most depositors are sticky and unresponsive to interest rates, yet deposit flows respond strongly to monetary policy. This paper resolves this puzzle by distinguishing between large and small deposits. I show that large deposit rates are significantly more sensitive to policy rates than small deposit rates (pass-through from policy rates to deposit rates of 0.7 versus 0.3). Banks use balance-tiered pricing, offering higher rates on larger balances especially when the policy rate is high. Large deposits account for the entire aggregate deposit flow response to monetary policy, while small deposits do not leave banks despite the low and sticky rates. These patterns are not explained by local deposit market concentration. The deposits channel thus works primarily through a small number of large, responsive depositors who account for a substantial share of bank funding, even though most depositors are sticky.

My findings have significant implications for understanding monetary policy transmis-

[40] Lending response is computed as follows. I assume that the lending response is approximately proportional to the deposit response. So, in this calculation, as monetary-policy-driven deposits response increases by 40% (from -250bps to -350bps), lending response would increase by about 40% as well, from -200bps to -280bps.

sion and bank balance sheet management. With rising wealth and income inequality, the composition of deposits is likely to tilt further towards large deposits in the near future. My estimates imply that this shift would increase both the aggregate deposit beta and the sensitivity of deposit flows to monetary policy shocks. At the same time, the shift towards large deposits may reduce the maturity transformation capacity of the banking system, as banks tend to hedge the more interest-sensitive large deposits with shorter-duration assets. Methodologically, my results highlight that focusing exclusively on retail deposit rates (e.g., Ratewatch) may be appropriate when studying retail depositors, but not when studying banks' overall deposit funding costs.

A few caveats are in order. First, data constraints require me to use a binary classification of deposits based on regulatory thresholds, but depositor stickiness likely varies continuously with deposit size and holder characteristics. Understanding this heterogeneity with more granular data is a promising area for future research. Second, this paper does not take a stance on the ultimate sources of depositor stickiness and hence is silent on the optimal consumer protection policies. Instead, I focus on monetary policy transmission through the deposits channel and show that the deposits channel works primarily through large, responsive depositors.

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Figures and tables

Figure 1. Deposit expense betas by share of large deposits, 1975-2024

This figure plots a binscatter of total deposit expense betas over monetary policy *tightening* cycles against the share of large deposits in the cross-section of banks. The banks are grouped into bins by large deposits share at the following percentiles: [0%, 30%), [30%, 40%), ..., [80%, 90%), [90%, 95%), [95%, 100%]. The dots represent the average deposit expense beta and the average share of large deposits within each bin. The deposit expense betas are computed over each monetary policy cycle as the change in total deposit interest expense rate divided by the change in the effective federal funds rate over that cycle. The share of large deposits is as of the start of each cycle. See main text for additional details on data construction. The shaded regions represent 95% confidence intervals based on Cattaneo et al. (2024).

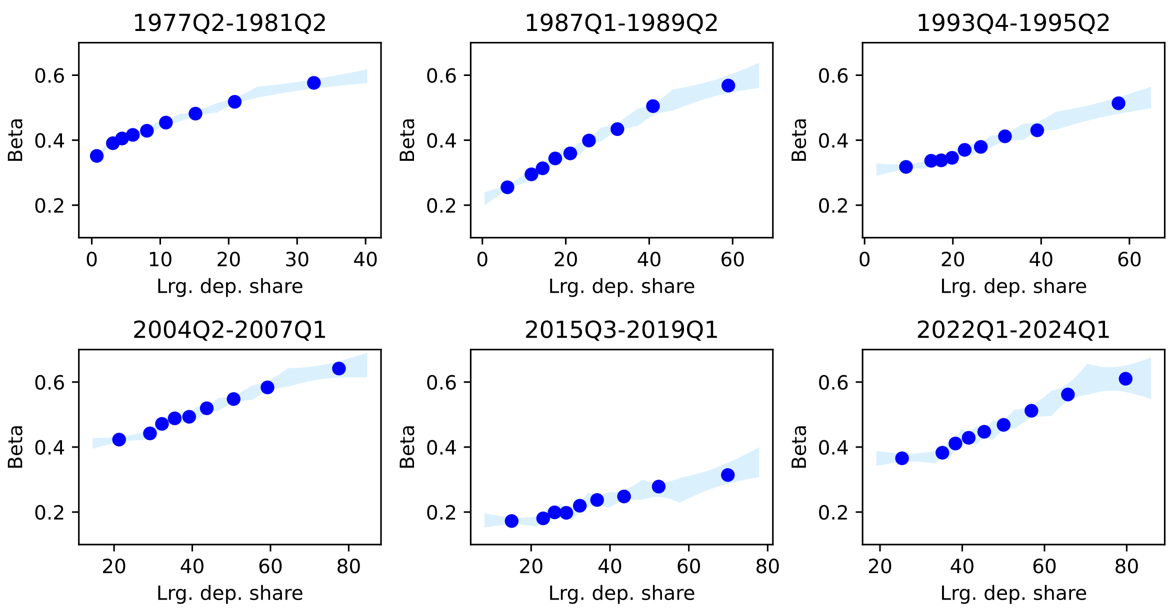


Figure 2. Impulse response of total deposit expense rates to monetary policy by share of large deposits

This figure plots the IRF from estimating the following local projections:

$$\Delta\text{Dep. exp. rate}_{i,t-1,t+h} = \alpha_t^h + \beta^h \Delta\text{FFR}_t \times \text{Lrg. dep. share}_{i,t-1} + \Gamma^h X_{i,t} + \varepsilon_{i,t+h}, \quad h = 0, \ldots, 8,$$

where ΔDep. exp. $\text{rate}_{i,t-1,t+h}$ is the change in deposit expense rate at bank i from $t-1$ to $t+h$, α_t^h is the time fixed effect, ΔFFR_t is the change in the federal funds rate from $t-1$ to t, and Lrg. dep. $\text{share}_{i,t-1}$ is the share of large deposits at bank i as of $t-1$. The vector $X_{i,t}$ includes 4 lags of the dependent variable and 4 lags of the short rate, all interacted with Lrg. dep. $\text{share}_{i,t-1}$ and interacted with controls—log of local deposit market HHI, log of bank age, share of bank's savings and time deposits that reprice within 3 months and between 3 and 12 months, book capitalization ratio and share of liquid assets (cash and securities) in total assets, all measured as of $t-1$. Panel A plots the IRF from the simple LP, Panels B and C plot the IRFs from LP-IV where ΔFFR_t is instrumented with Romer and Romer (2004) and high-frequency shocks (Bauer and Swanson 2023), respectively. The figure plots the estimates of β^h (solid blue line) along with 90% (dashed blue lines) and 95% (shaded blue area) confidence intervals based on standard errors double clustered by bank and time. The share of large deposits is standardized such that a one-unit change in this variable corresponds to an increase from the 25th to 75th percentile in its distribution within each quarter. The sample is all U.S. commercial banks over the period 1985Q1-2024Q1.

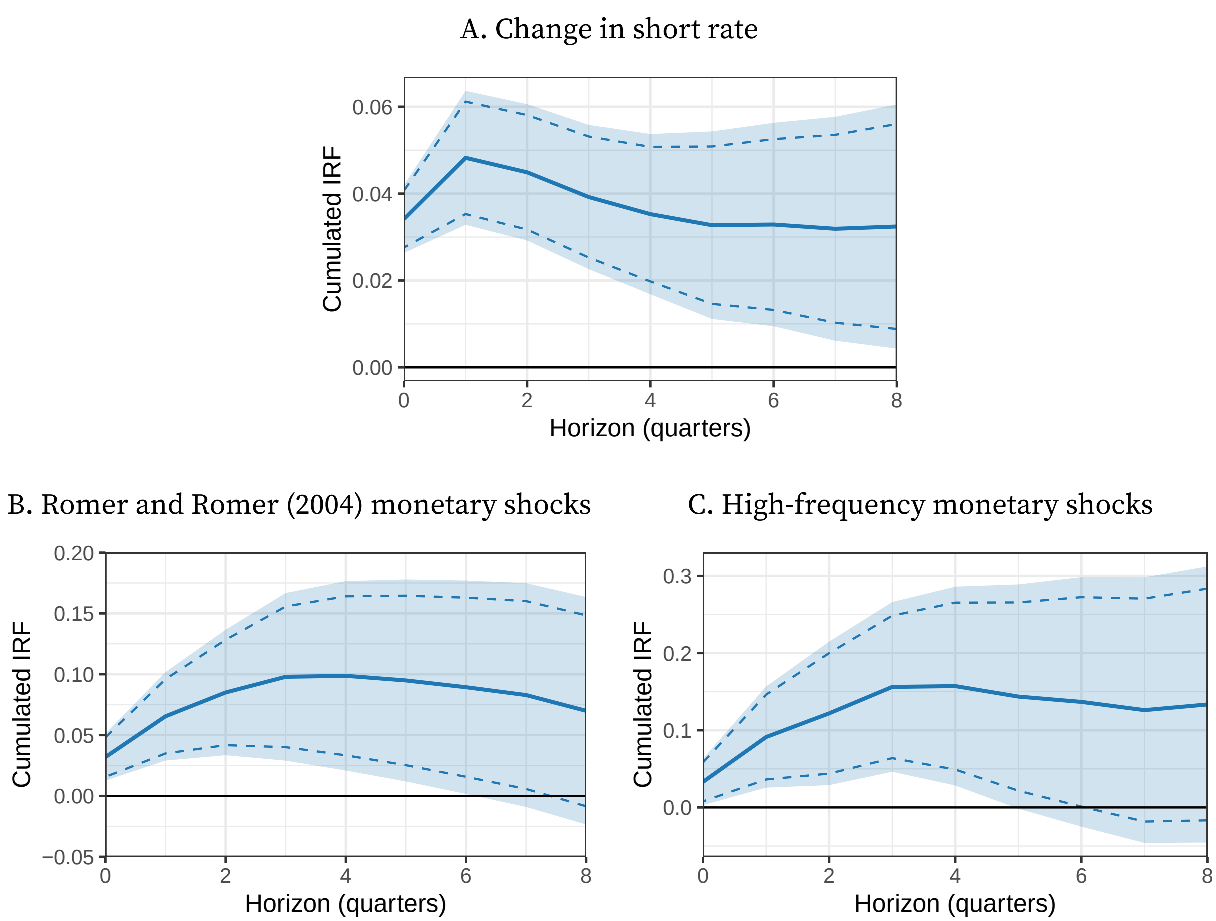


Figure 3. Call Report deposit expense betas vs Ratewatch small deposit betas by share of large deposits

This figure plots binscatters of savings deposit rate betas over monetary policy cycles since 2001. Blue dots represent savings deposit expense betas computed from Call Reports, while green dots represent betas on savings accounts with $2,500 minimum balance. The banks are grouped into bins by large deposits share at the following percentiles: [0%, 30%), [30%, 40%), ..., [80%, 90%), [90%, 95%), [95%, 100%]. The figure plots betas over all tightening (2004Q2-2007Q1, 2015Q3-2019Q1, 2022Q1-2024Q1) and easing (2007Q2-2009Q4, 2019Q2-2021Q2) cycles since 2001, when Ratewatch data becomes available. Ratewatch offered rates are aggregated to quarterly frequency by averaging within each quarter for each bank. See main text and the caption to Figure 1 for additional details.

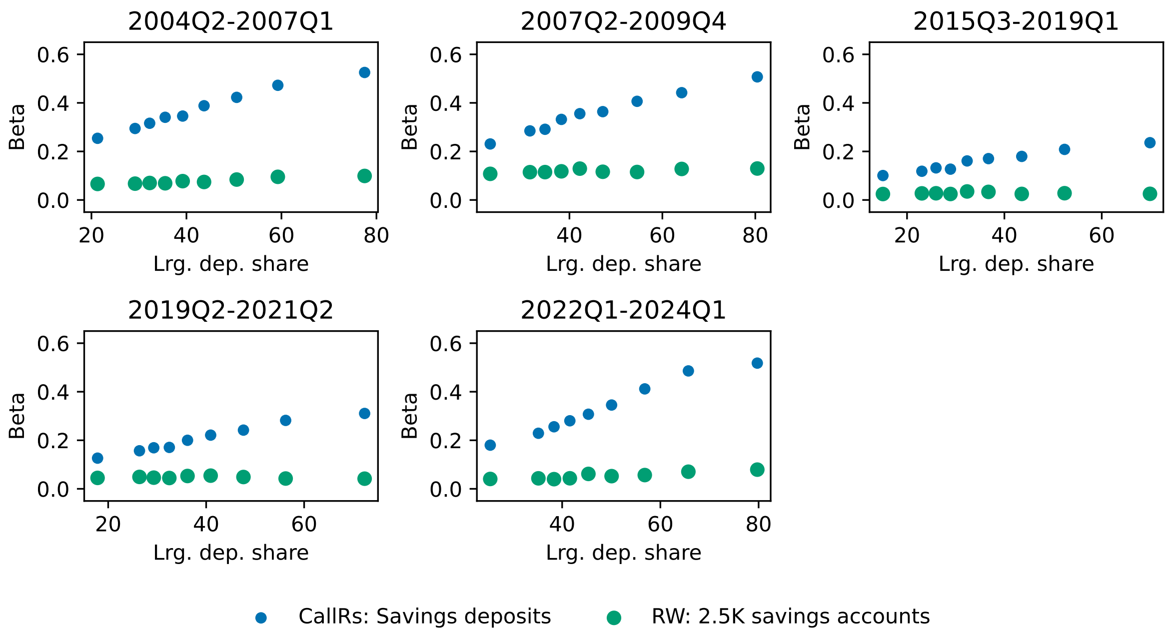


Figure 4. Inferred deposit expense betas for small and large deposits by monetary policy cycle

This figure plots inferred deposit expense betas for small and large deposits over each monetary policy cycle since 2001. The inferred small and large deposit betas are obtained by estimating the following regression for each cycle c:

$$\text{Dep. exp. beta}_{i,c} = \gamma_{0,c} + \gamma_{1,c}\text{Lrg. dep. share}_{i,c} + \varepsilon_{i,c},$$

where Dep. exp. beta$_{i,c}$ is the total deposit expense beta for bank i over cycle c and Lrg. dep. share$_{i,c}$ is the share of large deposits at bank i as of the beginning of the cycle c. $\gamma_{0,c}$ recovers an estimate of small deposit betas, $\gamma_{1,c}$ recovers an estimate of the difference between large and small deposit betas. $\gamma_{0,c} + \gamma_{1,c}$ thus recovers an estimate of large deposit betas. The figure plots these inferred small (green dots) and large (orange dots) deposit expense betas. For comparison, the figure also plots average deposit betas for four small retail deposit products from Ratewatch (pink crosses, see main text for details). Confidence bands based on heteroskedasticity-consistent standard errors are very small and therefore not shown.

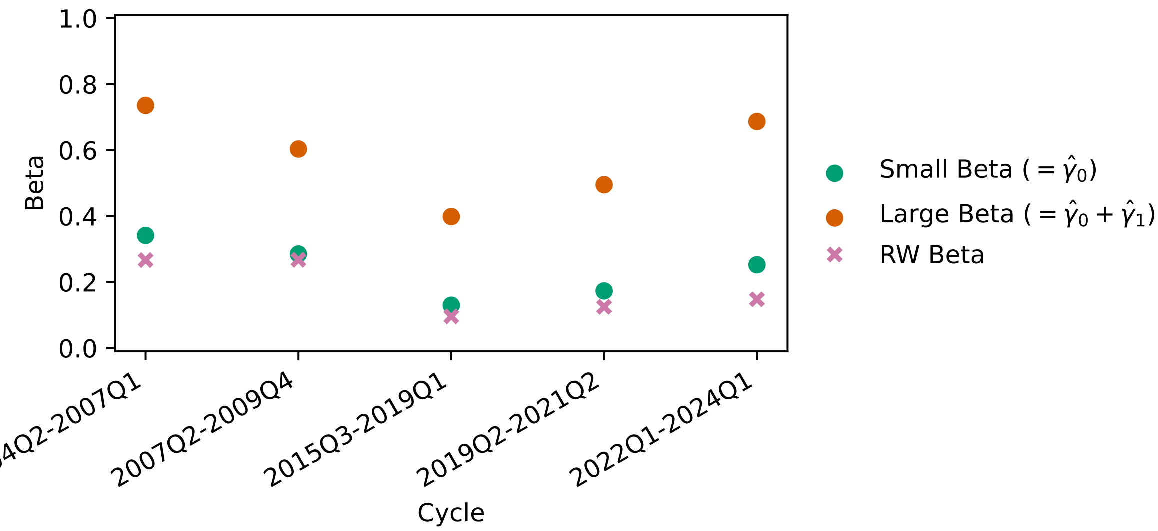
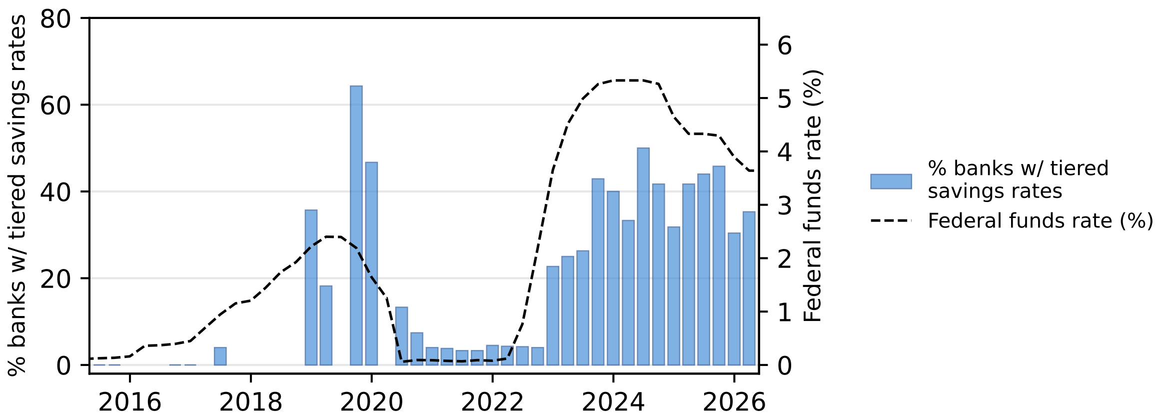


Figure 5. Tiered pricing of savings deposits across monetary policy cycles, 2015-2026

This figure documents balance-tiered pricing of savings deposits at the top-30 U.S. banks by total assets. The data are savings deposit and money market deposit account (MMDA) rates, hand-collected from each bank's website (for current rates) and from Internet Archive's Wayback Machine snapshots (for historical rates), aggregated to quarterly frequency. The sample excludes promotional rates and relationship-tier rates. Panel A plots the share of banks with balance-tiered savings deposit rates each quarter (blue bars, left axis) together with the effective federal funds rate (dashed black line, right axis). A bank-quarter is classified as "tiered" if any of its savings or MMDA products has at least two distinct tiers with a top-minus-bottom APY spread of at least 0.5 percentage points. Panel B plots, by quarter, the cross-bank mean (thick lines) and median (dotted lines) of the top-tier APY (orange) and the bottom-tier APY (green), where the top-tier (bottom-tier) APY for a bank-quarter is the maximum (minimum) APY across all of the bank's savings and MMDA products in that quarter. The dashed black line is the effective federal funds rate. Due to patchy coverage, the figures are restricted to quarters with data on at least 10 banks.

A. Share of banks with tiered savings deposit rates



B. Rates on top vs bottom tiers of savings deposits

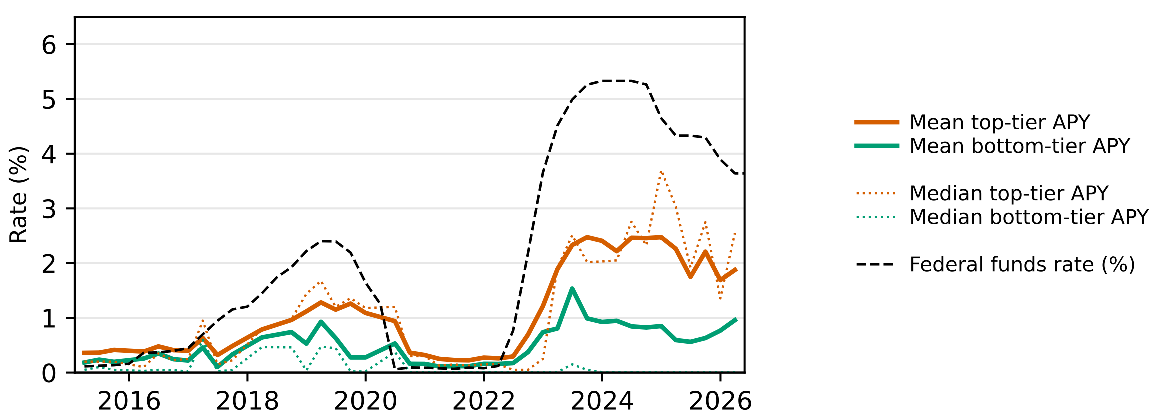


Figure 6. Aggregate deposit flow response to monetary policy shocks: Large vs small deposits

This figure plots impulse response functions (IRFs) of aggregate deposit flows to monetary policy shocks, estimated using the following local projections:

$$\Delta_{t-1,t+h} \log Y = \alpha^h + \beta^h \text{RR shock}_t + \Gamma^h X_t + \varepsilon_{t+h},$$

where $\Delta_{t-1,t+h} \log Y$ is the log-change in Y (total deposits, large deposits, or small deposits) from $t-1$ to $t+h$. RR shock$_t$ is Romer and Romer (2004) monetary policy shock, normalized to correspond to a 100bps increase in the effective federal funds rate. Controls X_t include two lags of the dependent variable and monetary shocks, real GDP growth and inflation (and their lags), as well as indicators for quarter and the zero lower bound period. IRFs are estimated for horizons $h = 0, 1, \ldots, 8$ quarters. The sample covers all U.S. commercial banks, 1991Q1-2024Q1. Confidence intervals (CI) are based on Newey-West standard errors with bandwidth 8 quarters. 90% CI are plotted as blue shaded regions and 68% CI are plotted as dashed blue lines.

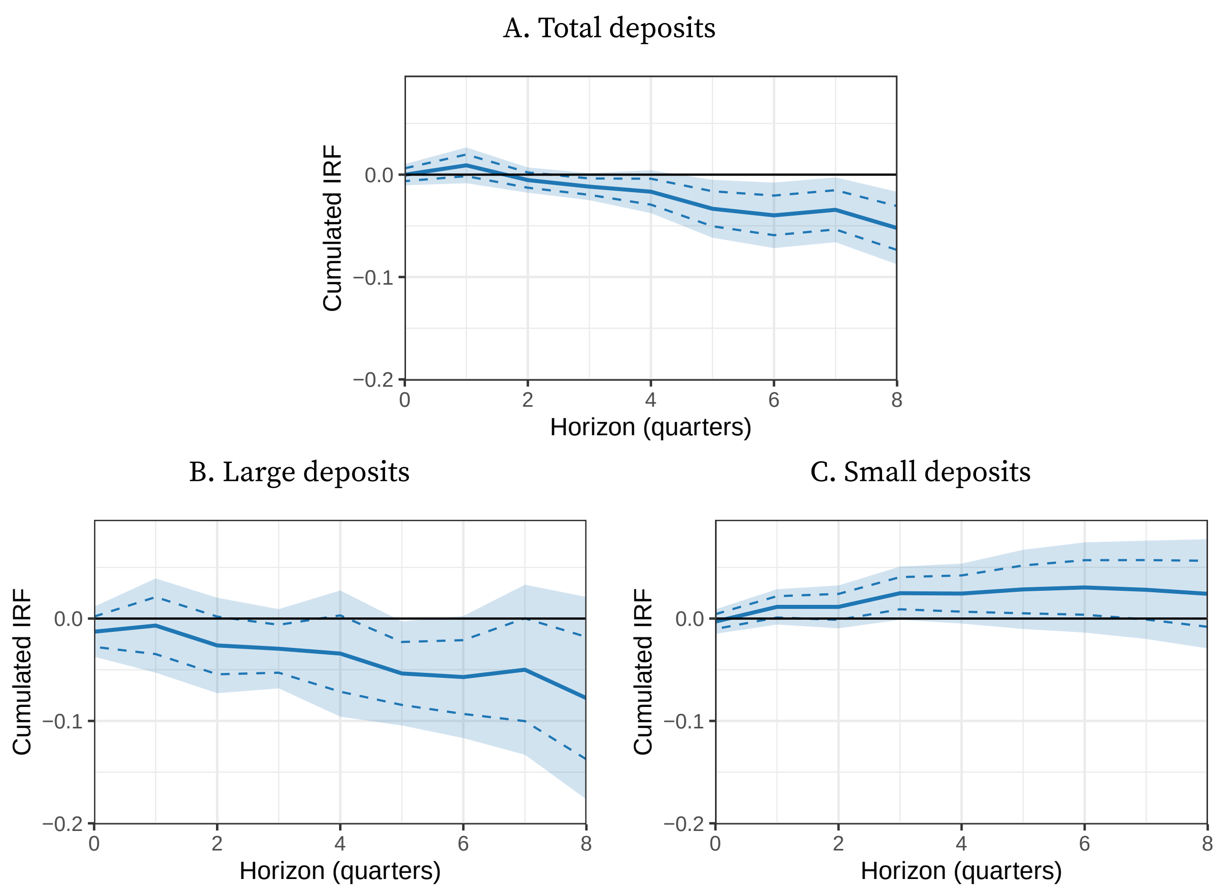
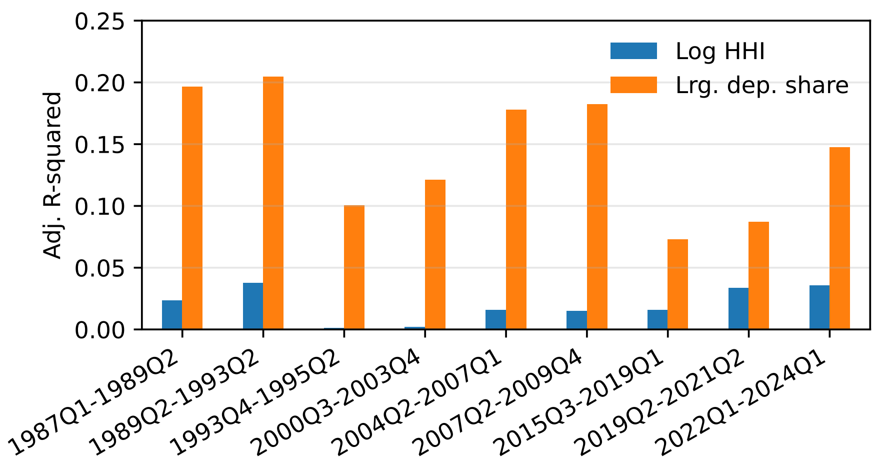


Figure 7. Large deposits share is more important than local deposit market concentration in explaining deposit pricing

Panel A of this figure plots the R^2 values from regressing total deposit expense betas over each cycle (see Section 4) on either large deposit share or local deposit market HHI at the beginning of that cycle. Panel B plots R^2 values from regressing total deposit expense betas calculated from Call Reports and retail deposit expense betas calculated from Ratewatch on local deposit market HHI at the beginning of each cycle.

A. Total deposit expense betas



B. HHI: Total vs retail deposit betas

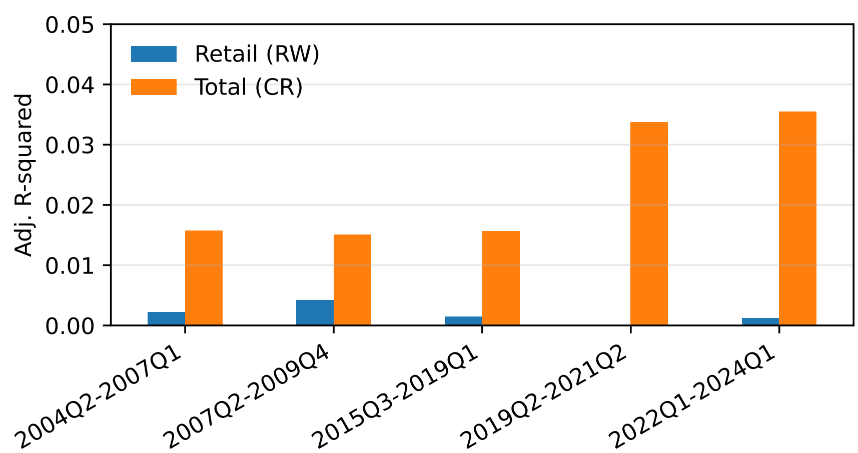
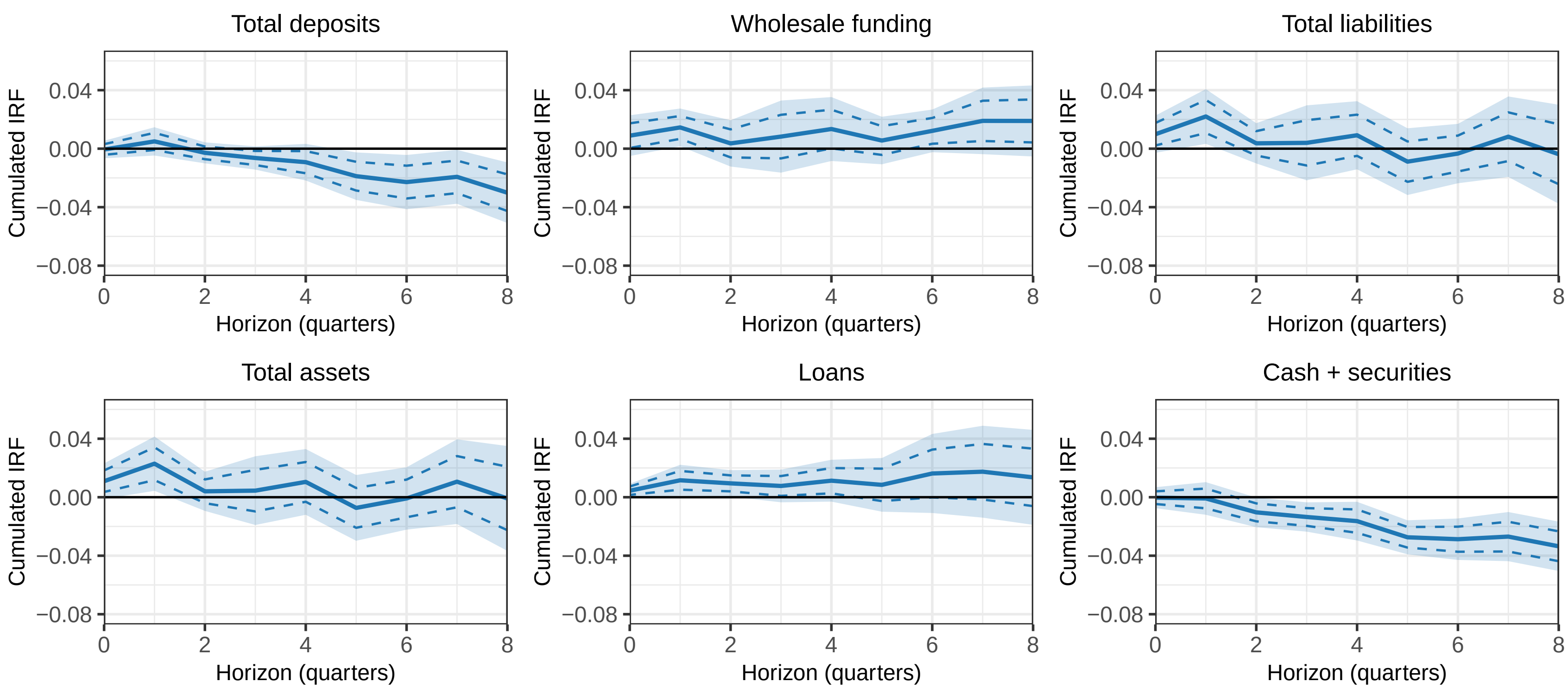


Figure 8. Monetary policy and the balance sheet of the banking system

This figure plots impulse response functions of banks' balance sheet components to Romer and Romer (2004) monetary shocks for all U.S. commercial banks (Panel A) and separately for large vs small banks (Panel B), estimated as in Equation 5. Large banks are defined as the top 1% of banks by total assets and small banks are the bottom 99% of banks by total assets. Solid lines show point estimates, and shaded areas show 90% confidence intervals based on Newey-West standard errors with 8 lags (dashed lines show 68% confidence intervals). Note that the balance sheet variables in this figure represent *contributions to growth* in total assets. That is, the dependent variable in Equation 5 is $\Delta_{t-1,t+h}Y/\text{Assets}_{t-1}$. This transformation makes magnitudes of the responses of different variables comparable. Results are qualitatively similar in the standard Equation 5 specification.

A. All commercial banks



B. Large vs small banks

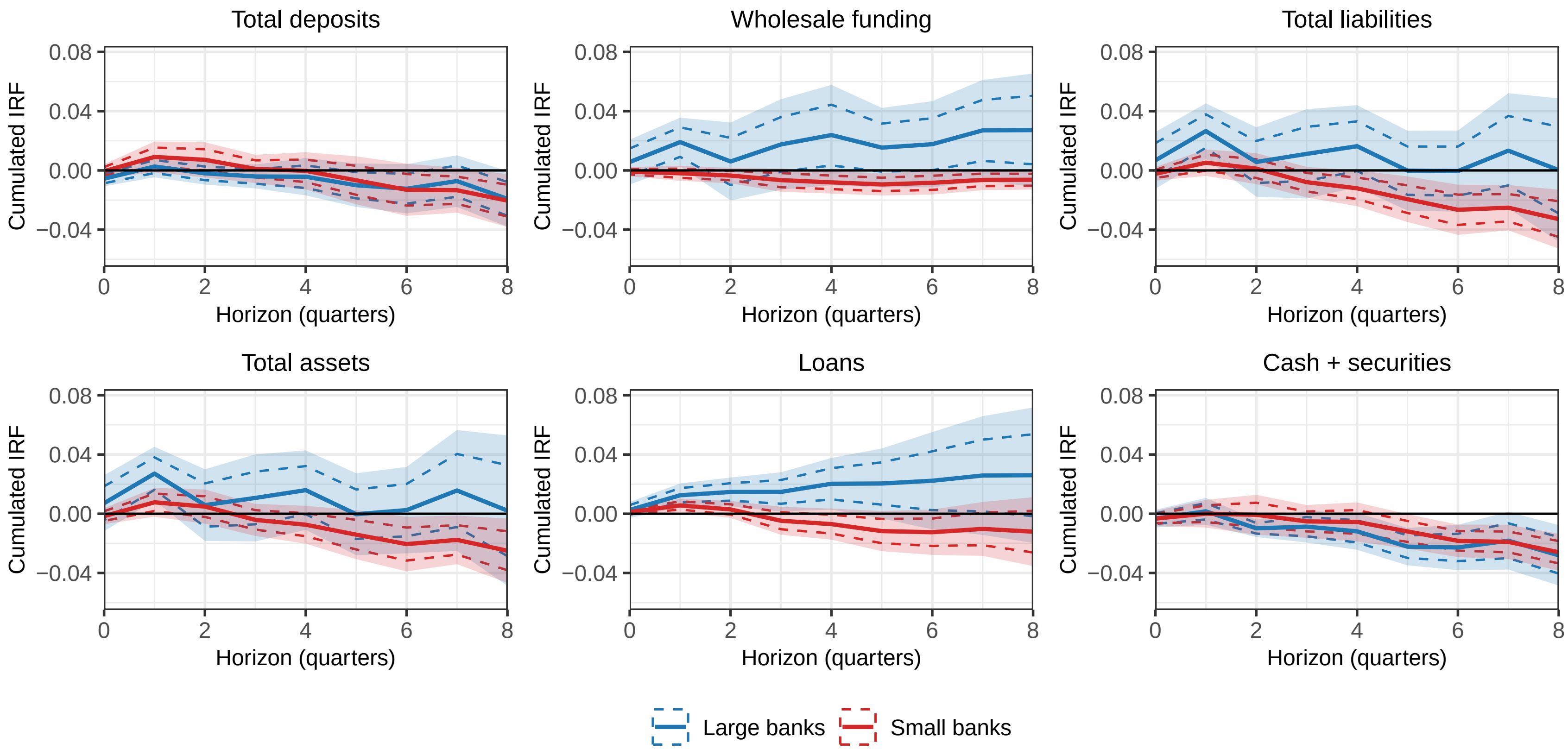


Table 1. Summary statistics

This table presents summary statistics for key variables used in the analysis. The sample is all U.S. commercial banks over the period 1975Q1-2024Q1. See main text for variable definitions. All rate and share variables are in percent. Growth rates are annualized quarter-on-quarter log changes deflated by CPI.

A. Bank-level rate variables

Variable	*N*	Mean	SD	p5	p25	p50	p75	p95
Total deposit rate	1,653,797	4.59	2.81	0.44	2.18	4.49	6.61	9.30
Savings deposit rate	1,211,403	2.59	1.94	0.15	0.71	2.56	3.95	5.79
Time deposit rate	1,218,238	4.23	2.30	0.73	2.10	4.48	5.85	7.90
Interest expense rate	1,664,805	3.42	2.11	0.32	1.67	3.34	5.01	6.98
Interest income rate	1,661,708	7.26	2.35	3.48	5.43	7.36	9.00	11.00
Net interest margin	1,661,527	3.86	0.97	2.41	3.27	3.81	4.38	5.45
12-month 10K CD rate	485,166	1.54	1.33	0.19	0.40	1.10	2.36	4.28
10K MMDA rate	462,062	0.66	0.71	0.05	0.15	0.35	1.00	2.10
2.5K savings account rate	482,709	0.48	0.53	0.05	0.10	0.25	0.70	1.51
2.5K checking account rate	464,539	0.32	0.40	0.02	0.05	0.15	0.45	1.08

B. Bank-level quantity variables

Variable	*N*	Mean	SD	p5	p25	p50	p75	p95
Deposit market HHI	1,900,776	1736	1390	239	840	1399	2231	4256
Large deposits share	1,524,830	26.07	16.75	4.88	13.98	23.13	34.66	57.28
C&I loans share	1,912,934	18.10	13.36	1.70	8.83	15.18	24.18	44.07
Total asset growth	1,900,482	0.05	0.34	-0.26	-0.07	0.02	0.13	0.42
Total deposit growth	1,899,433	0.06	0.51	-0.29	-0.09	0.02	0.14	0.47
Large deposit growth	1,023,196	0.09	0.99	-1.11	-0.25	0.07	0.42	1.37
Small deposit growth	1,025,233	0.06	0.61	-0.27	-0.08	0.00	0.10	0.52
Total loans growth	1,888,830	0.07	0.56	-0.31	-0.08	0.03	0.16	0.49
C&I loans growth	1,844,348	0.06	1.02	-0.97	-0.25	0.01	0.31	1.20
Liquid assets growth	1,887,957	0.03	0.73	-0.87	-0.26	-0.00	0.29	1.04

Table 2. Local projections of deposit expense rates on policy rate changes and share of large deposits

This table shows the results of estimating the following local projections:

$$\Delta\text{Dep. exp. rate}_{i,t-1,t+h} = \alpha_t^h + \beta^h \Delta\text{FFR}_t \times \text{Lrg. dep. share}_{i,t-1} + \Gamma^h X_{i,t} + \varepsilon_{i,t+h}, \quad h = 0, \ldots, 8,$$

where ΔDep. exp. rate$_{i,t-1,t+h}$ is the change in deposit expense rate at bank i from $t-1$ to $t+h$, α_t^h is the time fixed effect, ΔFFR_t is the change in the federal funds rate from $t-1$ to t, and Lrg. dep. share$_{i,t-1}$ is the share of large deposits at bank i as of $t-1$. The vector $X_{i,t}$ includes 4 lags of the dependent variable and 4 lags of the short rate, all interacted with Lrg. dep. share$_{i,t-1}$ and interacted with controls—log of local deposit market HHI, log of bank age, share of bank's savings and time deposits that reprice within 3 months and between 3 and 12 months, book capitalization ratio and share of liquid assets (cash and securities) in total assets, all measured as of $t-1$. The table shows only select interaction terms with ΔFFR_t, the coefficients on other variables are omitted for exposition. The share of large deposits and log HHI are standardized such that a one-unit change in this variable corresponds to an increase from the 25th to 75th percentile in its distribution within each quarter. The sample is all U.S. commercial banks over the period 1985Q1-2024Q1. Standard errors (in parentheses) are double clustered by bank and time. *, **, *** denote statistical significance at 10%, 5% and 1% levels, respectively.

	Horizon, quarters				
	$h = 0$	$h = 2$	$h = 4$	$h = 6$	$h = 8$
Lrg. dep. share$_{i,t-1}$ × ΔFFR_t	0.034***	0.045***	0.035***	0.033***	0.032**
	(0.004)	(0.008)	(0.009)	(0.012)	(0.014)
log(HHI$_{i,t-1}$) × ΔFFR_t	0.003	-0.001	0.008	0.001	-0.005
	(0.004)	(0.008)	(0.008)	(0.009)	(0.010)
log(Bank age$_{i,t-1}$) × ΔFFR_t	-0.008***	-0.014*	-0.015***	-0.015***	-0.018***
	(0.003)	(0.007)	(0.005)	(0.005)	(0.006)
Time FE	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓
N	919,249	919,249	919,249	919,249	919,249
Within R^2	0.074	0.147	0.199	0.227	0.248

Table 3. Inferred deposit expense betas for small and large deposits

This table shows the results of estimating the following regression for each monetary policy cycle c:

$$\text{Dep. exp. beta}_{i,c} = \gamma_{0,c} + \gamma_{1,c}\text{Lrg. dep. share}_{i,c} + \varepsilon_{i,c},$$

where Dep. exp. beta$_{i,c}$ is the total deposit expense beta for bank i over cycle c and Lrg. dep. share$_{i,c}$ is the share of large deposits at bank i as of the beginning of cycle c. The sample is all U.S. commercial banks with deposit expense and large deposits share data available for a given cycle. $\gamma_{0,c}$ recovers an estimate of small deposit betas, $\gamma_{1,c}$ recovers an estimate of the difference between large and small deposit betas. $\gamma_{0,c} + \gamma_{1,c}$ thus recovers an estimate of large deposit betas. The table reports the estimates of $\gamma_{0,c}$ (Constant) and $\gamma_{1,c}$ (Lrg. dep. share) for each cycle along with heteroskedasticity-consistent standard errors in parentheses. The table also reports the average deposit beta from Ratewatch for four small retail deposit products (RW beta, see main text for details) over each cycle for comparison. *, **, *** denote statistical significance at 10%, 5% and 1% levels, respectively.

	Cycle				
	2004Q2 - -2007Q1	2007Q2 - -2009Q4	2015Q3 - -2019Q1	2019Q2 - -2021Q2	2022Q1 - -2024Q1
Constant$_c$	0.341***	0.285***	0.130***	0.173***	0.252***
	(0.005)	(0.004)	(0.005)	(0.006)	(0.008)
Lrg. dep. share$_{i,c}$	0.394***	0.318***	0.269***	0.322***	0.434***
	(0.012)	(0.010)	(0.016)	(0.018)	(0.020)
RW Beta	0.267	0.268	0.096	0.125	0.148
Small Beta	0.341	0.285	0.130	0.173	0.252
Large Beta	0.736	0.603	0.399	0.495	0.687
R^2	0.178	0.182	0.073	0.087	0.148
Observations	7043	6599	5305	4857	4477

Table 4. Select examples of balance-tiered savings deposit pricing, 2015-2025

This table shows posted savings deposit and money market deposit account (MMDA) rates on select dates from 2015 to 2025 at three large U.S. banks: Wells Fargo (Panel A), TD Bank (Panel B), and Zions Bancorporation (Panel C). The rates are hand-collected from each bank's website (for current rates) and from Internet Archive's Wayback Machine snapshots (for historical rates). Panel A shows rates on Wells Fargo's Platinum Savings; Panel B shows rates on TD Bank's flagship savings account (Select/Beyond/Signature Savings, in chronological order); Panel C shows rates on Zions Bank's Money Market Account. The right column reports the effective federal funds rate (FFR) on each date for reference. The table illustrates that these banks use balance-tiered deposit pricing, paying higher rates on larger balances when the FFR is high, but often paying the same rate on all balances when the FFR is low.

A. Wells Fargo

Date	Rates (APY)	FFR, %
2015-09-05	0.06% on all balances	0.14
2017-04-08	0.06% on all balances	0.91
2019-04-21	0.05% on $0-$25K, 2.1% on >$25K	2.44
2020-09-20	0.02% on all balances	0.09
2021-05-06	0.02% on all balances	0.06
2022-05-20	0.02% on all balances	0.83
2022-12-09	0.26% on $0-$100K, 1.02% on $100K-$500K, 1.51% on $500K-$1M, 2.01% on >$1M	3.83
2023-12-07	0.25% on $0-$100K, 1.01% on $100K-$500K, 2.0% on $500K-$1M, 2.5% on >$1M	5.33
2024-05-19	0.25% on $0-$100K, 1.01% on $100K-$500K, 2.0% on $500K-$1M, 2.5% on >$1M	5.33

B. TD Bank

Date	Rates (APY)	FFR, %
2015-09-07	0.05% on $0-$50K, 0.5% on >$50K	0.14
2017-04-08	0.1% on $0-$15K, 0.35% on $15K-$25K, 0.45% on $25K-$50K, 0.5% on >$50K	0.91
2020-09-29	0.05% on $0-$20K, 0.2% on $20K-$50K, 0.25% on $50K-$100K, 0.35% on $100K-$250K, 0.5% on >$250K	0.09
2021-08-05	0.01% on $0-$20K, 0.02% on $20K-$50K, 0.03% on $50K-$100K, 0.04% on $100K-$250K, 0.05% on >$250K	0.10
2022-05-16	0.01% on $0-$20K, 0.02% on $20K-$50K, 0.03% on $50K-$100K, 0.04% on $100K-$250K, 0.05% on >$250K	0.83
2023-02-05	0.01% on $0-$10K, 1.5% on $10K-$25K, 1.75% on $25K-$50K, 2.0% on $50K-$100K, 2.5% on $100K-$250K, 3.0% on >$250K	4.58
2024-06-13	0.01% on $0-$10K, 2.0% on $10K-$25K, 2.25% on $25K-$50K, 2.5% on $50K-$100K, 4.0% on >$100K	5.33

C. Zions

Date	Rates (APY)	FFR, %
2017-04-08	0.1% on $1K-$100K, 0.15% on $100K-$250K, 0.18% on >$250K	0.91
2019-11-15	0.1% on $1K-$5K, 0.15% on $5K-$25K, 0.2% on $25K-$100K, 0.3% on $100K-$250K, 0.4% on >$250K	1.55
2020-09-23	0.02% on $1K-$25K, 0.05% on $25K-$100K, 0.08% on $100K-$250K, 0.1% on >$250K	0.09
2021-06-18	0.02% on $1K-$25K, 0.03% on $25K-$100K, 0.05% on >$100K	0.10
2022-05-29	0.02% on $1K-$25K, 0.03% on $25K-$100K, 0.04% on >$100K	0.83
2023-03-26	0.25% on $1K-$5K, 0.4% on $5K-$25K, 0.8% on $25K-$100K, 1.06% on $100K-$250K, 1.21% on >$250K	4.83
2023-09-29	1.11% on $5K-$100K, 1.61% on $100K-$250K, 1.71% on $250K-$500K, 2.02% on >$500K	5.33
2024-09-09	0.8% on $5K-$100K, 1.51% on $100K-$250K, 1.71% on $250K-$500K, 2.02% on >$500K	5.33
2025-01-23	0.4% on $1K-$100K, 0.9% on $100K-$500K, 0.95% on $500K-$1M, 1.01% on >$1M	4.33

Table 5. Deposits flow out more from banks that rely more on large deposits when monetary policy tightens

This table shows the results of estimating the following local projections:

$$\begin{aligned}\Delta \log \text{Deposits}_{i,t-1,t+h} = \alpha_t^h + \beta^{h,+}\Delta\text{FFR}_t^+ \times \text{Lrg. dep. share}_{i,t-1} + \beta^{h,-}\Delta\text{FFR}_t^- \times \text{Lrg. dep. share}_{i,t-1} \\ + \gamma^{h,+}\Delta\text{FFR}_t^+ \times \log(\text{HHI})_{i,t-1} + \gamma^{h,-}\Delta\text{FFR}_t^- \times \log(\text{HHI})_{i,t-1} + \Gamma^h X_{i,t} + \varepsilon_{i,t+h},\end{aligned}$$

for $h = 0, \dots, 8$, where $\Delta \log \text{Deposits}_{i,t-1,t+h}$ is the change in log deposits at bank i from $t-1$ to $t+h$, α_t^h is the time fixed effect, and the quarterly change in the federal funds rate, ΔFFR_t, is split into positive (tightening) and negative (easing) parts, $\Delta\text{FFR}_t^+ = \max(\Delta\text{FFR}_t, 0)$ and $\Delta\text{FFR}_t^- = \min(\Delta\text{FFR}_t, 0)$, respectively. Lrg. dep. $\text{share}_{i,t-1}$ is the share of large deposits in total deposits at bank i as of $t-1$, and $\log(\text{HHI})_{i,t-1}$ is the log of local deposit market HHI faced by bank i as of $t-1$. The vector $X_{i,t}$ includes 4 lags of the dependent variable and 4 lags of each of ΔFFR_t^+ and ΔFFR_t^-, all interacted with Lrg. dep. $\text{share}_{i,t-1}$, $\log(\text{HHI})_{i,t-1}$, log of bank age, and log of total assets, all measured as of $t-1$. The share of large deposits and log HHI are standardized such that a one-unit change corresponds to an increase from the 25th to 75th percentile in its distribution within each quarter. The sample is all U.S. commercial banks over the period 1991Q1–2024Q1. Standard errors (in parentheses) are double clustered by bank and time. *, **, *** denote statistical significance at 10%, 5% and 1% levels, respectively.

	Horizon, quarters				
	$h = 0$	$h = 2$	$h = 4$	$h = 6$	$h = 8$
Lrg. dep. $\text{share}_{i,t-1} \times \Delta\text{FFR}_t^+$	-0.004**	-0.005	-0.012**	-0.014**	-0.020**
	(0.002)	(0.004)	(0.006)	(0.007)	(0.008)
Lrg. dep. $\text{share}_{i,t-1} \times \Delta\text{FFR}_t^-$	0.000	0.003**	0.005**	0.006*	0.004
	(0.001)	(0.001)	(0.002)	(0.003)	(0.003)
$\log(\text{HHI})_{i,t-1} \times \Delta\text{FFR}_t^+$	-0.001	-0.004	-0.006	-0.005	-0.004
	(0.002)	(0.003)	(0.005)	(0.006)	(0.008)
$\log(\text{HHI})_{i,t-1} \times \Delta\text{FFR}_t^-$	-0.001	0.002*	0.002**	0.007***	0.004*
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Time FE	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓
N	804,769	804,769	804,769	804,769	804,769
Within R^2	0.126	0.163	0.170	0.179	0.175

Table 6. Large deposits, monetary policy, and small business lending: Bank-county-level results

This table reports the results of estimating the following regression:

$$\log(\text{Small business lending}_{i,c,t}) = \alpha_{ic} + \delta_{ct} + \beta^{+}\Delta\text{FFR}_t^{+} \times \text{Lrg. dep. share}_{i,t-1} + \beta^{-}\Delta\text{FFR}_t^{-} \times \text{Lrg. dep. share}_{i,t-1} + \Gamma X_{i,t} + \epsilon_{i,c,t},$$

where the dependent variable is the log of small business lending by bank i in county c in year t, α_{ic} are bank-county fixed effects, δ_{ct} are county-time fixed effects, and the annual change in the federal funds rate, ΔFFR_t, is split into positive (tightening) and negative (easing) parts, $\Delta\text{FFR}_t^{+} = \max(\Delta\text{FFR}_t, 0)$ and $\Delta\text{FFR}_t^{-} = \min(\Delta\text{FFR}_t, 0)$, each interacted with the share of large deposits in total deposits. Vector $X_{i,t}$ includes the share of large deposits (not interacted with the shock), as well as, in columns (2) and (4), additional controls for bank size and bank HHI. The controls for bank size and HHI also include interactions with both ΔFFR_t^{+} and ΔFFR_t^{-}. Following Drechsler, Savov, and Schnabl (2017), the sample includes all bank-county pairs with small business lending above $100,000 in 2010 dollars, from 1997 to 2013. Standard errors are clustered at the bank and county level.

	Small banks		Large banks	
	(1)	(2)	(3)	(4)
$\Delta\text{FFR}_t^{+} \times \text{Lrg. dep. share}_{i,t-1}$	-0.083**	-0.100***	0.043	0.021
	(0.034)	(0.032)	(0.084)	(0.084)
$\Delta\text{FFR}_t^{-} \times \text{Lrg. dep. share}_{i,t-1}$	0.012	0.022*	-0.021	-0.015
	(0.013)	(0.012)	(0.028)	(0.030)
Controls		✓		✓
County × Year FE	✓	✓	✓	✓
County × Bank FE	✓	✓	✓	✓
N	365,134	365,134	225,995	225,995
Within R^2	0.004	0.022	0.005	0.024

Appendix A. Model

I adapt the model of Drechsler, Savov, and Schnabl (2017), modifying it to allow for depositors with different elasticity of substitution between bonds and deposits. The model is static and there is no risk. Households maximize utility over final wealth, W, and liquidity services, l:

$$u(W_0) = \max\left(W^{\frac{\rho-1}{\rho}} + \lambda l^{\frac{\rho-1}{\rho}}\right)^{\frac{\rho}{\rho-1}} \tag{A1}$$

where ρ is the elasticity of substitution between wealth and liquidity services, and λ is a parameter that governs the relative weight of liquidity services in utility. I assume that there are two types of households, with different values of $\rho = \{\rho_L, \rho_H\}$, where $\rho_L < \rho_H$. Households with low ρ do not substitute from liquid assets into wealth easily. As in DSS (2017), wealth and liquidity services are complements, so $\rho_L < \rho_H < 1$. The population weights of the two types are α_L and α_H, with $\alpha_L + \alpha_H = 1$.

Liquidity services are derived from cash, M, and deposits, D, in the same way for both types of households:

$$l(M, D) = \left(M^{\frac{\epsilon-1}{\epsilon}} + \delta D^{\frac{\epsilon-1}{\epsilon}}\right)^{\frac{\epsilon}{\epsilon-1}} \tag{A2}$$

where ϵ is the elasticity of substitution between cash and deposits, and δ is a parameter that governs the relative weight of deposits in liquidity services. Cash and deposits are substitutes, so $\epsilon > 1$.

For each depositor type $j \in \{L, H\}$, deposits are a composite good produced by a set of N banks:

$$D_j = \left(\frac{1}{N}\sum_{i=1}^{N} D_{ji}^{\frac{\eta-1}{\eta}}\right)^{\frac{\eta}{\eta-1}}, \quad j \in \{L, H\} \tag{A3}$$

where D_{ji} are deposits of type j at bank i, and η is the elasticity of substitution between banks, $\eta > 1$. I assume for simplicity that η is the same for both types of depositors.

Households also invest in bonds, which pay market rate f. The budget constraint is:

$$W_j = W_0(1 + f) - M_j f - D_j s_j, \quad j \in \{L, H\} \tag{A4}$$

where $s_j \equiv \frac{1}{N}\sum_{i=1}^{N} \frac{D_{ji}}{D_j} s_{ji}$ is the deposit spread (the difference between market rate and the deposit rate) for depositor type j, deposit-weighted across banks with s_{ji} as the spread at bank i for depositor type j.

From households' optimization problem, we obtain deposit demand elasticity for each depositor type j:[41]

$$-\frac{\partial D_j}{\partial s_j}\frac{s_j}{D_j} = \left[\frac{1}{1+\delta^{\epsilon}\cdot\left(\frac{f}{s_j}\right)^{\epsilon-1}}\right]\epsilon + \left[\frac{\delta^{\epsilon}\cdot\left(\frac{f}{s_j}\right)^{\epsilon-1}}{1+\delta^{\epsilon}\cdot\left(\frac{f}{s_j}\right)^{\epsilon-1}}\right]\rho_j, \quad j \in \{L, H\}. \tag{A5}$$

The elasticity of demand for deposits of type j at a given bank i is given by:

$$-\frac{\partial D_{ji}}{\partial s_{ji}}\frac{s_{ji}}{D_{ji}} = \frac{1}{N}\left(-\frac{\partial D_j}{\partial s_j}\frac{s_j}{D_j}\right) + \eta\left(1-\frac{1}{N}\right), \quad j \in \{L, H\}. \tag{A6}$$

Note that for a given aggregate spread s_j, deposit demand elasticity at a given bank i is greater for depositor type H than for depositor type L:

$$-\frac{\partial D_{Hi}}{\partial s_{Hi}}\frac{s_{Hi}}{D_{Hi}} > -\frac{\partial D_{Li}}{\partial s_{Li}}\frac{s_{Li}}{D_{Li}}. \tag{A7}$$

Banks raise deposits from both types of households and invest in bonds. Their profit maximization problem is:

$$\pi = \max_{s_L, s_H} \alpha_L D_L(s_L) s_L + \alpha_H D_H(s_H) s_H. \tag{A8}$$

I now show that it is optimal for banks to price discriminate between the two depositor types, i.e. to set different spreads s_L and s_H.

Lemma A1 (Price discrimination). *It is optimal for banks to set different deposit spreads for each depositor type, i.e., $s_L > s_H$, whenever $\rho_L < \rho_H$.*

PROOF. Assume by contradiction that all banks set the same spread for both depositor types, i.e. $s_L = s_H = s$. Then the bank's profit maximization problem becomes:

$$\pi = \max_{s} \alpha_L D_L(s) s + \alpha_H D_H(s) s,$$

[41] I follow DSS (2017) and let $\lambda \to 0$ to obtain a closed-form solution. This removes the impact of cost of liquidity on total wealth. In unreported results, I solve the model more generally with $\lambda > 0$ and show numerically that the results are similar.

where I omit subscript i because all banks are symmetric. The first-order condition is:

$$\left[\alpha_L \frac{\partial D_L}{\partial s} + \alpha_H \frac{\partial D_H}{\partial s}\right] s^* + (\alpha_L D_L + \alpha_H D_H) = 0.$$

Rearranging:

$$\frac{\partial D_L}{\partial s}\frac{s^*}{D_L} \cdot \frac{\alpha_L D_L}{\alpha_L D_L + \alpha_H D_H} + \frac{\partial D_H}{\partial s}\frac{s^*}{D_H} \cdot \frac{\alpha_H D_H}{\alpha_L D_L + \alpha_H D_H} = -1$$

This is a weighted average of the elasticities of deposit demand for the two depositor types, with weights $\frac{\alpha_j D_j}{\alpha_L D_L + \alpha_H D_H}$ for $j \in \{L, H\}$. Since these weights are positive and sum to 1, the weighted average elasticity must lie between the two elasticities. But from (A7), the elasticity for type H is strictly greater than that for type L. Therefore, we have:

$$-\frac{\partial D_L}{\partial s}\frac{s^*}{D_L} < 1 < -\frac{\partial D_H}{\partial s}\frac{s^*}{D_H}$$

This implies that s^* is set on the "inelastic" side of the type L deposit demand curve and on the "elastic" side of the type H deposit demand curve. A bank can increase its profit by slightly increasing s_L above s^* and slightly decreasing s_H below s^*. Hence, it is optimal for any bank i to deviate from the pooling equilibrium. It is optimal to set $s_L > s_H$. □

Under price discrimination, spreads are set as:

$$\frac{\partial D_{ji}}{\partial s_{ji}}\frac{s_{ji}}{D_{ji}} = -1, \quad j \in \{L, H\}. \tag{A9}$$

As in DSS (2017), combining (A6) and (A9) yields the following equilibrium condition:

$$-\frac{\partial D_j}{\partial s_j}\frac{s_j}{D_j} = 1 - (\eta - 1)(N - 1) \equiv \mathcal{M}, \quad j \in \{L, H\}, \tag{A10}$$

where $\mathcal{M}$ is what DSS (2017) call "market power of the banking sector as a whole", and I will call "market concentration" parameter. Note that $\mathcal{M}$ is the same for both depositor types in this model.

Combining Equation A5 and Equation A10, we obtain the following result, as in DSS (2017), but now for each depositor type j.

Proposition A1 (Deposit spreads and betas). *If $\mathcal{M} < \rho_j$, then the equilibrium deposit spread*

s_j is 0. Otherwise,

$$s_j = \delta^{\frac{\epsilon}{\epsilon-1}} \left(\frac{\mathcal{M} - \rho_j}{\epsilon - \mathcal{M}} \right)^{\frac{1}{\epsilon-1}} f, \quad j \in \{L, H\}. \tag{A11}$$

The deposit spread beta, $\partial s_j / \partial f$, is increasing in market concentration $\mathcal{M}$ and decreasing in ρ_j. In particular, if $\rho_L < \rho_H$, then $s_L > s_H$ and $\partial s_L / \partial f > \partial s_H / \partial f$.

Proposition A1 shows that the more elastic depositors H get higher pass-through of market rates to deposit rates, than the less elastic depositors L.

I now show how depositor flows respond to changes in market rates. From the households' optimization problem, I obtain:[42]

$$D_j = s_j^{-\rho_j} \cdot \delta^{-\frac{\epsilon(1-\rho_j)}{\epsilon-1}} \cdot \left(1 + \delta^{-\epsilon} \cdot \left(\frac{s_j}{f} \right)^{\epsilon-1} \right)^{-\frac{\epsilon-\rho_j}{\epsilon-1}}, \quad j \in \{L, H\}.$$

Substituting for s_j/f from Equation A11 and differentiating with respect to f, I obtain the following result.

Proposition A2 (Deposit flows). *The semielasticity of deposits of type j with respect to market rate f is:*

$$-\frac{\partial D_j}{\partial f} \frac{1}{D_j} = \frac{1}{f} \rho_j, \quad j \in \{L, H\}. \tag{A12}$$

Following an increase in the market rate f, deposits decrease as long as $\rho_j > 0$. The semielasticity is increasing in ρ_j:

$$\frac{\partial}{\partial \rho_j} \left(-\frac{\partial D_j}{\partial f} \frac{1}{D_j} \right) = \frac{1}{f} > 0. \tag{A13}$$

In particular, since $\rho_L < \rho_H$, deposits of type L respond less to changes in market rates than deposits of type H:

$$-\frac{\partial D_L}{\partial f} \frac{1}{D_L} < -\frac{\partial D_H}{\partial f} \frac{1}{D_H}. \tag{A14}$$

[42] Again, I let $\lambda \to 0$ to obtain a closed-form solution. For the results on flows, I follow DSS (2017) and scale deposits by $\lambda^{\rho} W$. In unreported results, I solve the model more generally with $\lambda > 0$ and show numerically that the results are similar.

Together, Proposition A1 and Proposition A2 show the key prediction of this model: stickiness (modeled in reduced form as low elasticity of substitution between liquidity and wealth) leads to lower deposit betas and lower deposit outflows in response to monetary rate hikes. This is not the case for concentration ($\mathcal{M}$), which leads to lower deposit betas but does not affect deposit outflows.[43]

One implication of Proposition A2 is that the composition of low- vs high-elasticity depositors matters for the aggregate deposit response to changes in market rates. The more deposits are held by low-elasticity ("sticky") depositors, the lower the aggregate deposit response to changes in market rates, as the following corollary shows.

Corollary A1 (Aggregate deposits response to rate changes). *The semielasticity of aggregate deposits with respect to market rate f is:*

$$-\frac{\partial D}{\partial f}\frac{1}{D} = \frac{1}{f}\left(\frac{\alpha_L D_L}{D}\rho_L + \frac{\alpha_H D_H}{D}\rho_H\right). \tag{A15}$$

Given that $\rho_L < \rho_H$, the semielasticity is increasing in the population weight of high-elasticity depositors α_H.

Corollary A1 shows that if more deposits are held by high-elasticity depositors, then aggregate deposits respond more strongly to changes in market rates and, therefore, the deposits channel of monetary policy is stronger.

[43] The result that equilibrium deposit flow semielasticity with respect to monetary rate does not depend on market concentration $\mathcal{M}$ is specific to this model; in more general models, deposit outflows can depend on market concentration. In particular, allowing banks to invest in loans with positive but diminishing lending spreads over monetary rate f (as in DSS (2017) Section IV.B) makes deposit outflows depend on market concentration, with larger outflows in more concentrated markets. I show this numerically in unreported results.

Appendix B. Data construction

Income statement data. Income statement data is reported cumulatively year-to-date. That means, for example, that the total interest expense reported in 1995Q3 is interest paid in January-September of 1995. I convert these year-to-date values to quarterly interest expenses as follows:

$$\text{Interest expense}_{it}^{Qrt} = \text{Interest expense}_{it}^{ytd} - \text{Interest expense}_{i,t-1}^{ytd}.$$

I convert all other income statement variables to quarterly frequency in the same way. This approach is generally robust and popular in the literature (Drechsler, Savov, and Schnabl 2017, 2020; d'Avernas et al. 2024), but it may result in unreasonably large or low implied rates because of the lumpy nature of certain interest income and expense items (e.g., interest on time CD is paid only at maturity). This can be a problem, especially for the smaller banks. I deal with this by using an algorithm that determines abnormal 1-quarter drops or hikes in the income/expense rates (where abnormal is defined as one-quarter increase/decrease above 2 percentage points) and replacing the abnormal values with the average of the two neighboring values.

Large and small deposits. I measure large and small deposits using Schedule RC-O of the Call Report (Memorandum item 1), which since 1982Q2 reports deposits split at the FDIC insurance threshold: $100,000 from 1982Q2 through 2009Q2 and $250,000 from 2009Q3 onward, reflecting the Emergency Economic Stabilization Act's 2008 temporary increase (subsequently made permanent by the Dodd-Frank Act). From 1982Q2 through 1990, Schedule RC-O is filed only in June; from 1991 onward the schedule is filed quarterly. Two definitional changes generate breaks in these two variables when used as quantities (e.g. as the outcome variable in local projections). Before 2002Q1, the FFIEC instructions require the small-plus-large sum to equal domestic deposits (Schedule RC item 13.a; RCON2200), and the data satisfy this identity over 1984Q2-2001Q4. Starting in 2002Q1, the memo items also include deposits in insured branches in Puerto Rico and U.S. territories: this adds roughly 0.1% to (large + small) deposits relative to total domestic deposits, concentrated in a small set of banks with such branches. Starting in 2008Q1, the memo items are instead tied to "total deposit liabilities before exclusions" (Schedule RC-O item 1), which by FFIEC definition includes *interest accrued and unpaid* on all assessable deposits. This raises the sum relative to domestic deposits by an additional 1–3%, with the wedge growing during tightening cycles (peaking near 3% in 2019 and again in 2022-2023) and shrinking near the zero lower bound.

For *aggregate* growth-rate comparisons, the 2002Q1 break is immaterial. The 2008Q1 break is important in magnitude, but the direction of the bias goes *against* my results. Formally, for $j \in \{L, S\}$ let D_t^j denote true deposits and DI_t^j accrued (but unpaid) interest at quarter t; from 2008Q1 onward the memo item measures $\widetilde{D}_t^j = D_t^j + DI_t^j$ instead of D_t^j. Letting $s_t^j \equiv DI_t^j / D_t^j$ denote the accrual ratio, a first-order expansion gives

$$\Delta \log \widetilde{D}_t^L - \Delta \log \widetilde{D}_t^S \approx \underbrace{\left(\Delta \log D_t^L - \Delta \log D_t^S\right)}_{\text{true differential}} + \underbrace{\left(\Delta s_t^L - \Delta s_t^S\right)}_{\text{measurement wedge}} .$$

I show that large deposits earn higher rates than small deposits, with the gap widening when policy rates rise. Hence, under a tightening shock $\Delta s_t^L > \Delta s_t^S > 0$, so the measurement wedge is positive. Since my main finding is that the measured differential is negative under tightening, the true differential is likely even *more negative*. The same logic applies when I infer "large non-time" and "small non-time" deposits by subtracting relevant time deposits (which do not include accrued interest): since large time deposits accrue more interest in tightening, this again goes against the findings in this paper (e.g. Figure A26).

For *panel* regression analyses, I treat 2002Q1 and 2008Q1 as a break for banks for which the difference between (large + small) deposits and total domestic deposits is larger than 0.5% of total deposits. This means that any growth rates that span 2002Q1 and 2008Q1 are deleted before the analyses.

Concentration. I compute local deposit concentration at the holding company level, keeping all depository institutions (i.e., commercial banks, savings banks, savings and loan associations, cooperative banks). Before computing local market concentration, I remove the largest branches of banks that have a lot of brokered deposits (2 standard deviations above the average), as well as the branches of banks that have a lot of deposits per branch (2 standard deviations above the average). The idea is to filter out branches that do not, in reality, source deposits in that particular market. For example, Wells Fargo Bank NA (3rd largest bank in the US as of 2023) is headquartered in Sioux Falls, SD—a city with a population of 209,289 people as of 2023. Yet, Wells Fargo's Sioux Falls branch posted \$295.8 billion deposits in that branch (22% of its total deposits) in 2023. This can happen under the SOD instructions if, for example, these are corporate deposits which Wells Fargo assigns to headquarters for "compensation or similar purposes"[44]. Similarly, there are online banks or credit card banks or similar institutions which source mainly wholesale deposits from outside the area their branches are located in. My approach accounts for

[44] https://www.fdic.gov/resources/bankers/call-reports/summary-of-deposits/2023-sod-instructions.pdf

this in computing local deposit market concentration.

As a baseline, I compute concentration measures at the "market" level, meaning either MSA if a county belongs to an MSA or a county if it does not. Since MSA boundaries change substantially over time, I use provided latitude and longitude of bank branches (and geocode these for the 1975-1993 historical SOD data), together with MSA maps from the Nation Historical Geographic Information System (NHGIS) to assign branches to historically accurate MSAs. For robustness, I compute a county-level HHI using banks (not bank holding companies) as the aggregation units.

Bank bond data. I use FISD to obtain the initial sample of corporate bonds issued by banks. I use the TRACE-CRSP crosswalk from Wharton Research Data Services (WRDS) to assign PERMCOs to FISD, and use the CRSP-FRB Link from the Federal Reserve Bank of New York[45] to merge in bank regulatory ID numbers. I focus on the subset of bonds thus matched as the set of bonds issued by banks. I then retrieve pricing data on these bonds from TRACE, following the cleaning routine of Scheuch et al. (2024)[46]. I aggregate the resulting data to daily frequency using trading volume as weights. For each bond, I compute yield to maturity (YTM) given bond characteristics, and then subtract maturity-matched Treasury yield computed from the estimated model of Gürkaynak, Sack, and Wright (2007). I aggregate the resulting spreads to monthly and quarterly levels by taking means and medians, checking that the results are robust to either one of these choices.

[45] https://www.newyorkfed.org/research/banking_research/crsp-frb

[46] Scheuch, C., Voigt, S., Weiss, P., & Frey, C. (2024). Tidy Finance with Python (1st ed.). Chapman and Hall/CRC https://www.tidy-finance.org

Appendix C. Hand-collected data on posted deposit rates

Overview. I supplement Ratewatch with a hand-collected panel of posted deposit rates scraped from large U.S. banks' own websites and from the Internet Archive's Wayback Machine. The current sample covers the 32 largest retail banks by 2015–2024 average total assets (after dropping institutional, custodial, brokerage, and credit-card banks).[47] Coverage runs from 2015Q1 through 2026Q1; the harmonized quarterly panel contains roughly 48,000 bank-product-tier-quarter observations across 45 quarters. Coverage by bank is reported in Table A2.

Sources. The bulk of the data comes from each bank's own website. A given bank typically requires combining several first-party source types to obtain a continuous timeline, because banks have repeatedly changed both how and where they publish their rates. I use, in rough order of preference:

1. *Server-rendered rate pages* where APYs and balance tiers appear directly in the HTML markup (e.g., Bank of America's `save.go` pages for 2014–2016, Wells Fargo's consumer and business rate pages for 2016–2025, Huntington's relationship-savings page for 2016–2025, HSBC's interest-rates page for 2018–2026, and First Horizon's compare-rates page across three URL eras for 2012–2026).
2. *PDF rate sheets*, used by Chase (with regional variants of the form `rxx1.pdf`, e.g., `rdny1`), Bank of America (regional variants of `DigitalDeposit_`*`REGION`*`.pdf`), Citibank, and Zions.
3. *JSON or JSONP APIs* that post-2018 sites use to load rates client-side after the page mounts—when the Wayback Machine captured both the HTML shell and the API response, I use the latter directly because it carries clean, structured tier data (e.g., Ally's `ally.com/services/competitor/rates/json` with 101 monthly snapshots for 2015–2025; Discover's `discoverbank.com/rates/legacy/featured.json` with 111 snapshots for 2015–2026; analogous endpoints for U.S. Bank, PNC, KeyBank, Synchrony, Fifth Third, M&T, and Capital One).
4. *Embedded JavaScript variables*, used by Capital One's ING-Direct–era subsidiary, which served all 360 product rates from a single file (`home.capitalone360.com/js/accounttype.js`) defining JavaScript variables of the form `var type_`*`code`*`_`*`field`*`='`*`value`*`'`; the Wayback Machine archived 156 monthly snapshots of this file for 2013–2023.

For historical coverage, I query the Internet Archive's CDX index for each first-party

[47] This is a work-in-progress and I plan to expand coverage across banks

URL pattern, filter to status-200 responses, and download the raw archived bytes via the `web.archive.org/web/tsid_/url` endpoint.[48]

Why automating this collection is hard. Even with the assistance of modern LLM tools, building this dataset is complicated, for three reasons.

First, several large banks deploy commercial bot-protection (Incapsula, Akamai, F5 ASM, hCaptcha) that returns 403s, infinite redirects, or HTTP/2 errors to any non-interactive client. Regions, BMO, Citizens, and Zions are unreachable from a plain HTTP client, while Fifth Third and Synchrony block headless Chrome but expose their rates through internal API endpoints that one can identify by inspecting how the live page loads. Most large banks additionally gate their rate pages behind a ZIP-code prompt—Chase, Bank of America, Citibank, U.S. Bank, Truist, PNC, M&T, Synovus, Fifth Third, and TD all require selecting a region before any rates appear—even though these banks largely post the same rate across geographies (Granja and Paixao 2024; Begenau and Stafford 2025).

Second, most rate pages built after 2017 do not contain the rates themselves: the page loads first, and a separate request then fetches the rates from an internal API and inserts them into the page. The Wayback Machine archives the page but rarely captures the accompanying API endpoint, so the archived rate cells render empty. Citibank's `online.citibank.com/.../detail.do`, for example, has 440 archived snapshots between 2011 and 2015, not one of which records a single rate; Citizens Bank's modern site is similar. Whether a bank's historical rates can be reconstructed therefore depends on whether Wayback happened to crawl the right API endpoint at the right moment. The ZIP-code gate common on bank websites exacerbates this problem. Wayback Machine crawlers do not input ZIP-codes and thus archive the unrendered/unloaded page they first encounter.

Third, even when a server-rendered page *is* archived, the page itself may not have been updated. Silicon Valley Bank's Private Bank Money Market page, for example, was archived ten times between 2019 and 2022 but always shows the same rates "effective January 1, 2019"; only a separately posted, dated PDF rate sheet (`svb-pb-money-market-account-as-of-3-30-20.pdf`) on the live site reveals that rates were in fact cut sharply in March 2020. Reconstructing a continuous timeline therefore requires tracking down rate sheets at URLs

[48]When first-party sources cannot be made to yield a continuous timeline—typically because a bank's site went JavaScript-only during a critical period and its API responses were never archived—I supplement with monthly snapshots of the bank's `https://www.depositaccounts.com` page from the Wayback Machine. `depositaccounts.com` is a third-party rate tracker that scrapes roughly 5,000 U.S. banks daily and embeds structured rate data, including balance tiers, in server-rendered HTML; because the HTML is server-rendered, it is well-archived. I use `depositaccounts.com` strictly as a gap-filler.

that no longer exist on the live site: BB&T's `compare-savings-accounts.page` (active only December 2015 to mid-2017, before the Truist merger), SunTrust's CD-rates page (2017–2021), First Tennessee's pre-2020 rate page (before the First Horizon rebrand), and Bank of America's pre-2018 PDF naming convention (`DigitalDeposit_NY.pdf` versus the post-2018 `DigitalDeposit_NY_NY_Tri_State_Area.pdf`). Locating these typically requires reading the archived HTML source, following dead links across earlier homepage snapshots, and inferring obsolete file-naming conventions. Each bank therefore requires its own custom and time-consuming investigation.

Pipeline. For each bank I follow the same procedure:

1. *Discovery*: browse the live site to locate current rate pages, rate-sheet PDFs, and any rate APIs visible in the network panel.
2. *Wayback Machine query*: run wildcard queries against the Internet Archive's CDX index for each candidate URL pattern and filter to status-200 responses.
3. *Download*: fetch raw archived bytes via the `id_` Wayback endpoint and decompress where needed.
4. *Extraction*: per-source-type parsers convert each raw file into a row-level CSV with a uniform schema (bank, product, product type, balance min/max, APY, snapshot date, effective date, relationship tier, region).
5. *Harmonization*: product names are mapped to canonical types (`savings`, `mma`, `checking`, `cd`); promotional and online-only flags are set; and exact duplicates are dropped.
6. *Quarterly panel*: for each bank-product-tier-quarter cell I keep the last observation in the quarter.
7. *Quality control*: rate-continuity checks flag jumps above 100 basis points between consecutive quarters and a bank-by-quarter observations matrix flags gaps in coverage.

Appendix D. Discussion of banks' deposit pricing strategies

D.1. Premium and relationship deposit products

Banks use "premium" and "relationship" deposit products to attract high-value customers and deepen engagement across multiple financial services. Premium deposit accounts reward customers for meeting high minimum balance requirements, offering benefits such as lower or waived fees, higher interest rates, and enhanced services. These products target affluent customers with balance thresholds ranging from $20,000 to $250,000: HSBC Premier requires $100,000 in deposits and investments, Wells Fargo Premier requires $250,000, and Citigold requires $200,000 in combined balances. Benefits include waived foreign exchange and wire transfer fees, loan interest rate discounts, and relationship rates on linked savings accounts and CDs.[49]

Relationship accounts are similar but generally do not require minimum balances on the products themselves. Instead, to qualify for a relationship product (e.g., a relationship savings account), a customer typically needs to maintain an active checking account with the same bank—for example, by setting up direct deposit or conducting a minimum number of transactions per month.[50]

For depositors with large balances, these premium and relationship requirements are effectively non-binding. A customer maintaining $1 million in deposits would automatically qualify for premium status at any major bank, as the highest thresholds ($250,000) represent only one-quarter of such balances. Similarly, relationship banking requirements—maintaining multiple accounts with the same institution—are naturally satisfied by large-balance customers who typically hold checking, savings, and investment accounts.[51] Consequently, when comparing accounts across balance levels—such as a $1 million account versus a $2,500 account—the relevant distinction is the balance itself rather than the nominal "premium" or "relationship" designation.

D.2. Discontinuous CD pricing

In addition to balance-tiered pricing discussed in the main text, banks use highly discontinuous pricing strategies for their CDs. Figure A17 shows screenshots of posted CD rates

[49] https://www.cnbc.com/select/best-premium-checking-accounts/
https://www.wellsfargo.com/premier/
https://account.chase.com/sapphire/brand

[50] https://web.archive.org/web/20230912032915/https://www.pnc.com/en/rates/money-market/95120/NA

[51] https://www.chase.com/personal/banking/education/basics/relationship-banking

at select large banks as of early 2024 and at Bank of America in late 2018. The screenshots show that banks post a few discrete rates for CDs with different maturities, and these rates are highly discontinuous across balance tiers. For example, as of July 2024, JPMorgan Chase posted a CD rate (APY) of 4.25% for "featured terms" of 2 months and 9 months; but a rate of 2% on 12-month CDs. Similarly, in December 2018 Bank of America posted a 37-month CD rate of 2.2%, but a rate of 0.55% on all other tenors between 36 and 47 months.

These highly abrupt and discontinuous patterns cannot be explained by varying term premia or yield curve shape. Instead, they might reflect banks' strategic decisions to attract deposits at specific maturities that align with their asset-liability management needs, as well as exploiting inattention of certain depositors to these discontinuities or their lack of financial sophistication (see also Fleckenstein and Longstaff 2024).

Appendix E. Concentration and retail deposit pricing: Difference-in-differences evidence using bank mergers

In this section, I closely follow Liebersohn (2024) who studies the effect of competition in banking markets on bank lending using bank antitrust rules as a source of quasi-exogenous variation in local banking market concentration. See Liebersohn (2024) for an in-depth discussion on the institutional background of the research design.

In the U.S., bank mergers require regulatory approval, with screening based on the expected changes to the Herfindahl-Hirschman Index (HHI) in local banking markets due to the merger. If the expected change in HHI in a given geographic market exceeds 200 and the post-merger HHI exceeds 1,800, [52] the merger is subject to further scrutiny. The typical remedy involves the merging banks divesting branches in the affected markets to reduce the increase in HHI. Importantly, regulators have discretion in approving mergers even when the HHI thresholds are exceeded, and they may require divestitures even when the thresholds are not exceeded. The discretion may lead to *realized* mergers being endogenous to *future* economic conditions. The hard-coded and discontinuous review rules, however, allow us to predict *ex ante* which markets will receive the "treatment" of divestitures. These rules, therefore, create "intent-to-treat" where local markets experiencing bank mergers can be classified into "treated" vs "control" based on the predicted changes in HHI due to the merger, rather than the realized changes. This allows me to identify variation in deposit market concentration that is exogenous to future economic conditions.

Following Liebersohn (2024), I therefore classify markets as "treated" if the predicted change in HHI due to the merger exceeds 200 and the post-merger predicted HHI exceeds 1,800, and as "control" otherwise. I similarly limit the analysis to markets where pre-merger HHI is within 800 points of the 1,800 threshold (i.e., with pre-merger HHI of 1,000 to 2,600). I use the same sample of bank mergers and market definitions as in Liebersohn (2024).[53] I match these data to branch-product-level Ratewatch data on retail deposit rates. I approximate deposit betas at the branch level by dividing deposit rates by the Federal funds rate. This is because estimating betas separately before and after the treatment in the regression framework, when only a few observations are available for each period is challenging. The approximation is inspired by the Drechsler, Savov, and Schnabl (2017) model (see Appendix A). I remove branches of the merging banks and aggregate the remaining branches' deposit betas and rates to the market-year level by first averaging across months within branch-year pairs, and then averaging across branches

[52] HHI ranges from 0 to 10,000.

[53] These data are taken from the replication files of Liebersohn (2024), available here.

within market-year pairs. I have 221 merger-market pairs in total, with 157 that are ever treated and 64 that are never treated.

I use a staggered difference-in-differences design to compare treated and control markets before and after the mergers. To address the set of problems with staggered difference-in-differences designs (Goodman-Bacon 2021; Callaway and Sant'Anna 2021), I use the estimator of Wooldridge (2025):

$$Y_{i,t} = \sum \delta_{c(i),t} + \sum \gamma_{m(i)} + \sum_{c,t>c(i)} \beta_{c(i),t} \text{Post}_{c(i),t} \times \text{Treated}_i + \varepsilon_{i,t}, \tag{A16}$$

where $Y_{i,t}$ is either local deposit market HHI, deposit beta or deposit rate in market i at time t, $\delta_{c(i),t}$ are cohort-time fixed effects, $\gamma_{m(i)}$ are market fixed effects, $\text{Post}_{c(i),t}$ is an indicator for post-merger periods for cohort $c(i)$ (one for each year after the merger), and Treated_i is an indicator for treated markets. The estimation window is limited to 10 years before and 10 years after each merger. I cluster standard errors at the market level.

This regression effectively compares treated and control markets within each merger cohort, thereby not relying on comparisons across cohorts that may be invalid if treatment effects are dynamic or vary across cohorts (Baker, Larcker, and Wang 2022). The parameters of interest are the $\beta_{c(i),t}$ which capture the treatment effects for each cohort $c(i)$ at time t relative to the merger year. I aggregate these treatment effects across cohorts by taking weighted averages, with weights proportional to the number of observations in each cohort. The treatment effects are aggregated over time similarly.

I test for pre-trends following Wooldridge (2025) by estimating a similar regression but replacing the $\text{Post}_{c(i),t}$ dummies with indicators for pre-merger periods and limiting the sample to periods before mergers. Table A13 reports the results of these tests. I find no evidence of differential pre-trends in deposit market HHI, deposit rates, or deposit betas between treated and control markets.

Figure A30 plots the estimated dynamic treatment effects from Equation A16. Panel A shows that local deposit market HHI decreases significantly in treated markets following the mergers, confirming that breaching the antitrust thresholds, on average, predicts decreases in local deposit market concentration due to divestitures. Panel B shows that deposit rates on select retail deposit products (interest-bearing checking accounts with minimum balance $2,500, savings accounts with minimum balance $2,500, money market accounts with minimum balance $10,000, and 12-month CDs with minimum balance $10,000) do not change significantly in treated markets following the mergers. Panel C shows that deposit betas similarly do not change significantly in treated markets following the mergers. Table A14 reports the average treatment effects across all post-merger years. The results confirm that while local deposit market concentration decreases significantly in treated markets following the mergers, there is no significant change in deposit rates or deposit betas on retail deposit products.

Overall, these results further show that small deposits are sticky. This is consistent with Egan et al. (2025), who show theoretically that when depositors are sticky ("sleepy" in their parlance), the relationship between market competition and pricing is weak.

Appendix F. Additional figures and tables

Figure A1. Large-deposit and large non-time deposit shares

This figure plots the share of large deposits (blue) and large non-time deposits (orange) over time. The sample is all U.S. commercial banks for the period 1982Q2–2024Q1. Large deposits are defined in Section 3. The left panel shows both total large and non-time large deposits as a share of total deposits, and the right panel shows non-time large deposits as a share of *non-time* deposits.

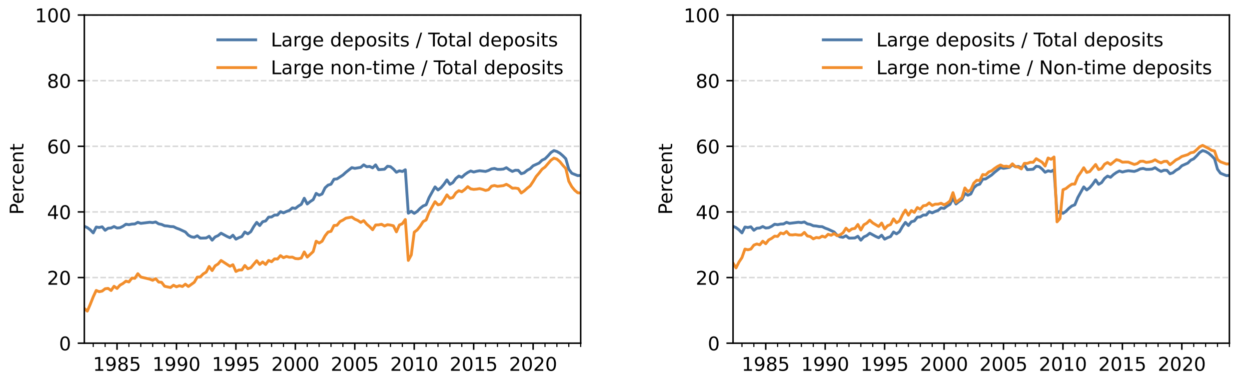
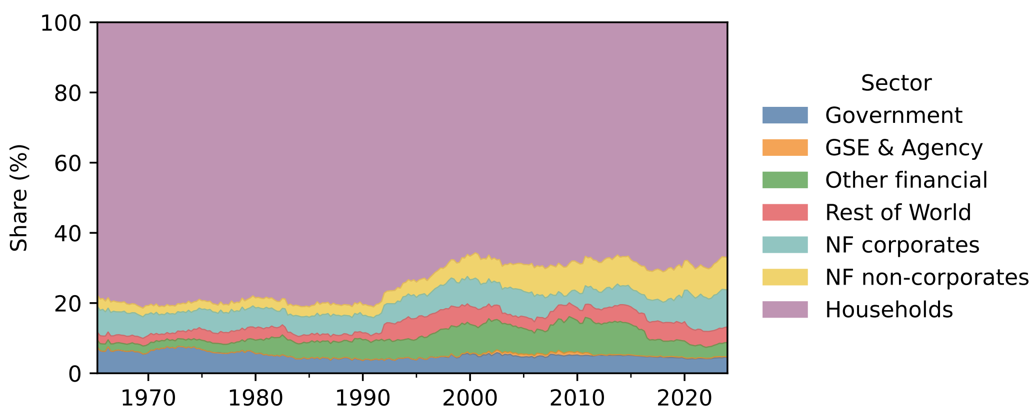


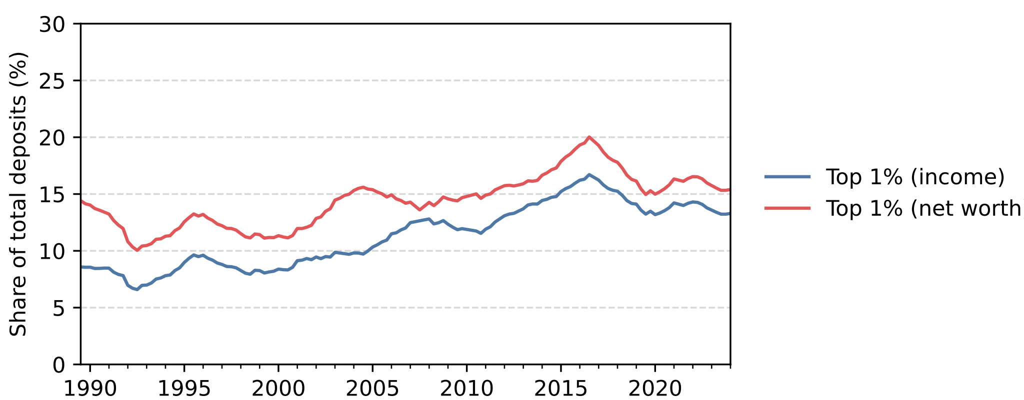
Figure A2. Sectoral composition of deposits, the top-1% household share, and the large-deposit share

Panel A plots composition of total deposits at U.S.-chartered banks by holder sector, from the "From Whom to Whom" (FWTW) tables of the Financial Accounts of the United States. Panel B plots the share of total deposits held by the top 1% of households by income and by net worth, from the Distributional Financial Accounts (DFA). The "FWTW" dataset covers 1965Q2-2024Q1, and the DFA data cover 1989Q3–2024Q1. "NF (non-)corporates" refers to nonfinancial (non-)corporate businesses, and "Other financial" incorporates money market funds, insurance companies, finance companies, pensions, mortgage REITs, and other financial businesses. Note: Panel B plots shares of top-1% of households by income/net worth in *total* deposits (household + non-household). In Panel C, we compare the share of total deposits held outside the bottom 99% of households by income (green line) and the share of large deposits in total deposits (dashed orange line).

A. Deposit composition by sector



B. Top-1% household share



C. Large deposits vs non-household + top-1% household deposits

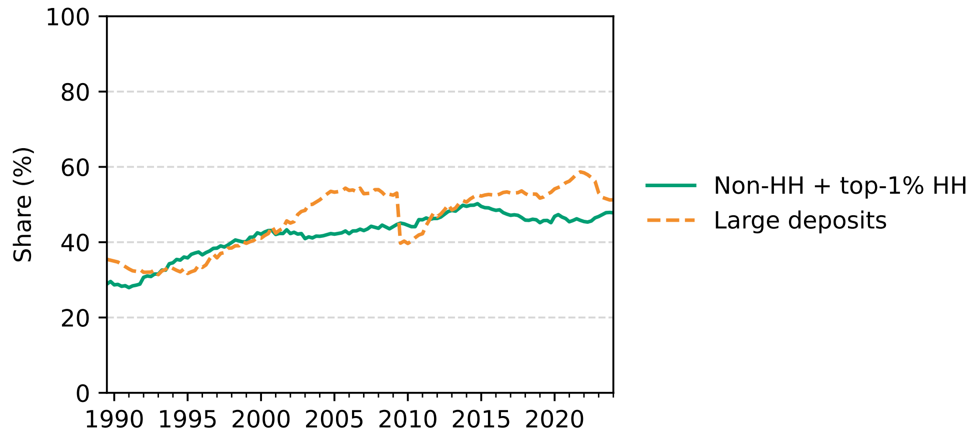


Figure A3. Effective federal funds rate and monetary policy cycles

This figure plots the quarterly average of the effective federal funds rate from 1975Q1 to 2024Q1. The red areas highlight monetary policy tightening cycles, defined as periods when the federal funds rate increases from a local trough to a local peak. The green areas highlight monetary policy easing cycles, defined as periods when the federal funds rate decreases from a local peak to a local trough.

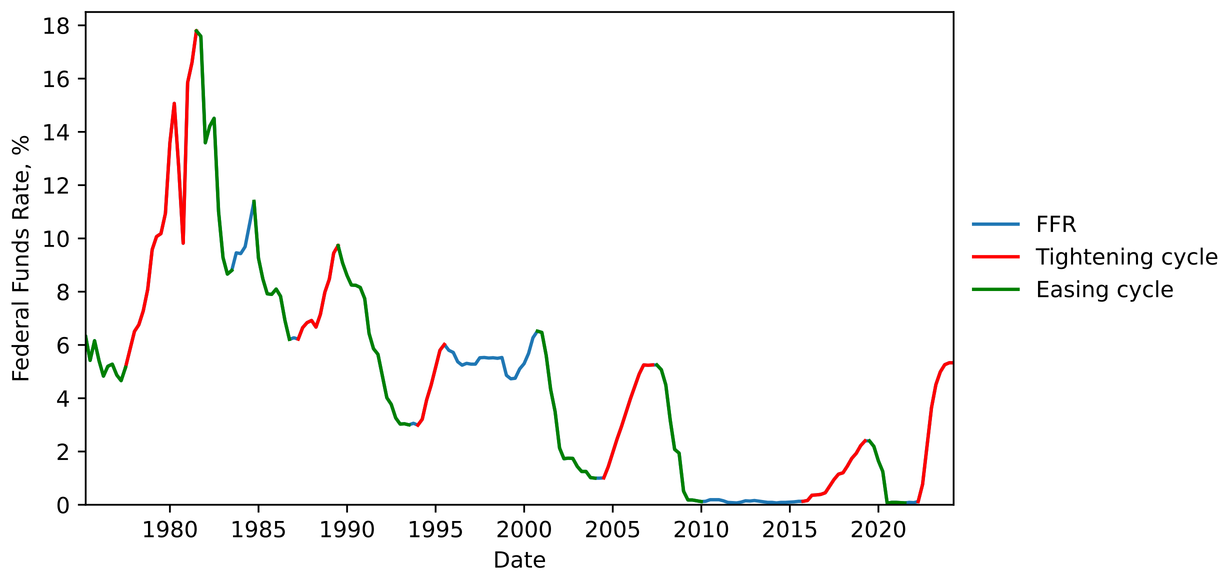


Figure A4. Deposit expense betas by share of large deposits: Easing cycles

This figure is similar to Figure 1, but for monetary policy easing cycles. The sample is all U.S. commercial banks for the period 1975Q1-2024Q1.

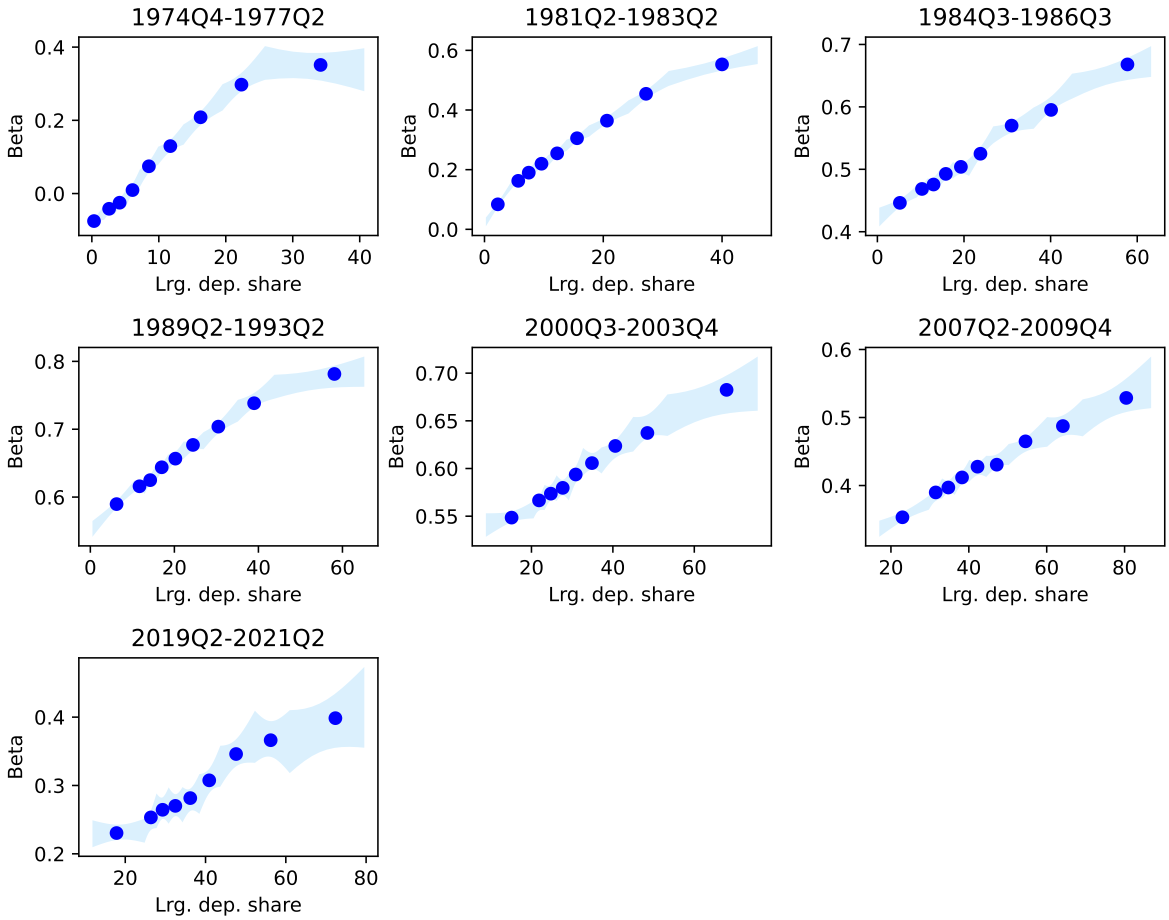


Figure A5. Deposit expense betas by share of large deposits: Controlling for local deposit market concentration and age

This figure is similar to Figure 1 and Figure A4, but controls for bank age and local deposit market concentration as measured by HHI.

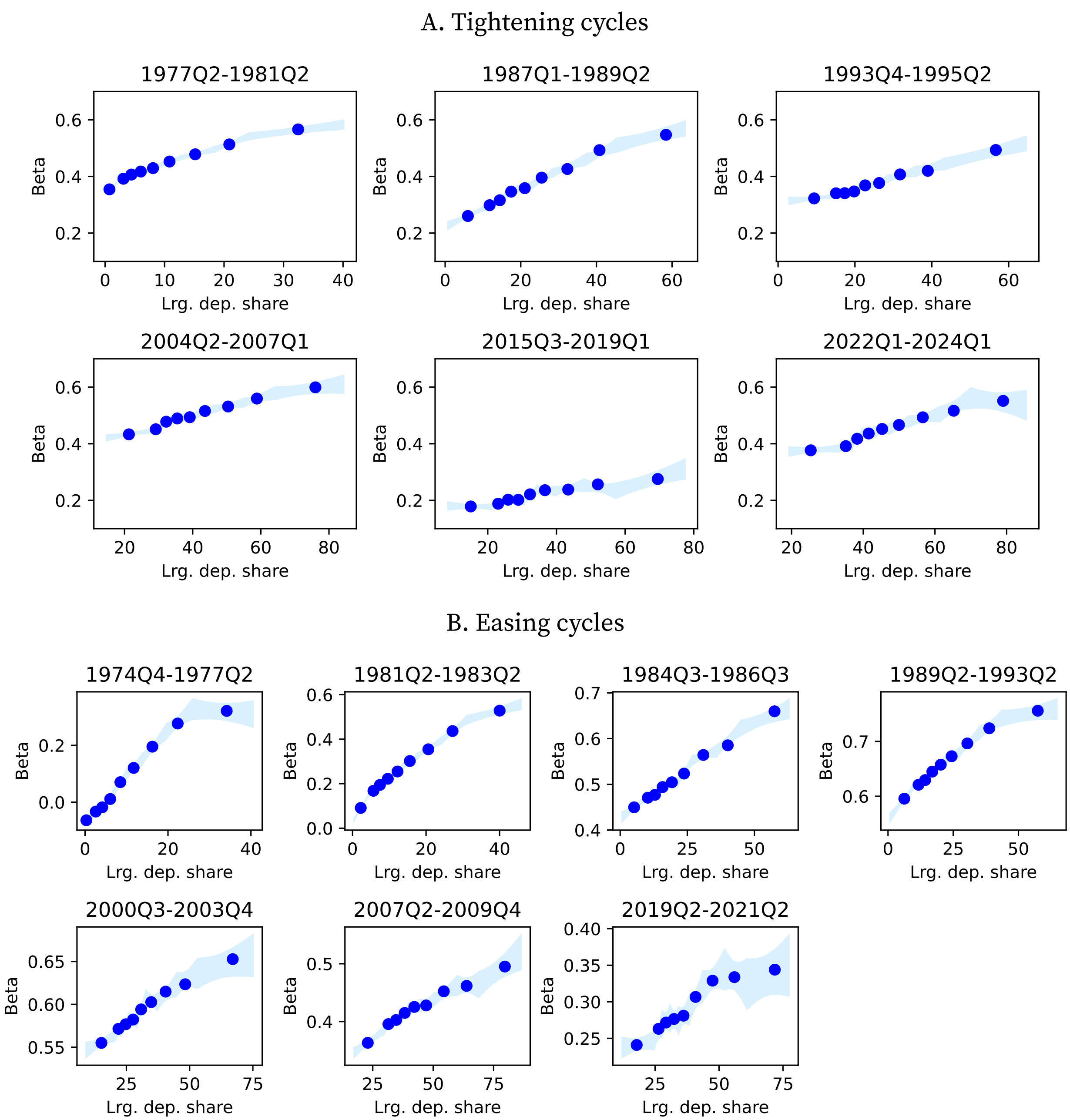
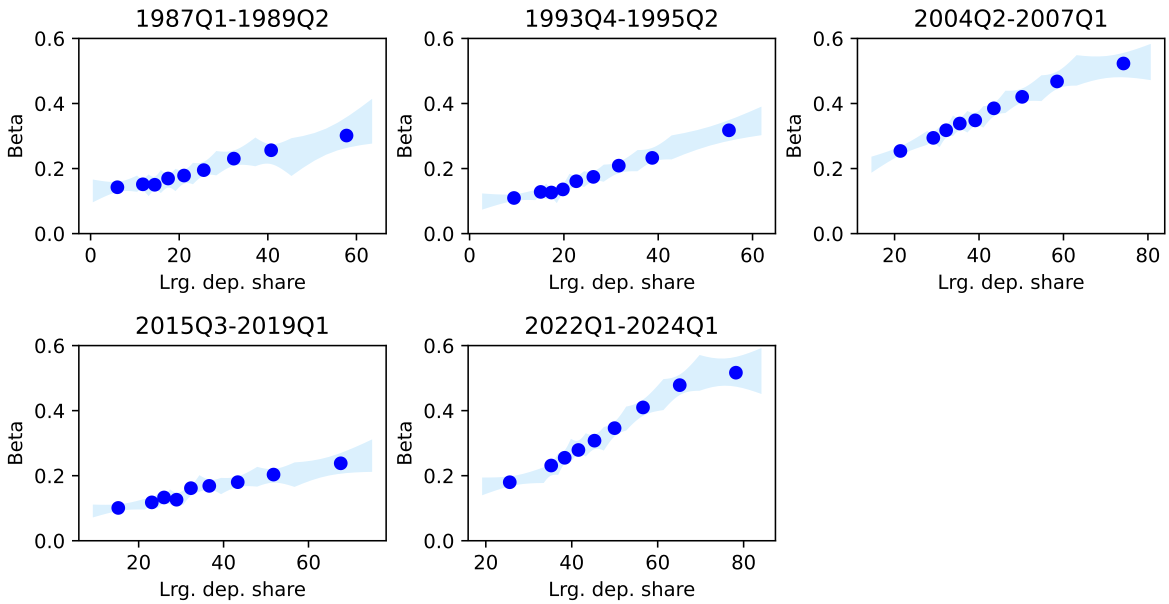


Figure A6. Savings deposit expense betas by share of large deposits

This figure is similar to Figure 1 and Figure A4, but for savings deposits expense betas. The sample is all U.S. commercial banks for the period 1987Q1-2024Q1 because interest expense on savings deposits is reported only since 1987Q1.

A. Tightening cycles



B. Easing cycles

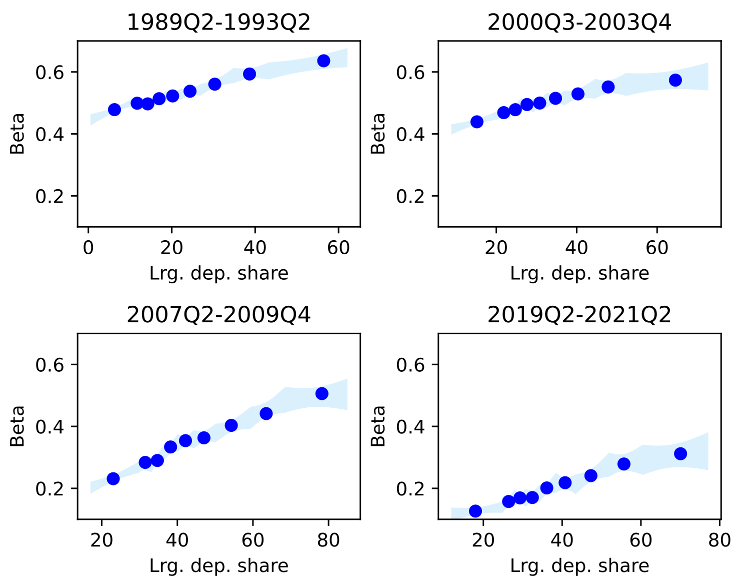
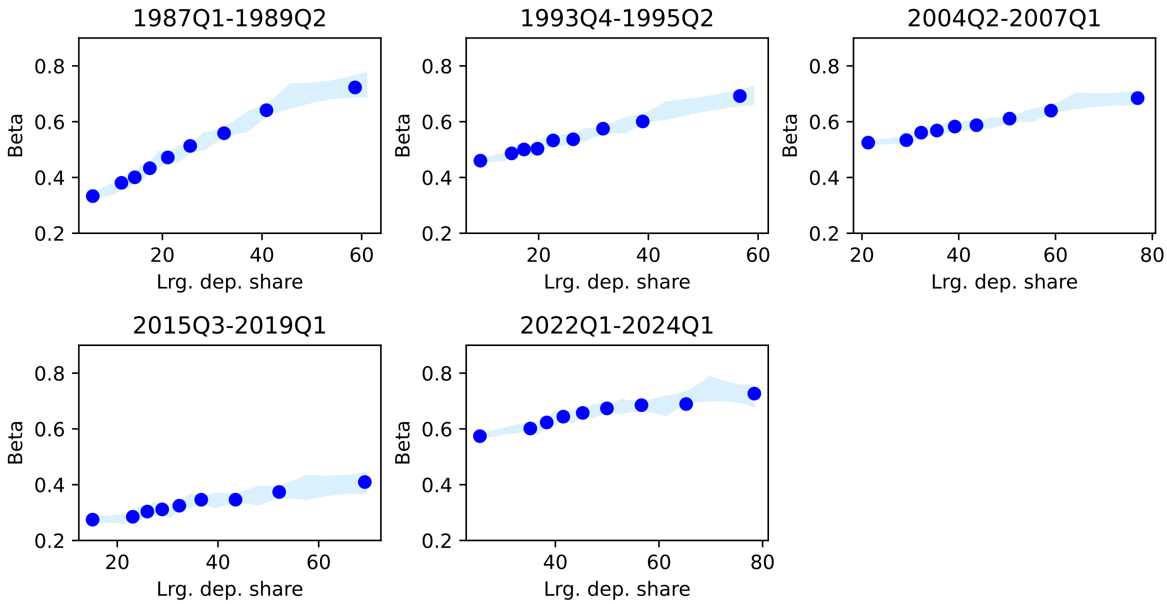


Figure A7. Time deposit expense betas by share of large deposits

This figure is similar to Figure 1 and Figure A4, but for time deposits expense betas. The sample is all U.S. commercial banks for the period 1987Q1-2024Q1 because interest expense on time deposits is reported only since 1987Q1.

A. Tightening cycles



B. Easing cycles

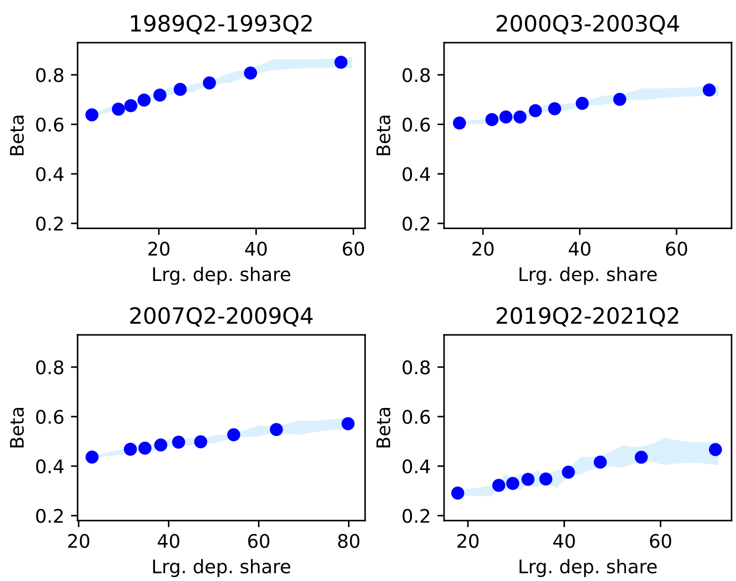


Figure A8. Total deposit expense rates at the start and end of tightening cycles by share of large deposits

This figure plots binscatters of total deposit expense rates by share of large deposits. On the x-axis, banks are grouped into bins as in Figure 1. Blue dots show the average deposit expense rate at the beginning of each monetary policy cycle, and red dots show the average deposit expense rate at the end of each cycle. Dashed blue line shows the level of the short rate (federal funds rate) at the start of the cycle, and the dashed red line shows the level at the end of the cycle. The sample is all U.S. commercial banks for the period 1975Q1-2024Q1.

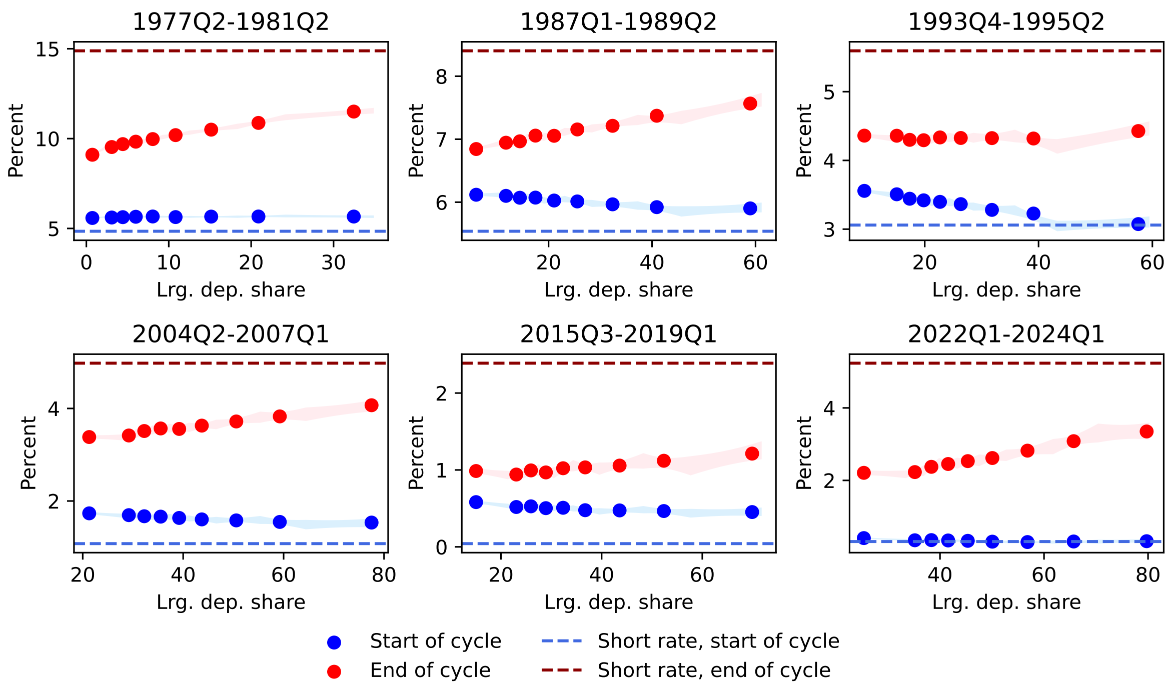
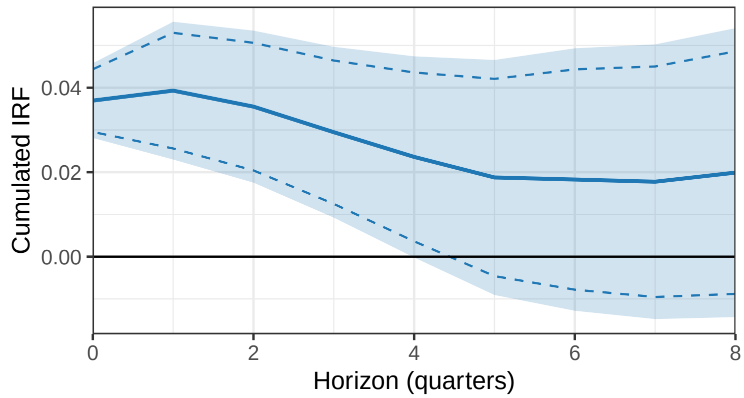


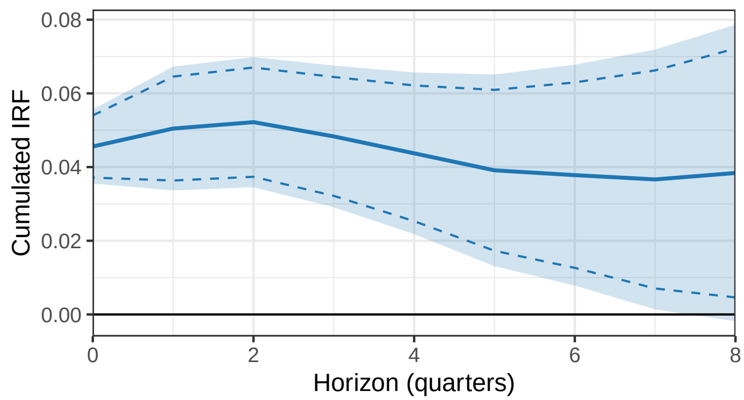
Figure A9. Impulse response of deposit expense rates to a federal funds rate change by share of large deposits: Core, savings, and time deposits

This figure is similar to Figure 2, but plots IRFs for deposit subsets: core deposits (Panel A), savings deposits (Panel B), and time deposits (Panel C).

A. Core deposits



B. Savings deposits



C. Time deposits

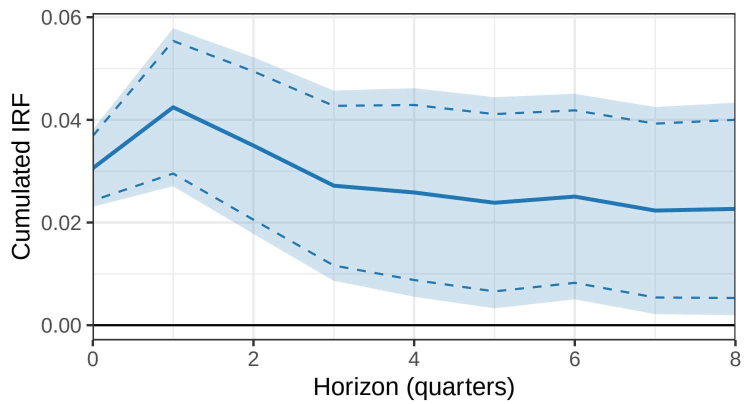
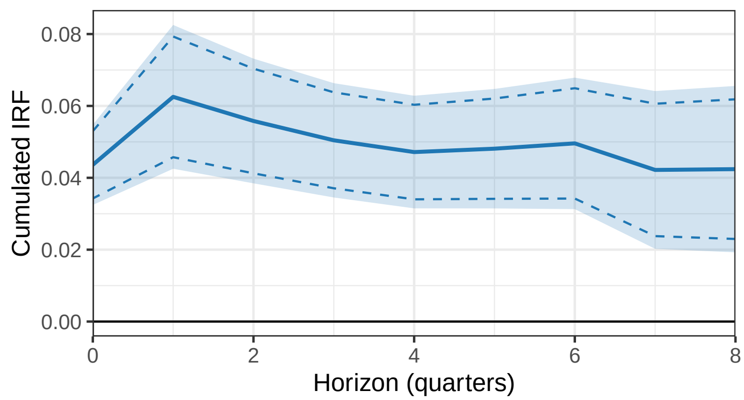


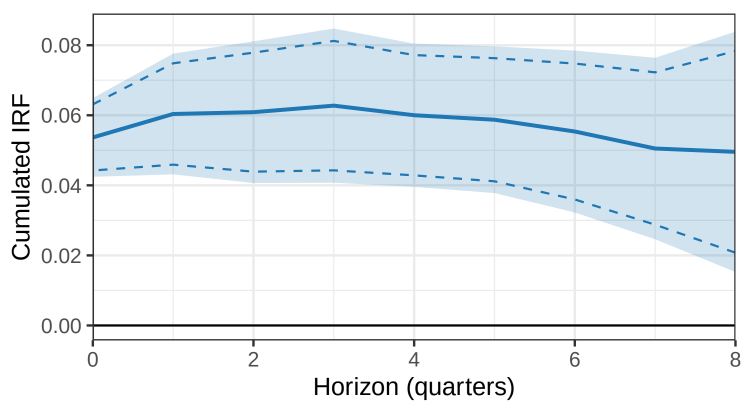
Figure A10. Impulse response of deposit expense rates to a federal funds rate change by share of large deposits: Top-10% sample

This figure is similar to Figure 2, but plots IRFs for the sample of banks that are in the top 10% of banks by total assets at least 5% of the time when this bank is in the sample. Panel A shows results for total deposits, Panel B for savings deposits, and Panel C for time deposits.

A. Total deposits



B. Savings deposits



C. Time deposits

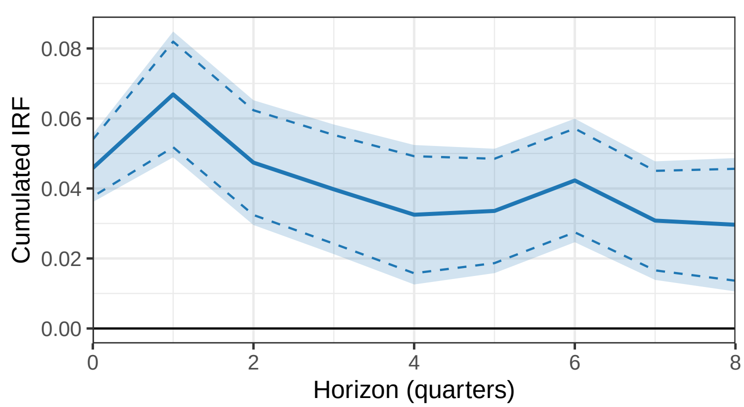
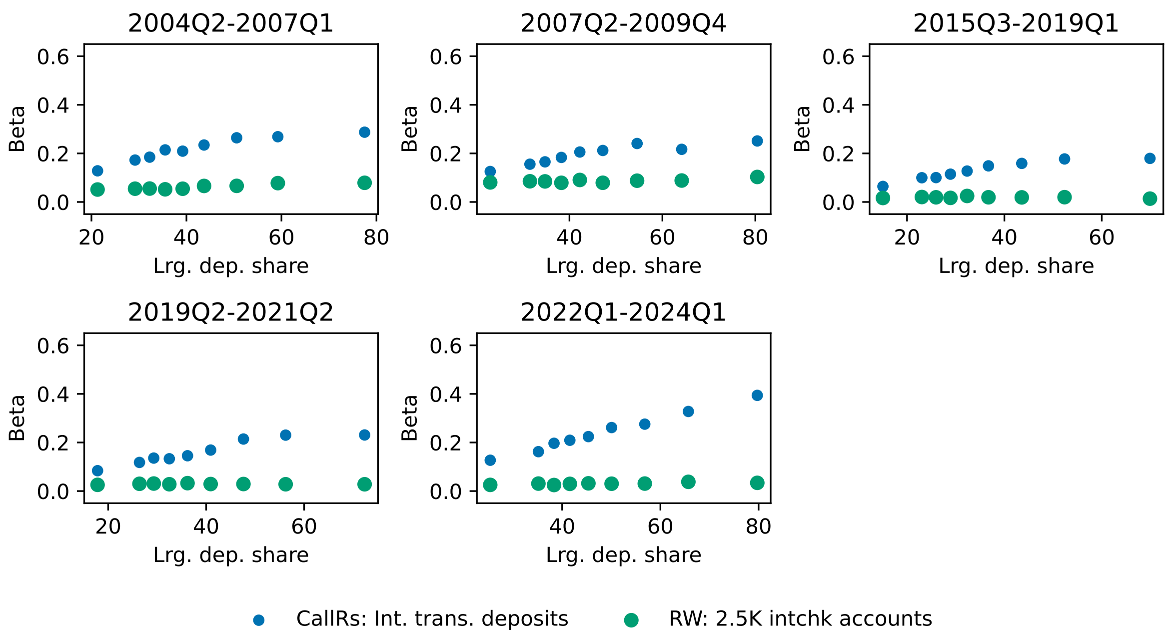


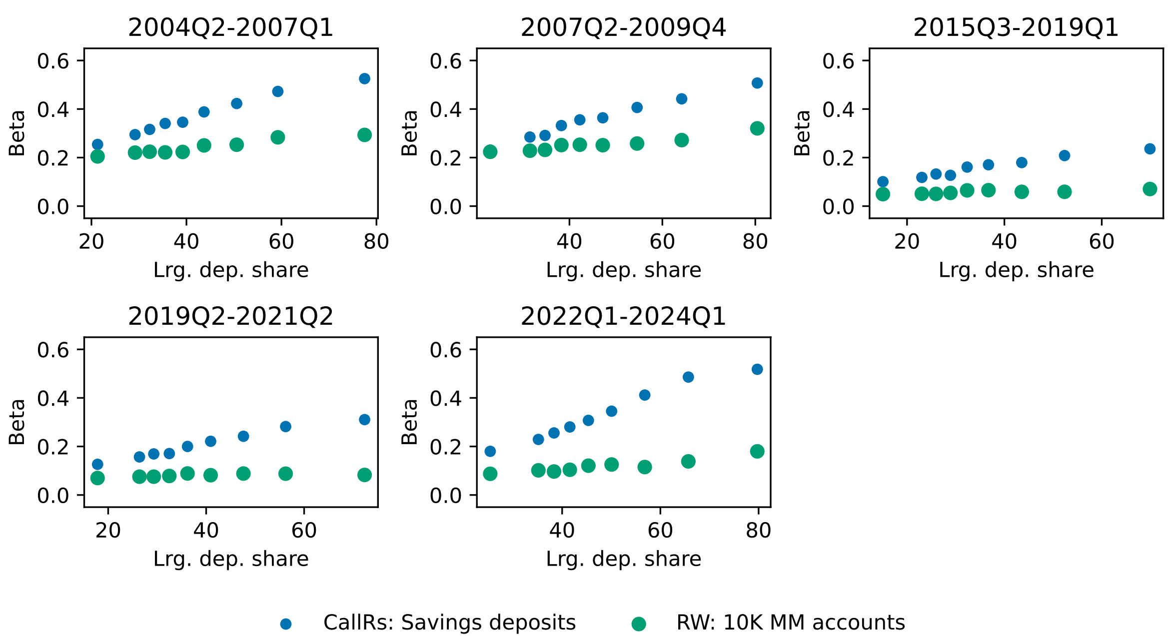
Figure A11. Call Report deposit expense betas vs Ratewatch small deposit betas by share of large deposits: Additional retail deposit products

This figure is similar to Figure 3, but for interest-bearing checking accounts with minimum balance of $2,500 (Panel A), money market deposit accounts with minimum balance of $10,000 (Panel B), and 12-month certificates of deposit (CDs) with minimum balance of $10,000 (Panel C).

A. Interest checking accounts ($2.5K minimum)



B. Money market deposit accounts ($10K minimum)



C. 12-month certificates of deposit ($10K minimum)

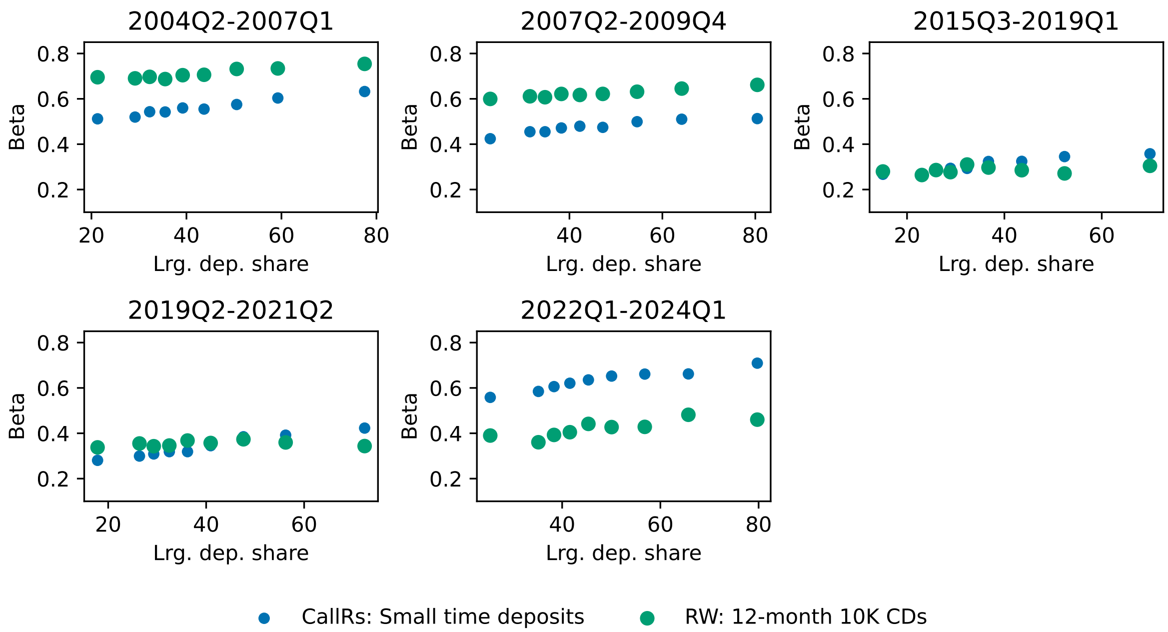


Figure A12. Small and large savings deposit rate betas

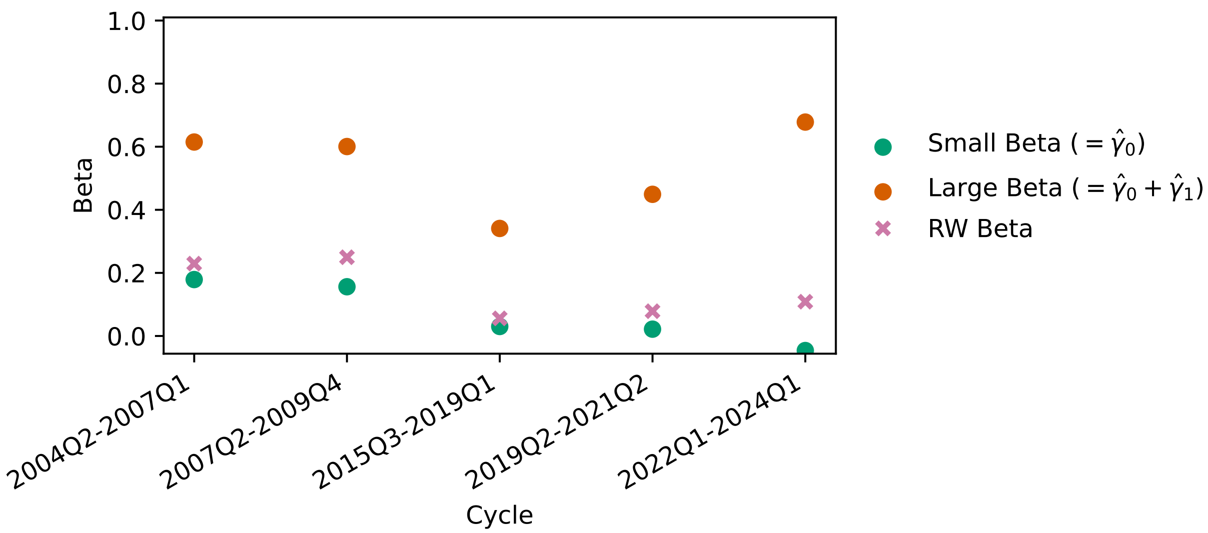
This figure is similar to Figure 3. It plots the same binscatter of rate betas on small savings deposits for monetary tightening and easing cycles since 2004 (green). It also plots betas on large deposits (orange). These are inferred from Equation 1 using deposit expense betas Dep. exp. $\text{beta}_{i,t_0\to t_1}$ on savings deposits computed from Call Reports, share of large deposits computed from Call Reports α^{Large}_{i,t_0}, and rate beta on small savings deposits computed from Ratewatch Dep. $\text{beta}^{Small}_{i,t_0\to t_1}$, as:

$$\text{Dep. beta}^{Large}_{i,t_0\to t_1} = \frac{\text{Dep. exp. beta}_{i,t_0\to t_1} - \left(1-\alpha^{Large}_{i,t_0}\right)\text{Dep. beta}^{Small}_{i,t_0\to t_1}}{\alpha^{Large}_{i,t_0}}.$$

Figure A13. Inferred deposit expense betas for small and large deposits by monetary policy cycle: Deposit subtypes

This figure is similar to Figure 4, but for savings deposits (Panel A) and interest-bearing transaction deposits (Panel B).

A. Savings deposits



B. Interest-bearing transaction deposits

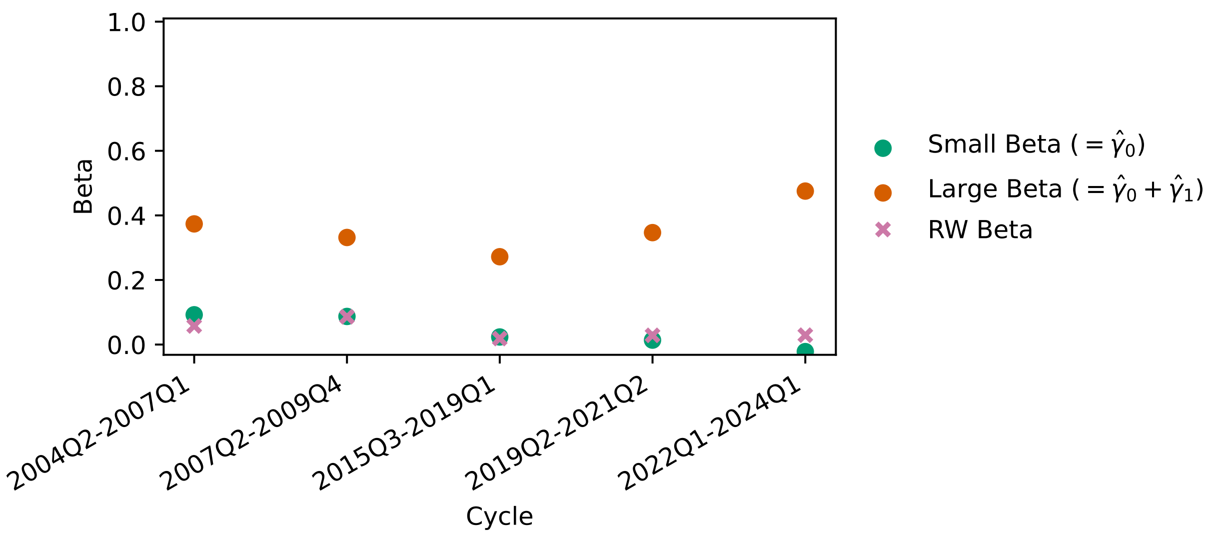


Figure A14. Inferred deposit expense betas for small and large deposits by monetary policy cycle: 1984-2024

This figure is similar to Figure 4, but for the 1984-2024 sample period. I start this analysis in 1984 because this is when total deposits start being broken down into large and small deposits. In Figure 1 and other similar figures, I use the sample starting in 1975 by proxying large deposits share with large time deposits share. This procedure introduces additional measurement error in this exercise, leading to estimated large deposit betas above 1.

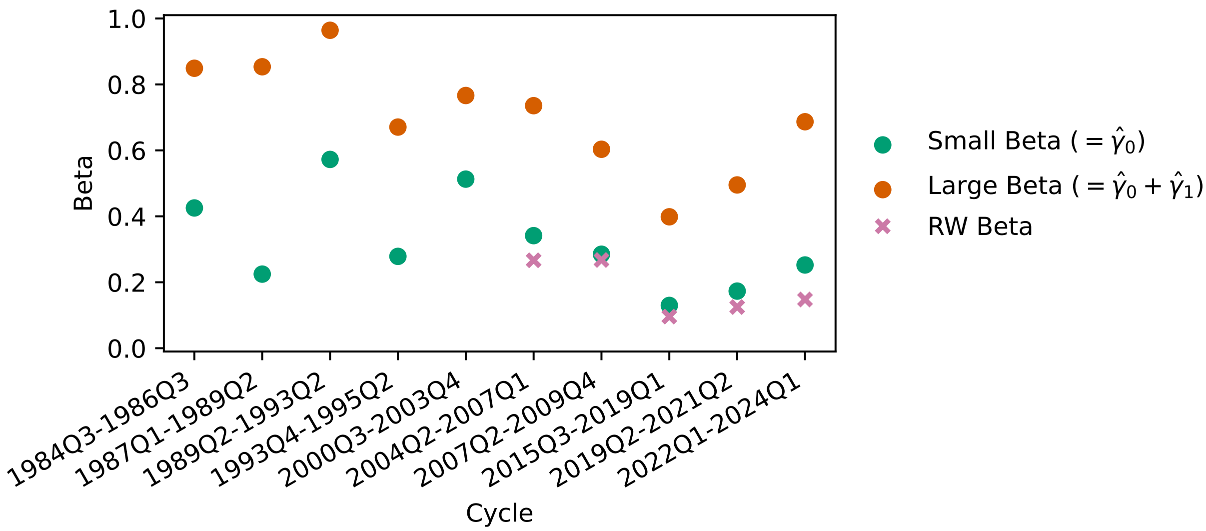
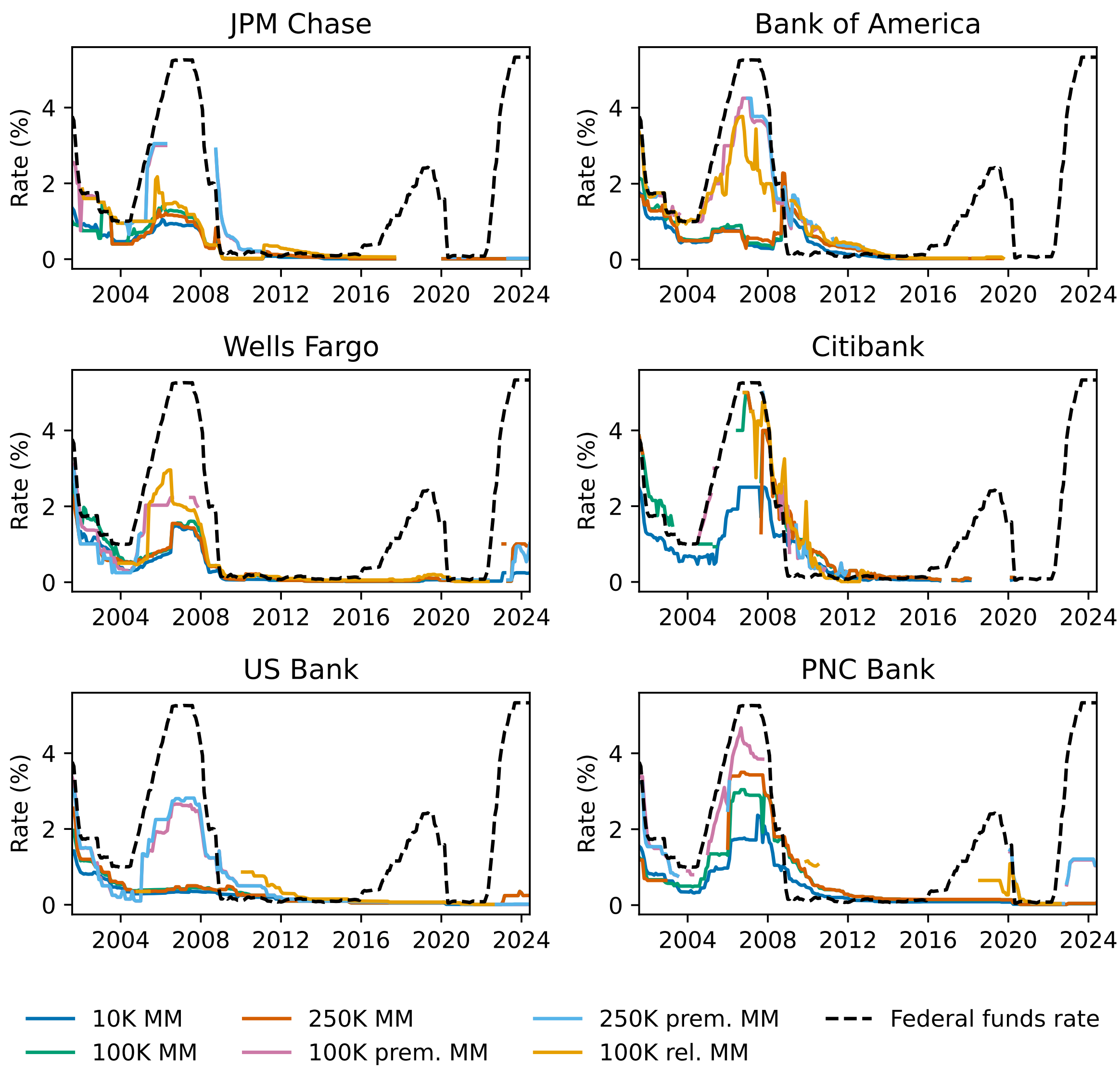


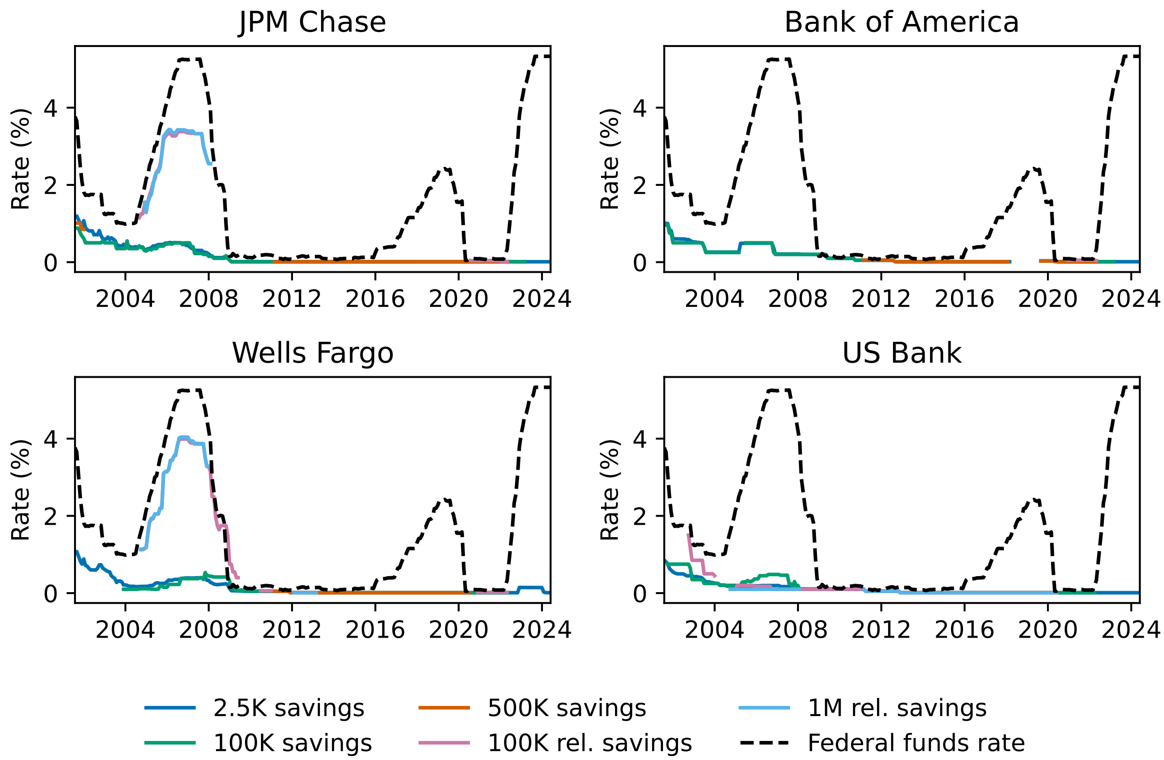
Figure A15. Rates on small and large deposit products at select banks

This figure plots rates on select deposit products at select large banks. Data are from Ratewatch. Panel A plots money market deposit account (MMDA) rates with $10,000, $100,000, and $250,000 minimum balance, as well as "premium" accounts with $100,000 minimum balance, and with $250,000 minimum balance. Panel B plots savings account rates with $2,500, $100,000, and $500,000 minimum balance as well as "relationship" accounts with $1 million minimum balance. Panel C shows rates on corporate sweep accounts with minimum balance of $100,000 and $1 million, as well as $2,500 savings accounts for comparison. All charts plot the federal funds rate (dashed black line) for reference. The Ratewatch data are monthly (month-end offered rates), July 2001-May 2024. See main text for additional details.

A. Money market deposit accounts



B. Savings accounts



C. Corporate sweep accounts

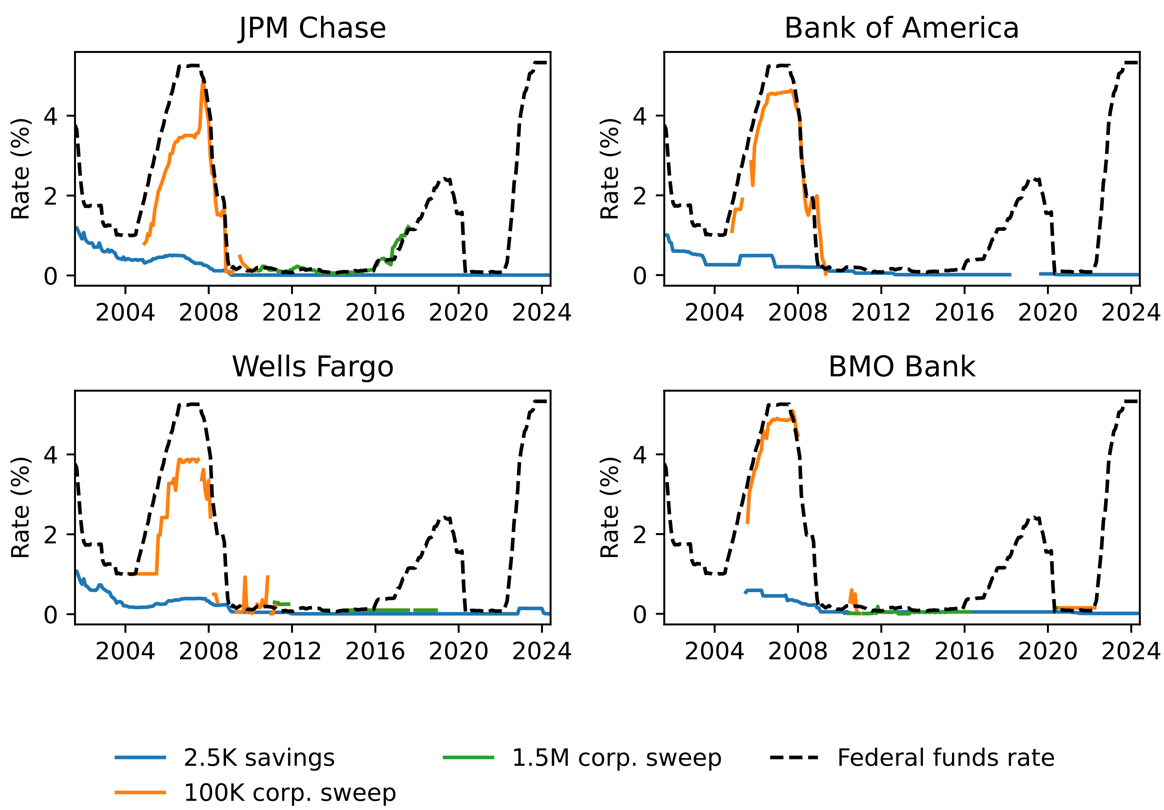


Figure A16. Screenshots of posted savings and MMDA rates at select banks

This figure shows screenshots of posted savings and money market deposit account (MMDA) rates from select banks: Wells Fargo (Panel A), PNC (Panel B), Zions Bancorporation (Panel C), and First Horizon (Panel D). The rates are hand-collected from each bank's website using Internet Archive's Wayback Machine. The screenshots illustrate that these banks use balance-tiered deposit pricing, paying higher rates on larger balances.

A. Wells Fargo, March 2024

Balance	Standard Interest Rate	Annual Percentage Yield (APY)
$0 - $99,999.99	0.25%	0.25%
$100,000 - $499,999.99	1.00%	1.01%
$500,000 - $999,999.99	1.98%	2.00%
$1,000,000 or more	2.47%	2.50%

B. PNC, September 2023

Premiere Money Market

Service Charges and Fees
Relationship Rates[2] with Performance Select Checking

Balance to Earn Interest	Interest Rate
$1.00 - $9,999.99	2.77%
$10,000.00 - $24,999.99	3.44%
$25,000.00 - $49,999.99	3.44%
$50,000.00 - $99,999.99	3.44%
$100,000.00 - $249,999.99	3.44%
$250,000.00 - $499,999.99	3.44%
$500,000.00 - $999,999.99	3.44%
$1,000,000.00 and above	3.44%

Standard Rates

Balance to Earn Interest	Interest Rate
$1.00 - $9,999.99	0.99%
$10,000.00 - $24,999.99	0.99%
$25,000.00 - $49,999.99	0.99%
$50,000.00 - $99,999.99	1.04%
$100,000.00 - $249,999.99	1.49%
$250,000.00 - $499,999.99	1.59%
$500,000.00 - $999,999.99	1.64%
$1,000,000.00 and above	1.74%

C. Zions, October 2024

Money Market

This is the money market your savings have been looking for

If you want to boost your earnings, Money Market Saving accounts come with a competitive tiered rate[3] that increases with your balance.

Rates effective as of: 10/02/2024 Displaying rates for: Idaho

BALANCE	Interest Rate[3]	Variable APY[3]
$0.00 - $999.99	0.00%	0.00%
$1,000.00 - $99,999.99	0.50%	0.50%
$100,000.00 - $249,999.99	1.20%	1.21%
$250,000.00 - $499,999.99	1.20%	1.21%
$500,000.00 - $999,999.99	1.25%	1.26%
$1,000,000.00 +	1.25%	1.26%

Premier Money Market

Ease of entry, premium rate benefits

Exclusively for Premier and Premier Elite clients, the Premier Money Market [7] account offers our highest interest rates for a Money Market account[3].

Rates effective as of: 10/02/2024 Displaying rates for: Idaho

BALANCE	Interest Rate[3]	Variable APY[3]
$0.00 - $4,999.99	0.00%	0.00%
$5,000.00 - $99,999.99	0.80%	0.80%
$100,000.00 - $249,999.99	1.25%	1.26%
$250,000.00 - $499,999.99	1.45%	1.46%
$500,000.00 - $999,999.99	1.80%	1.82%
$1,000,000.00 +	1.80%	1.82%

D. First Horizon, October 2023

Savings rates

Type	Balance	APY*	Next steps
Money Market Savings	$0 – $24,999	0.60%	APPLY NOW
	$25,000 – $49,999	0.60%	
	$50,000 – $99,999	1.51%	
	$100,000 – $249,999	1.51%	
	$250,000+	1.51%	
TotalView Money Market Savings	$0 – $24,999	1.76%	LEARN MORE
	$25,000 – $49,999	1.76%	
	$50,000 – $99,999	2.02%	
	$100,000 – $249,999	2.02%	
	$250,000+	2.02%	
Traditional Savings	All balances	0.30%	APPLY NOW

Figure A17. Screenshots of posted CD rates at select banks

This figure shows screenshots of posted certificate of deposit (CD) rates from select banks on select dates: JPMorgan Chase (Panel A), Bank of America (Panels B and C), and Fifth Third Bank (Panel D). The rates are hand-collected from each bank's website using Internet Archive's Wayback Machine.

A. JPMorgan Chase, July 2024

Months (m) / Days (d)		CD RELATIONSHIP RATES						CD STANDARD RATES	
New CD/ Term Change	Existing CD Auto Renewal (m/d)	$1,000–$9,999		$10,000–$99,999		$100,000+		$1,000+	
Featured Terms		Interest Rate	APY	Interest Rate	APY	Interest Rate	APY	Interest Rate	APY
2m	2 / 60 - 89	4.16%	4.25%	4.16%	4.25%	4.64%	4.75%	0.01%	0.01%
6m	6 - 8 / 180 - 269	2.96%	3.00%	2.96%	3.00%	2.96%	3.00%	0.01%	0.01%
9m	9 - 11 / 270 - 364	4.16%	4.25%	4.16%	4.25%	4.64%	4.75%	0.01%	0.01%
Other Terms									
1m	1 / 31 - 59	0.02%	0.02%	0.02%	0.02%	0.02%	0.02%	0.01%	0.01%
3m	3 - 5 / 90 - 179	1.98%	2.00%	1.98%	2.00%	1.98%	2.00%	0.01%	0.01%
12m	12 - 14 / 365 - 454	1.98%	2.00%	1.98%	2.00%	1.98%	2.00%	0.01%	0.01%

B. Bank of America, December 2018

Featured CD/IRA†‡	Rate %	APY %
12 Month CD	0.07	0.07
12 Month IRA	0.07	0.07
13 Month CD	1.98	2.00
13 Month IRA	1.98	2.00
25 Month CD	2.08	2.10
25 Month IRA	2.08	2.10
37 Month CD	2.42	2.45
37 Month IRA	2.42	2.45

Minimum to open: $10,000 CDs/$2,000 IRAs

C. Bank of America, December 2023

Featured CD/IRA‡‡

7 Month

Account Balance	Rate %	APY %
Less than $10,000	3.20%	3.25%
$10,000 - $99,999	3.20%	3.25%
$100,000 - $999,999	3.45%	3.51%
$1,000,000 and over	3.45%	3.51%

10 Month

Account Balance	Rate %	APY %
Less than $10,000	0.05%	0.05%
$10,000 - $99,999	0.05%	0.05%
$100,000 - $999,999	0.05%	0.05%
$1,000,000 and over	0.05%	0.05%

13 Month

Account Balance	Rate %	APY %
Less than $10,000	3.74%	3.80%
$10,000 - $99,999	3.74%	3.80%
$100,000 - $999,999	3.98%	4.05%
$1,000,000 and over	3.98%	4.05%

25 Month

Account Balance	Rate %	APY %
Less than $10,000	2.96%	3.00%
$10,000 - $99,999	2.96%	3.00%
$100,000 - $999,999	2.96%	3.00%
$1,000,000 and over	2.96%	3.00%

37 Month

Account Balance	Rate %	APY %
Less than $10,000	0.05%	0.05%
$10,000 - $99,999	0.05%	0.05%
$100,000 - $999,999	0.05%	0.05%
$1,000,000 and over	0.05%	0.05%

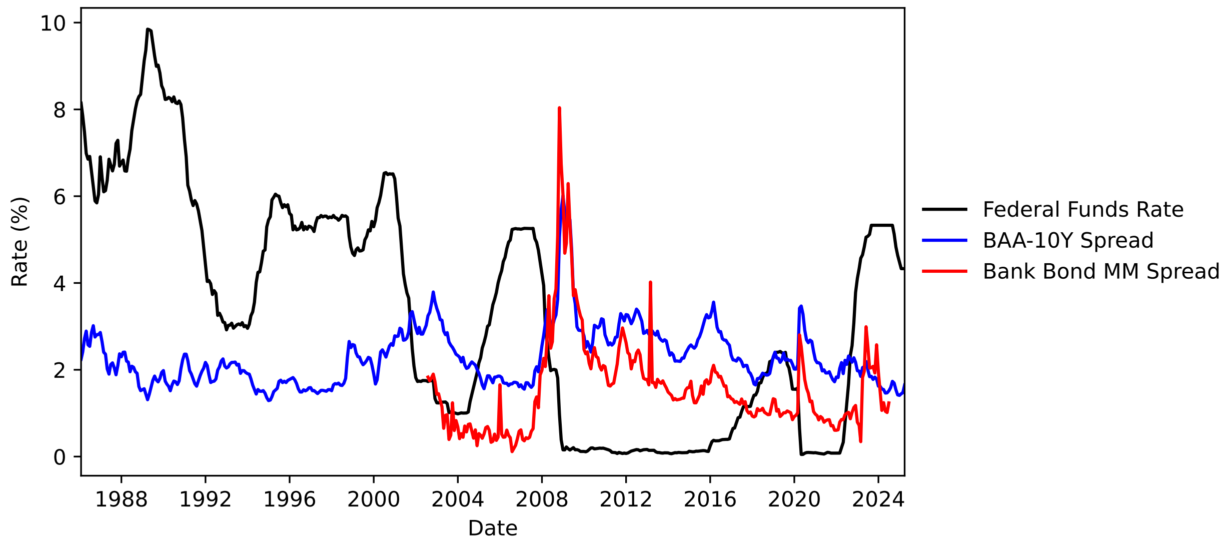
D. Fifth Third Bank, March 2024

Fifth Third Bank (OH) CD Rates

APY	MIN	MAX	ACCOUNT NAME
5.20%	$5k	-	4 Month Promo CD
5.00%†	$5k	-	6 Month Promo CD
4.30%†	$5k	-	12 Month Promo CD
3.50%†	$5k	-	24 Month Promo CD
0.01%†	-	$100k	7-89 Day Standard CD
0.01%†	$500	$100k	3-6 Month Standard CD
0.01%†	$500	$100k	6-12 Month Standard CD
0.01%†	$500	$100k	12-24 Month Standard CD
0.01%†	$500	$100k	24-36 Month Standard CD
0.01%†	$500	$100k	36-48 Month Standard CD
0.01%†	$500	$100k	48-60 Month Standard CD
0.01%†	$500	$100k	60-84 Month Standard CD
0.01%†	$500	$100k	84 Month Standard CD

Figure A18. Baa corporate bond spread and bank bond spreads, 1985-2024

This figure plots monthly average of Baa corporate bond spread relative to 10-year Treasury yield, sourced from FRED, in blue. In red, it plots maturity-matched bank bond spreads averaged across all banks with available data in a given month. The bank bond spreads are computed as described in Appendix B. I plot the federal funds rate in black for reference. Below the chart, I show correlation between the two spreads and the federal funds rate.



Correlation FFR vs BAA-10Y: -0.52
Correlation FFR vs Bank Spread: -0.30

Figure A19. Bank bond spreads by large deposits share, 2004-2024

This figure plots binscatters similar to Figure 1, but on the y-axis it plots median change in bank bond spreads over monetary policy tightening cycles in a given bin of large deposits share. The sample is U.S. commercial banks with available bond spread data for the period 2004-2024.

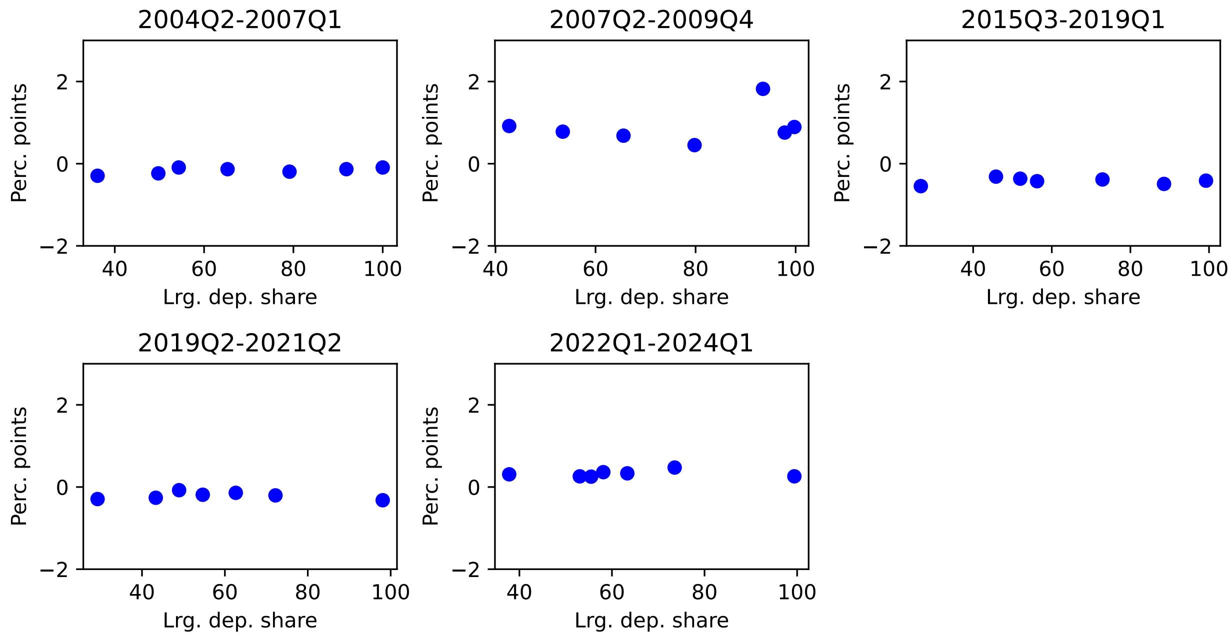


Figure A20. Bank bond spreads by large deposits share, 2004-2024: Levels at the start and end of monetary policy cycles

This figure is similar to Figure A19, but it plots levels of bank bond spreads at the start and end of monetary policy cycles.

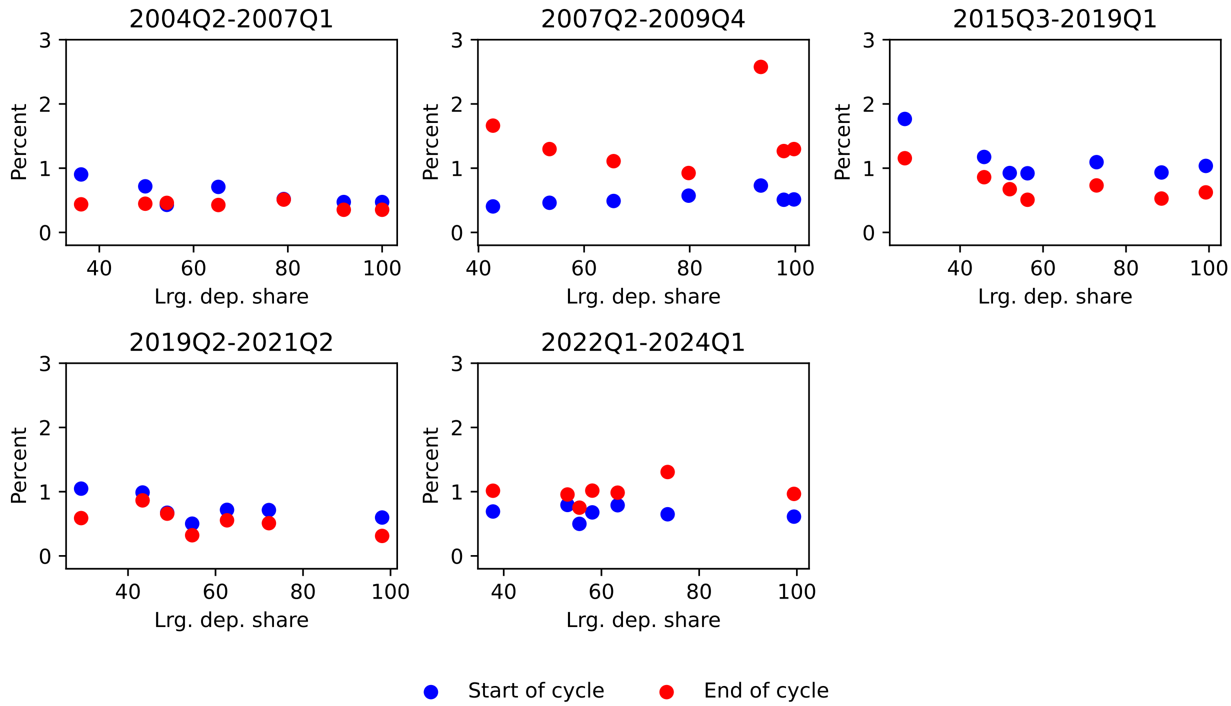
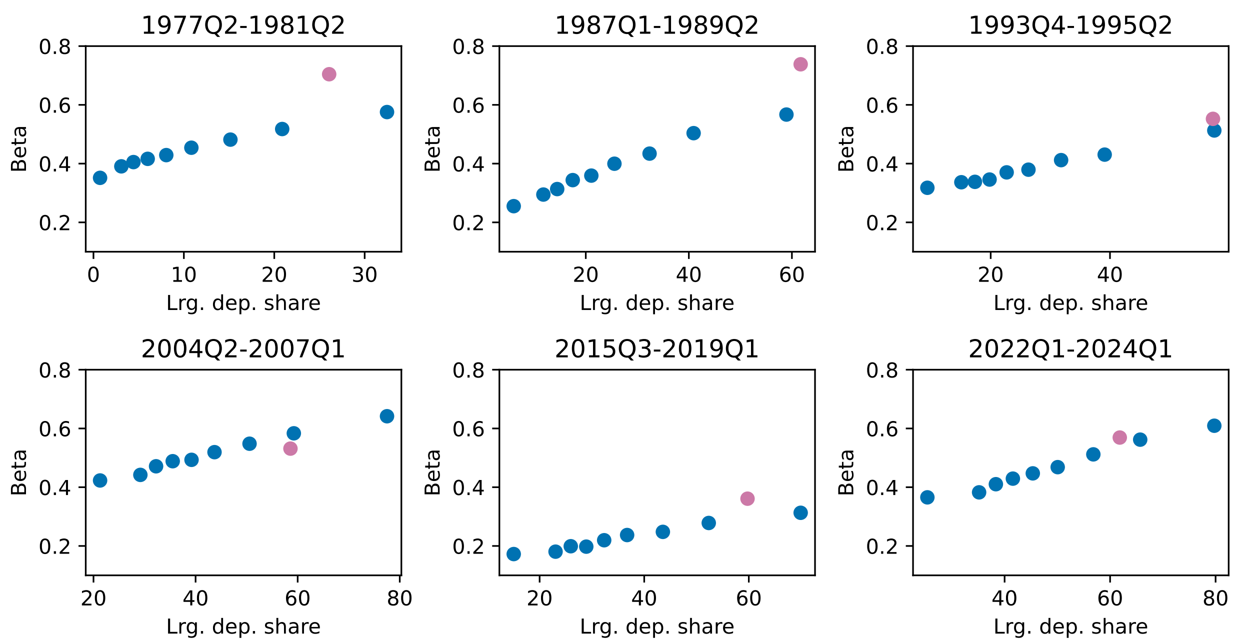


Figure A21. "Too-big-to-fail" banks, large deposits share, and deposit expense betas

Panel A plots binscatters similar to Figure 1, but splits out largest 5 banks (by total assets) as of the beginning of each monetary cycle into their own bin, plotted in red. Panel A focuses on tightening cycles for exposition, results are similar for easing cycles. Panel B is similar to Figure 3, but it also splits out the largest 5 banks into their own bin, plotted in orange for Call Report betas and in red for Ratewatch betas.

A. Call Report sample, total deposits



B. Ratewatch sample, savings deposits

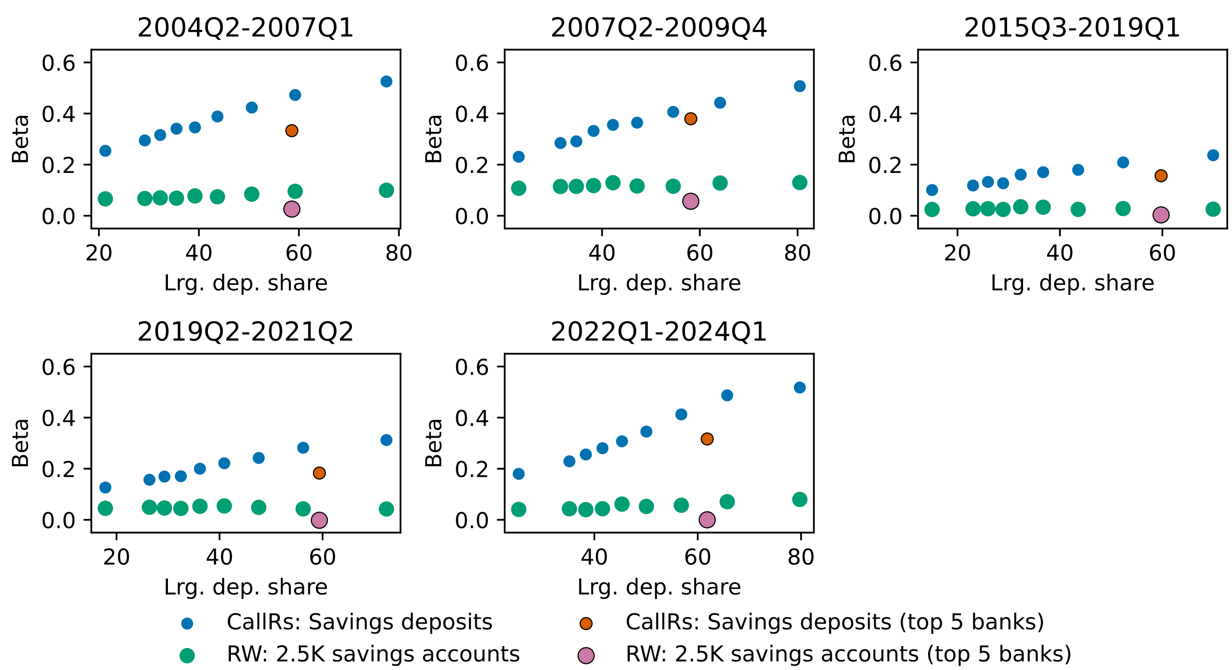
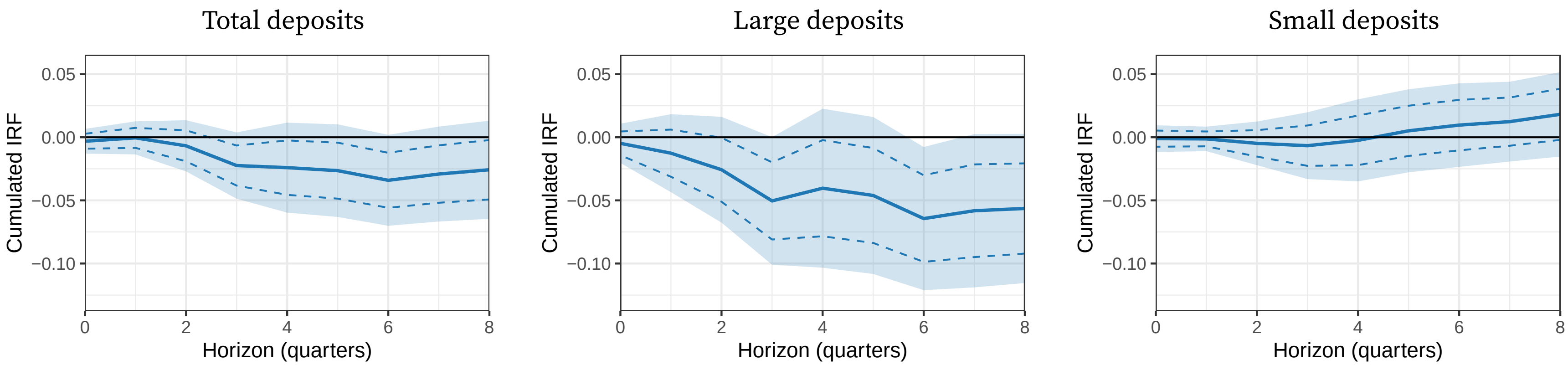


Figure A22. Aggregate deposit flow response to monetary policy: Alternative monetary shocks

This figure is similar to Figure 6, but it plots IRFs to changes in the short rate (Panel A) and to high-frequency monetary shocks from Bauer and Swanson (2023) (Panel B). The high-frequency shock is normalized to a 100bps increase in the federal funds rate.

A. Change in short rate



B. High-frequency monetary shocks

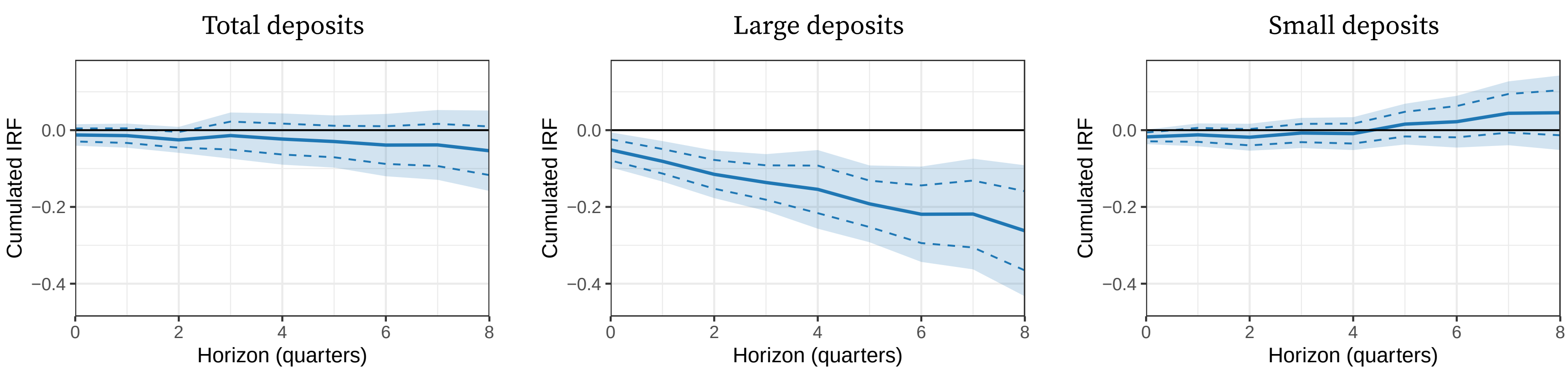
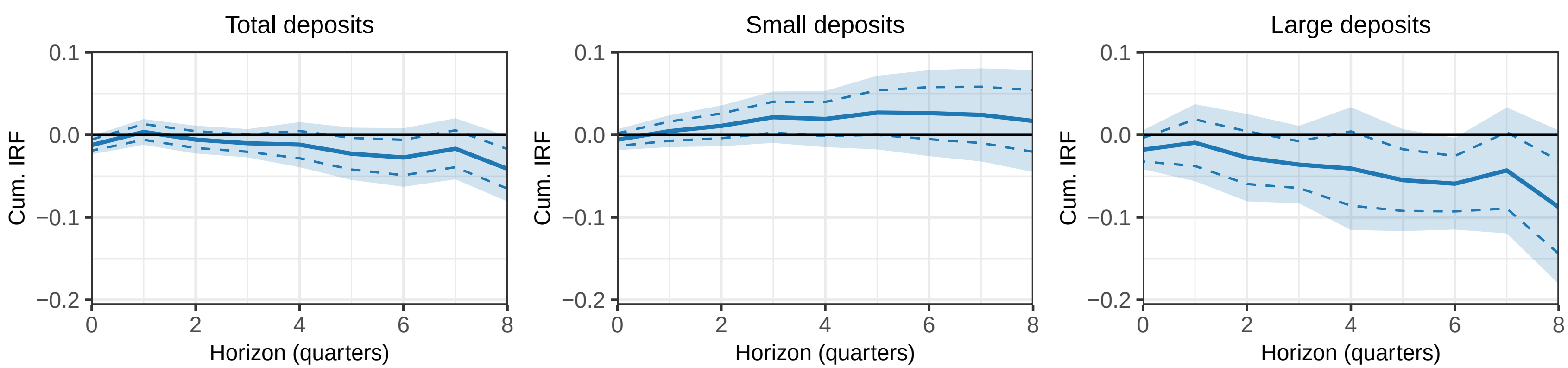


Figure A23. Large vs small deposits' response to monetary policy shocks by bank size

This figure is constructed similarly to Figure 6, but it plots the IRFs of total deposits (left column), small deposits (middle column), and large deposits (right column) separately for large banks (Panel A, defined as banks that belong to the top 1% by assets) and small banks (Panel B, defined as all other banks). All IRFs are to Romer and Romer (2004) monetary shocks, normalized so that the IRFs correspond to a 100bps increase in the federal funds rate. See the main text for further details on the data construction.

A. Large banks (top 1% by assets)



B. Small banks (bottom 99% by assets)

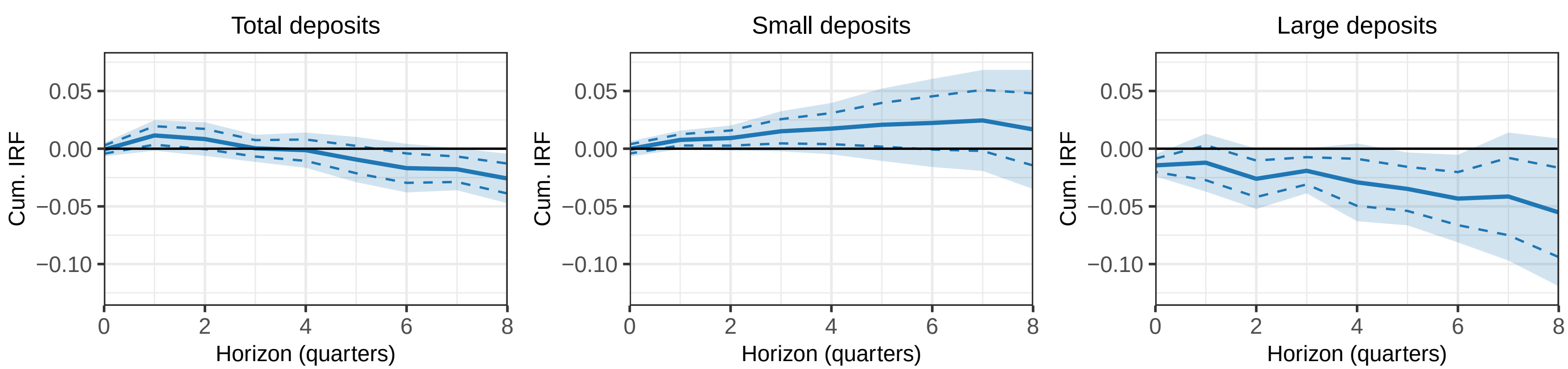
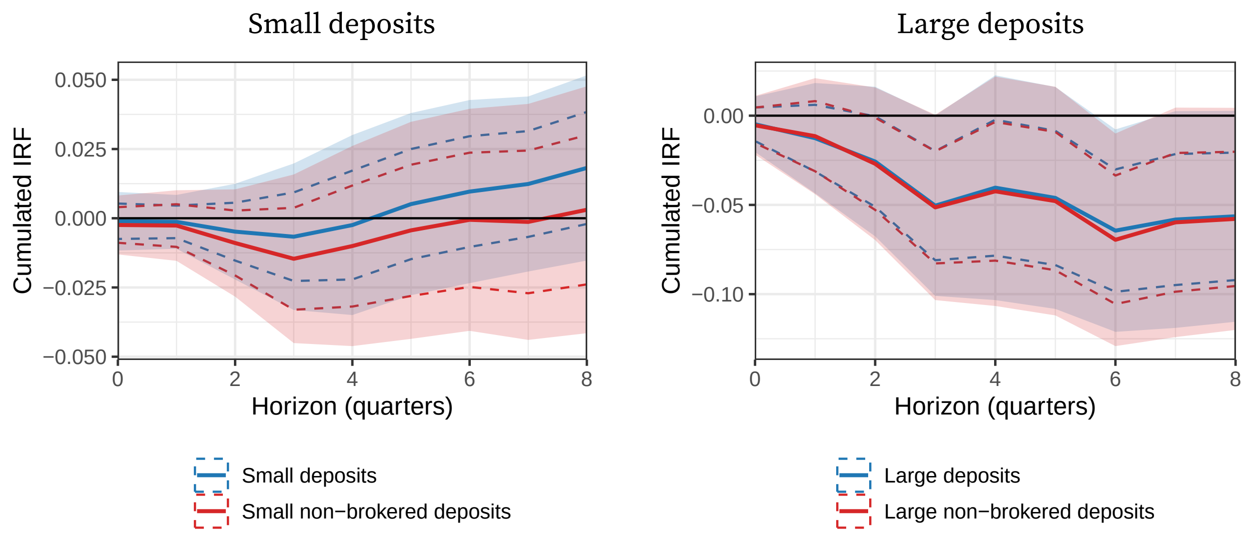


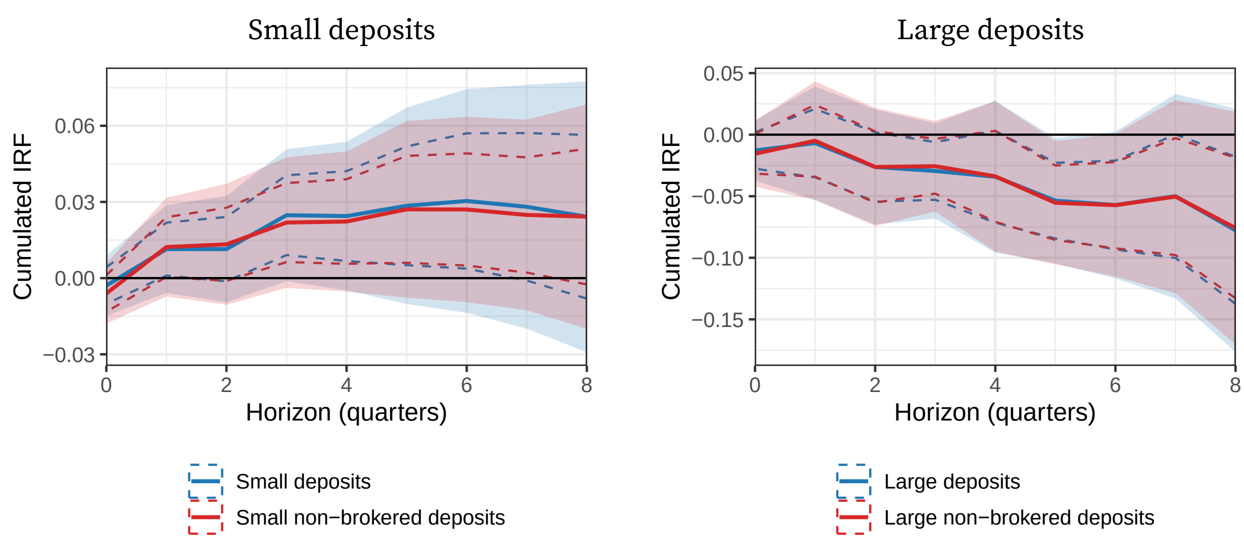
Figure A24. Brokered deposits do not drive small vs large deposits' flow response to monetary policy shocks

This figure is constructed similarly to Figure 6. It plots IRFs of small deposits and large deposits to monetary policy, splitting both small and large deposits into brokered and non-brokered deposits. Monetary policy is measured as changes in the short rate (Panel A), Romer and Romer (2004) monetary shocks (Panel B), and Bauer and Swanson (2023) high-frequency monetary shocks (Panel C).

A. Change in short rate



B. Romer and Romer (2004) monetary shocks



C. High-frequency monetary shocks

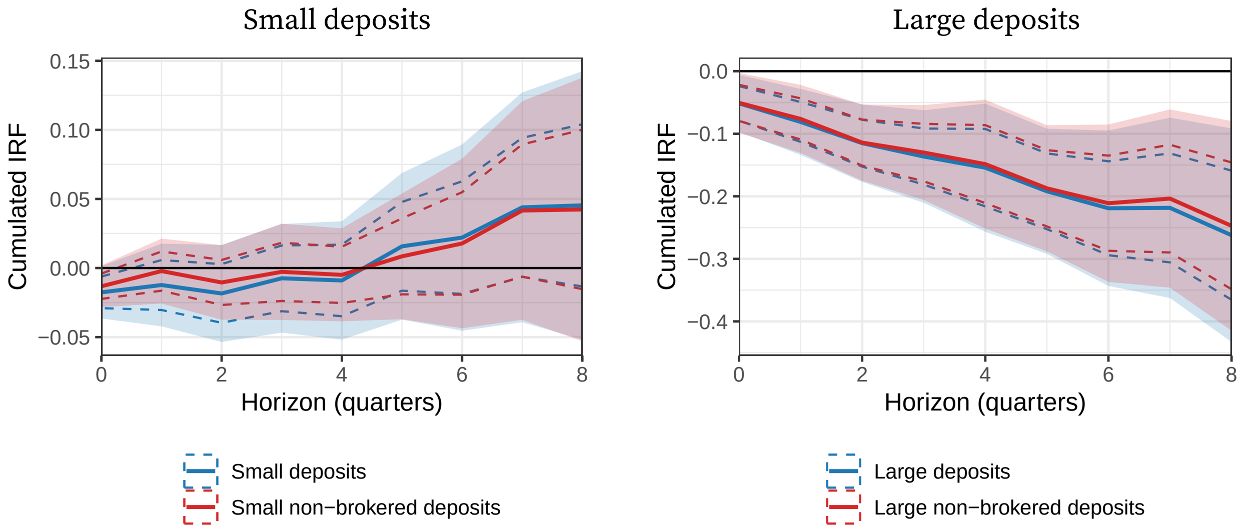


Figure A25. Deposit growth decomposed: Small vs large deposits

This figure plots year-on-year log-growth in real total deposits (blue line) and splitting it into growth in small deposits (orange line) and large deposits (red line). Deposit growth rates are plotted on the left y-axis. On the right y-axis, the figure plots the effective federal funds rate (black dashed line). Deposit data are aggregated from all U.S. commercial banks in Call Reports. The sample is 1985Q1-2024Q1. The missing data in 2010 for small and large non-time deposits are due to the change in definition of large deposits in Call Reports (see main text for details).

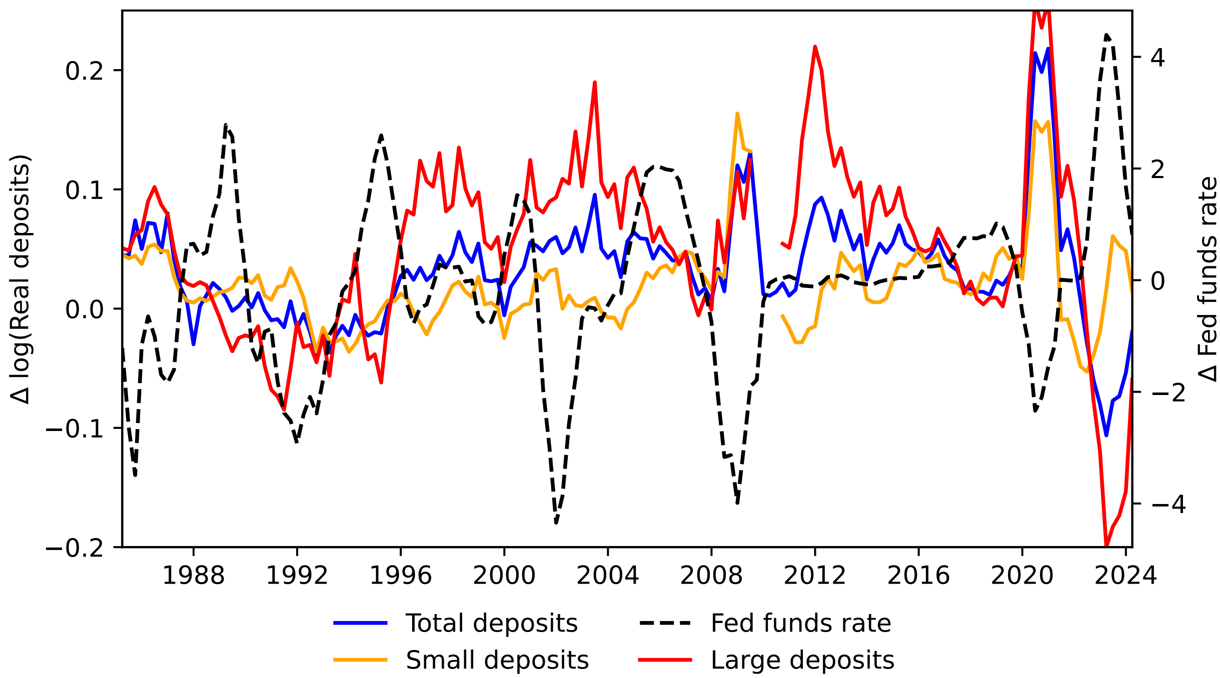
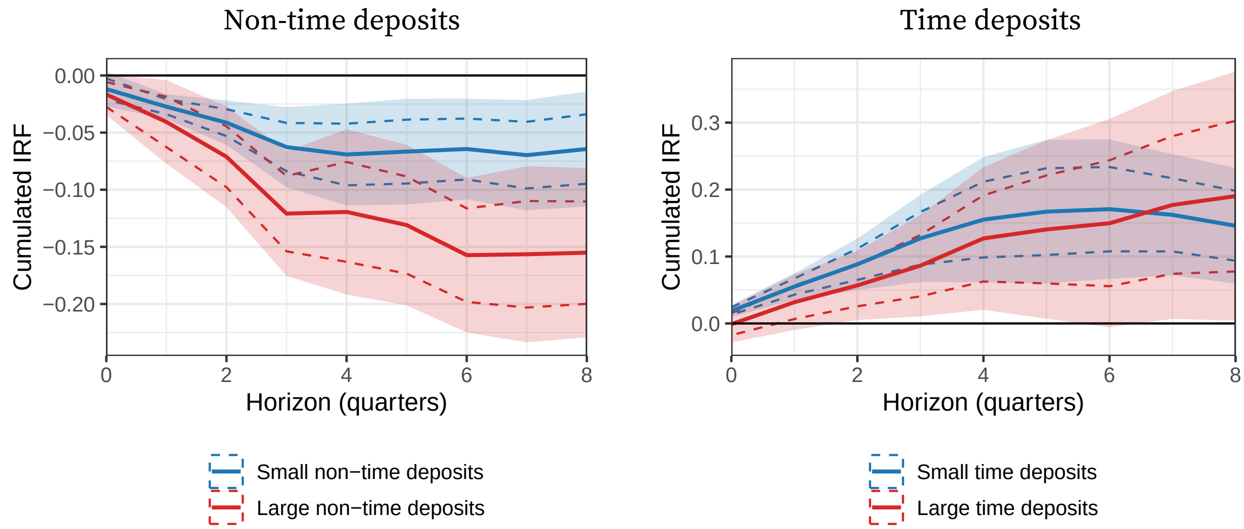


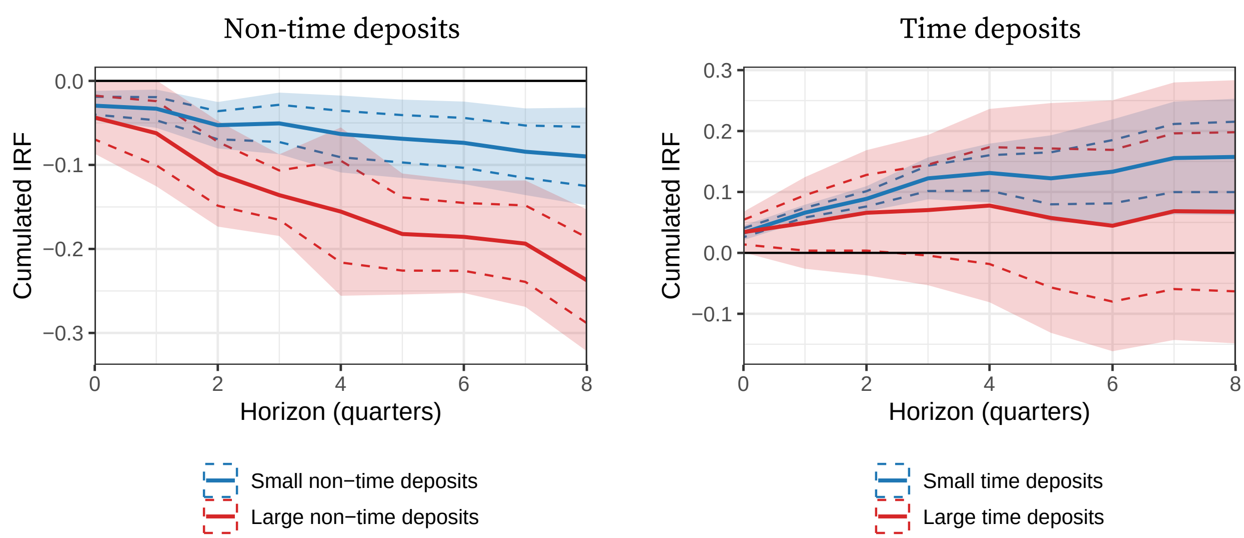
Figure A26. Time vs non-time deposits response to monetary policy shocks

This figure is constructed similarly to Figure 6. It plots IRFs of non-time deposits and time deposits to monetary policy, splitting both non-time and time deposits into large and small deposits. Monetary policy is measured as changes in the short rate (Panel A), Romer and Romer (2004) monetary shocks (Panel B), and Bauer and Swanson (2023) high-frequency monetary shocks (Panel C). The shocks are normalized to a 100bps change in the federal funds rate.

A. Change in short rate



B. Romer and Romer (2004) monetary shocks



C. High-frequency monetary shocks

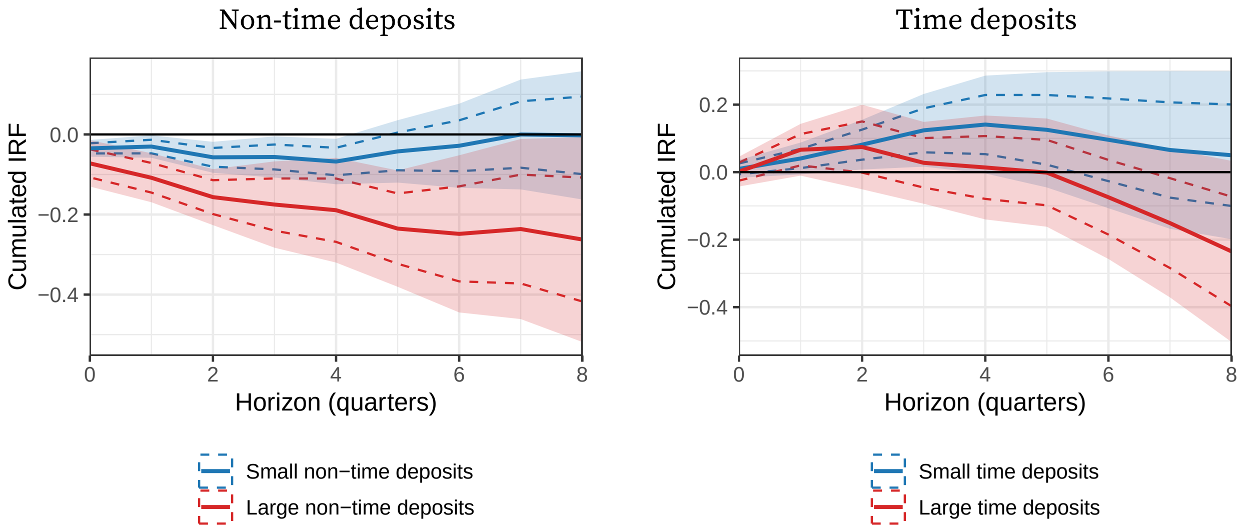


Figure A27. Deposit flow response to monetary policy by sector

This figure is constructed similarly to Figure 6. It plots IRFs of deposits to Romer and Romer (2004) monetary policy shocks, separately by sector. Household groups (bottom 99% and top 1% by net worth) are constructed from the Distributional Financial Accounts; firm sectors (nonfinancial corporate, nonfinancial noncorporate, and other financial) are constructed from the Flow of Funds ("From-Whom-To-Whom") data.

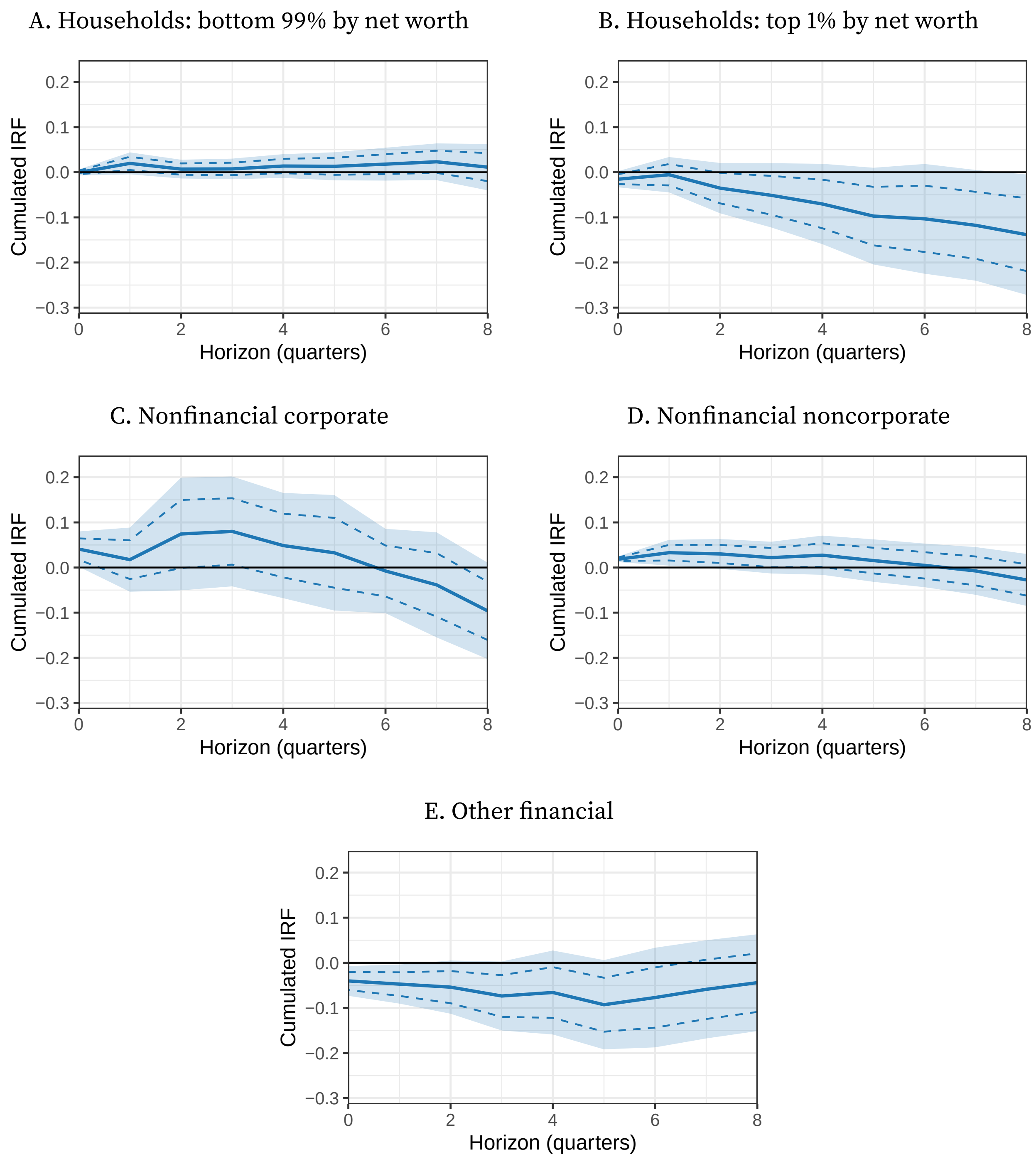


Figure A28. Household deposit flow response to monetary policy by net-worth group

This figure is constructed similarly to Figure 6. It plots IRFs of household deposits to Romer and Romer (2004) monetary policy shocks, separately for households in the bottom 50%, middle 50–99%, and top 1% of the net-worth distribution. Deposits by net-worth group are constructed from the Distributional Financial Accounts.

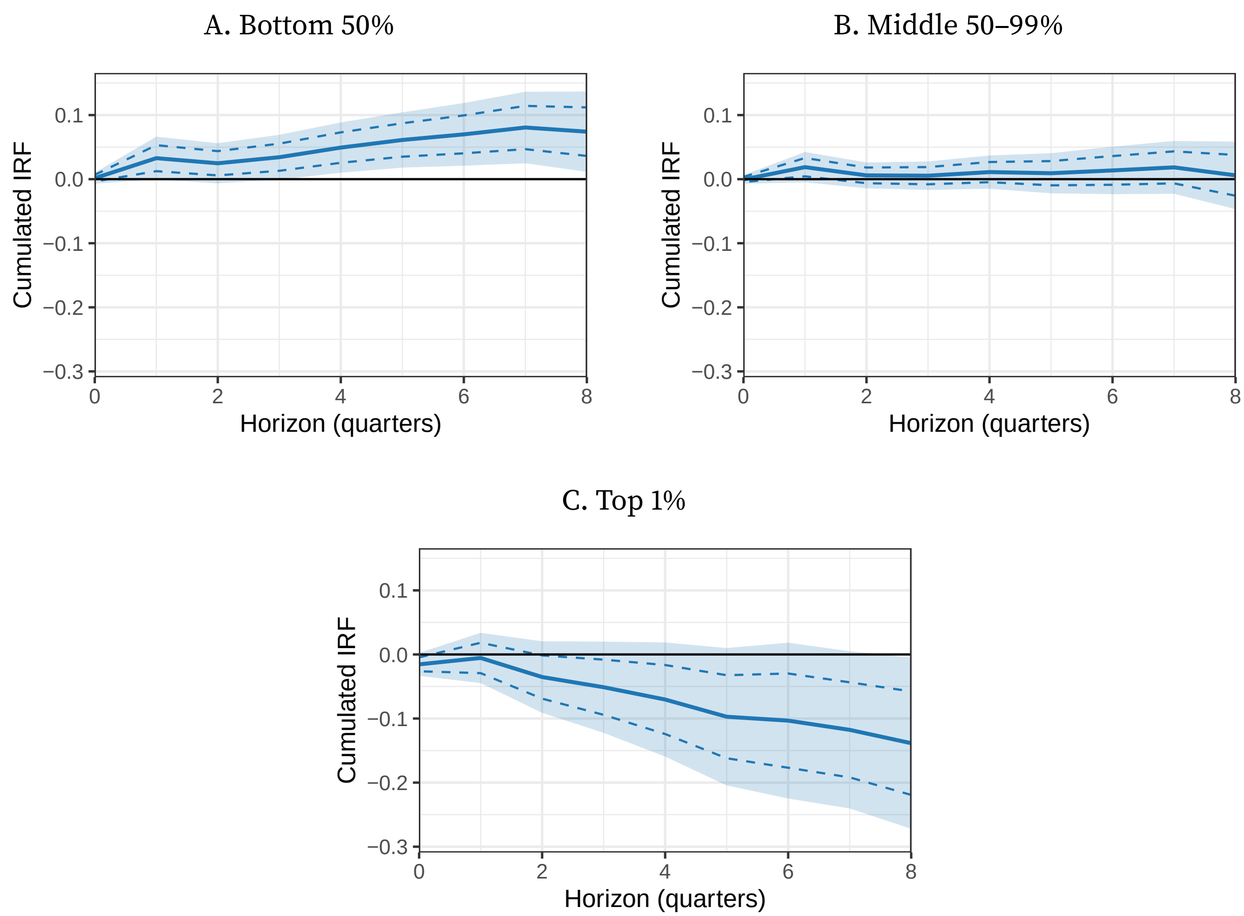
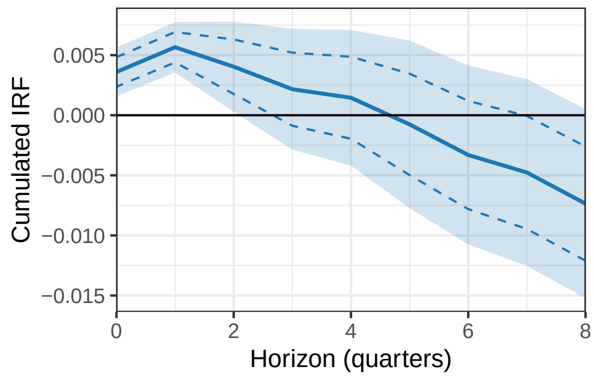


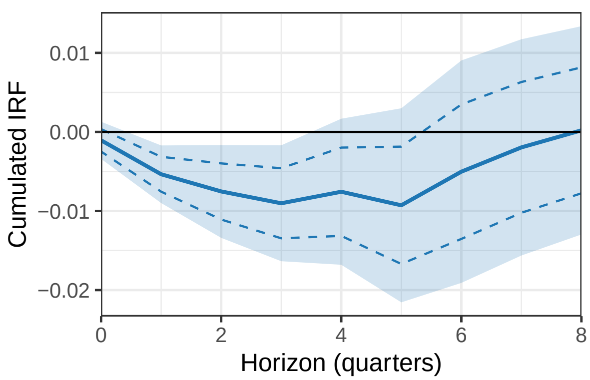
Figure A29. Real GDP response to monetary policy shocks

This figure plots impulse response functions of log real GDP to monetary policy shocks: change in the federal funds rate (Panel A), Romer and Romer (2004) shocks (Panel B), and Bauer and Swanson (2023) high-frequency shocks (Panel C). Romer and Romer (2004) and Bauer and Swanson (2023) shocks are scaled to a 100bps change in the short rate. Solid lines show point estimates, shaded areas show 90% confidence intervals, and dashed lines show 68% confidence intervals.

A. Change in short rate



B. Romer and Romer (2004) monetary shocks



C. High-frequency monetary shocks

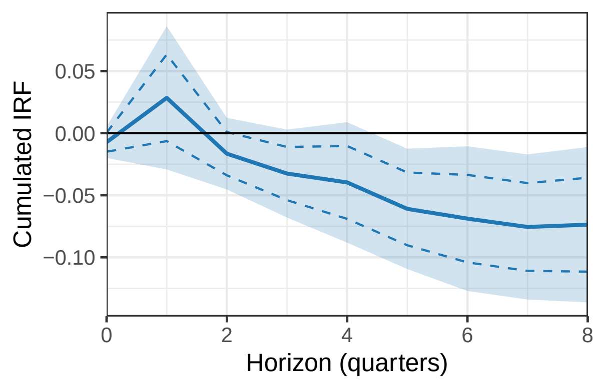


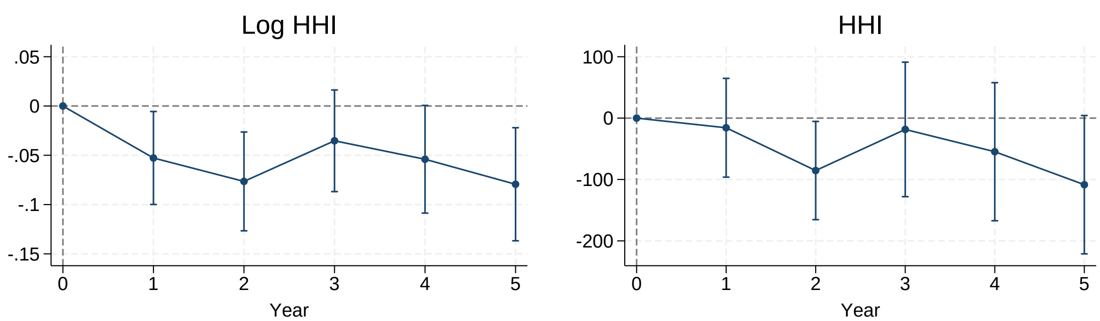
Figure A30. Quasi-experimental evidence on retail deposit pricing: Dynamic effects

This figure plots dynamic effects from estimating the following difference-in-differences regression:

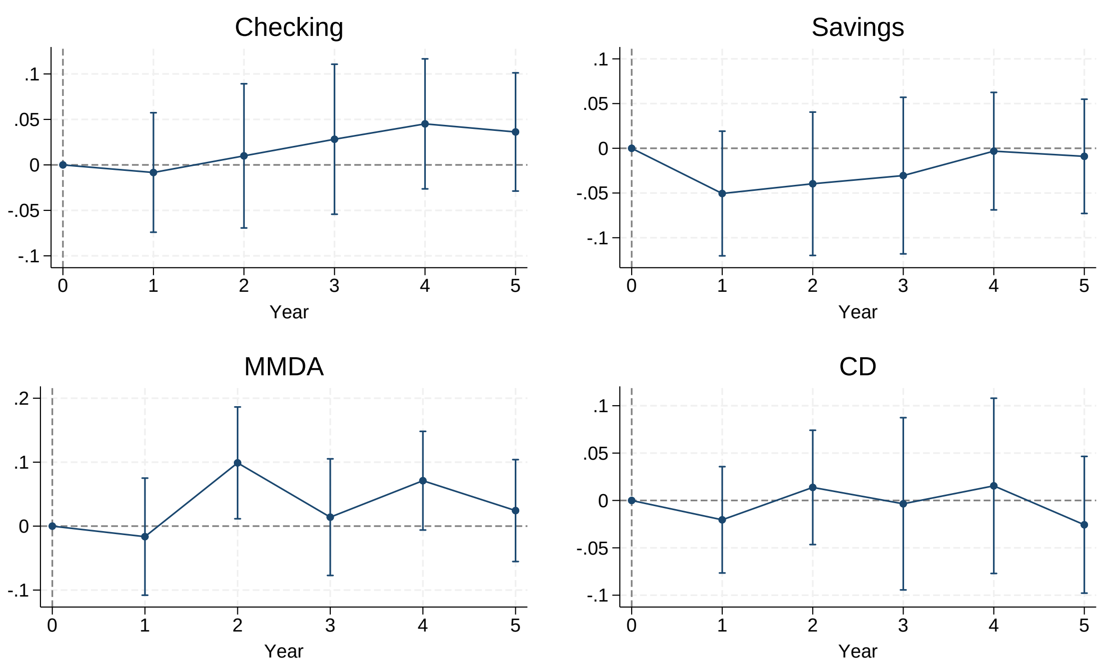
$$Y_{i,t} = \sum \delta_{c(i),t} + \sum \gamma_{m(i)} + \sum_{c,t>c(i)} \beta_{c(i),t} \text{Post}_{c(i),t} \times \text{Treated}_i + \varepsilon_{i,t},$$

where $Y_{i,t}$ is either deposit market HHI (Panel A), APY on select deposit products (Panel B), or deposit betas (Panel C), $\text{Post}_{c(i),t}$ is an indicator for whether t is after the merger in cohort $c(i)$, and Treated_i is an indicator for whether market-merger pair i is in the treatment group. The figure plots the coefficients on the interaction term $\text{Post}_{c(i),t} \times \text{Treated}_i$ aggregated for each year relative to the merger as in Wooldridge (2025), along with 95% (spiked lines) confidence intervals based on standard errors clustered at the banking market level. Panels B and C report results for APYs and betas on the following retail deposit products: "checking" (interest-bearing checking accounts with minimum balance $2,500), "savings" (savings accounts with minimum balance $2,500), "MMDA" (money market accounts with minimum balance $10,000) and "CD" (1-year certificates of deposit with minimum balance $10,000). See Appendix E for additional details.

A. Deposit market concentration



B. Retail deposit rates



C. Retail deposit betas

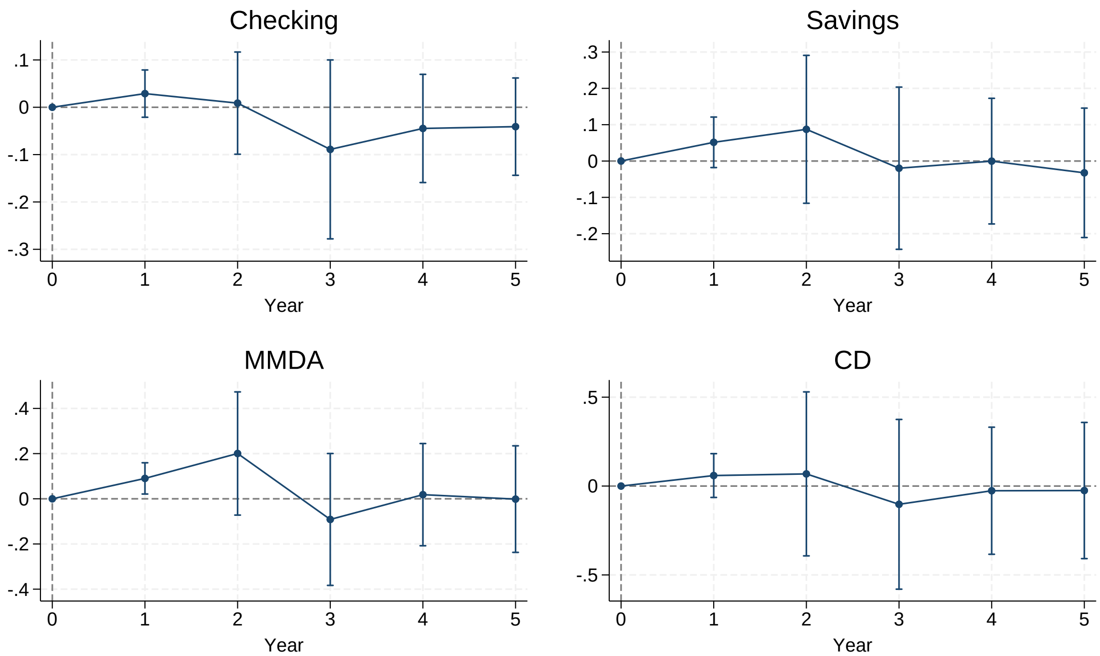


Figure A31. Deposit rates response to monetary policy shocks by large deposit share and market concentration

This figure plots impulse response functions as in Figure 2. Panel A reproduces Panel B of that figure, while Panel B plots IRFs by log HHI. Both large deposits share and log HHI are standardized so that a unit increase corresponds to moving from the 25th to the 75th percentile of their respective distributions within each quarter. Shaded areas represent 95% confidence intervals, while dashed lines represent 90% confidence intervals. Confidence intervals are computed using standard errors double-clustered at the bank and quarter levels. The sample is U.S. commercial banks for the period 1985Q1-2024Q1.

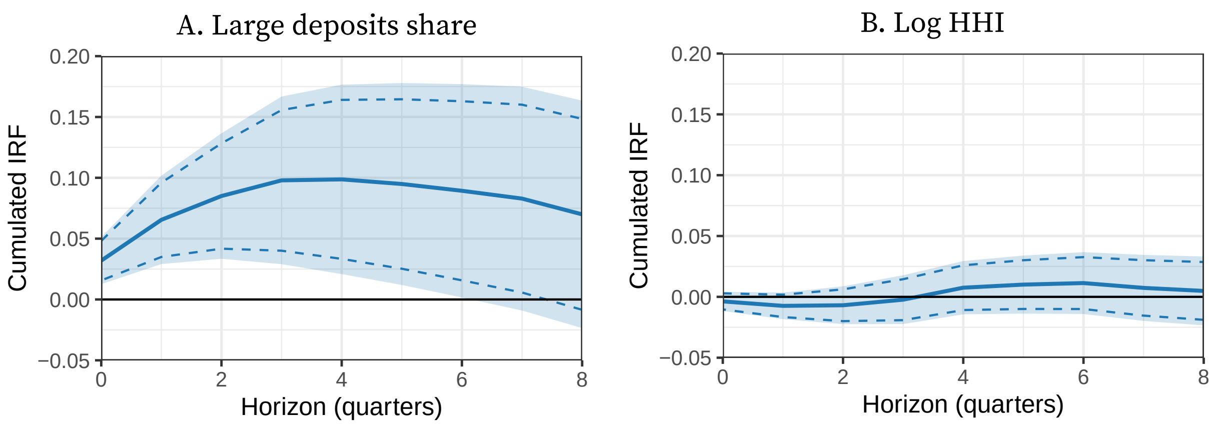


Figure A32. Share of large deposits is more important than local deposit market concentration in explaining deposit pricing across banks: Savings deposits

This figure is similar to Figure 7 Panel A, but for savings deposits.

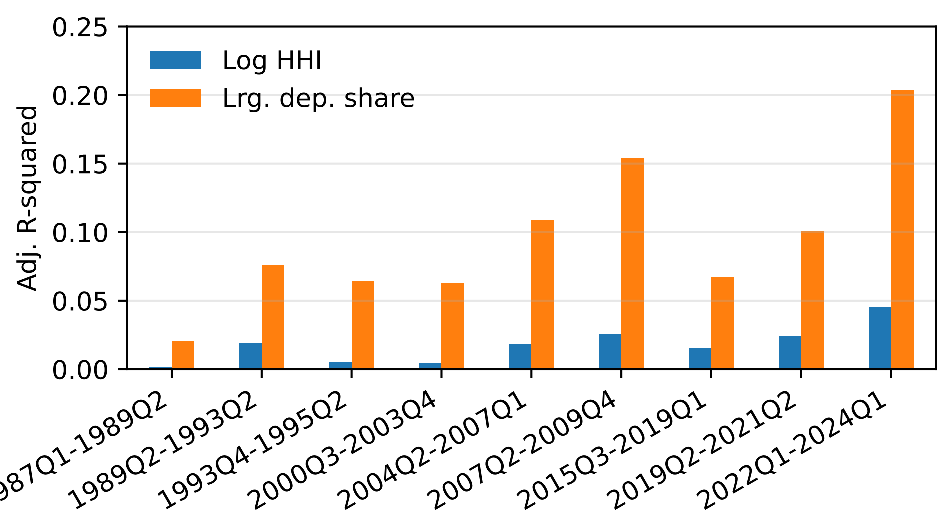
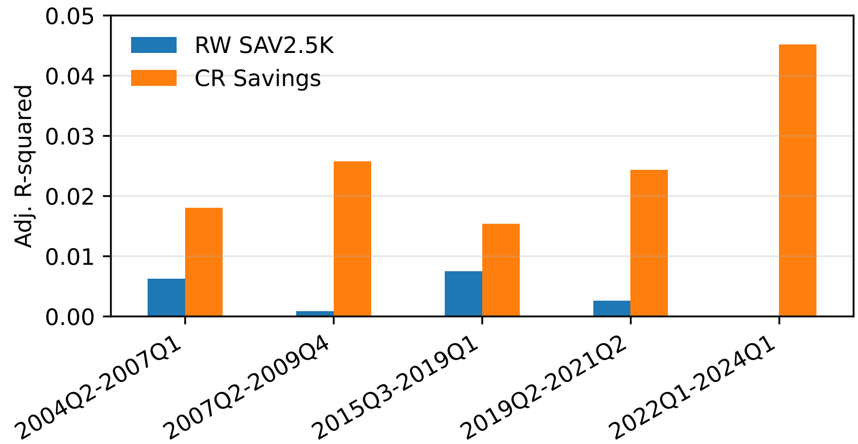


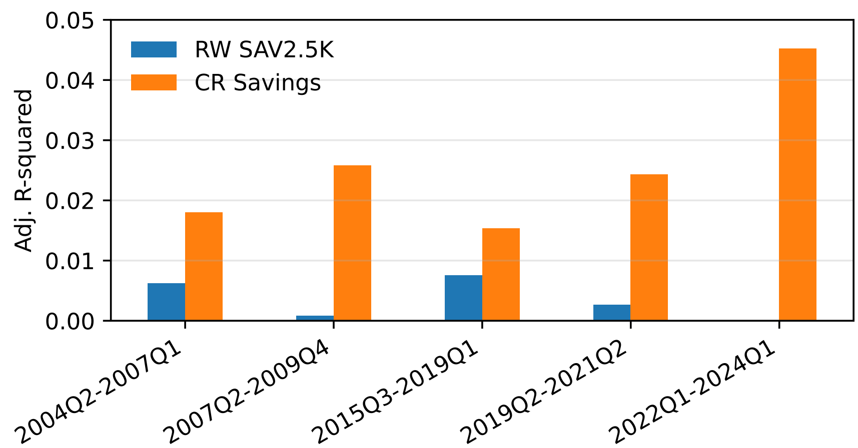
Figure A33. HHI has weak explanatory power for *retail* deposit pricing: Analysis by deposit product

This figure is similar to Figure 7 Panel B, but for select retail deposit products separately.

A. $2.5K savings accounts



B. $10K money market deposit accounts



C. 12-month $10K certificates of deposit

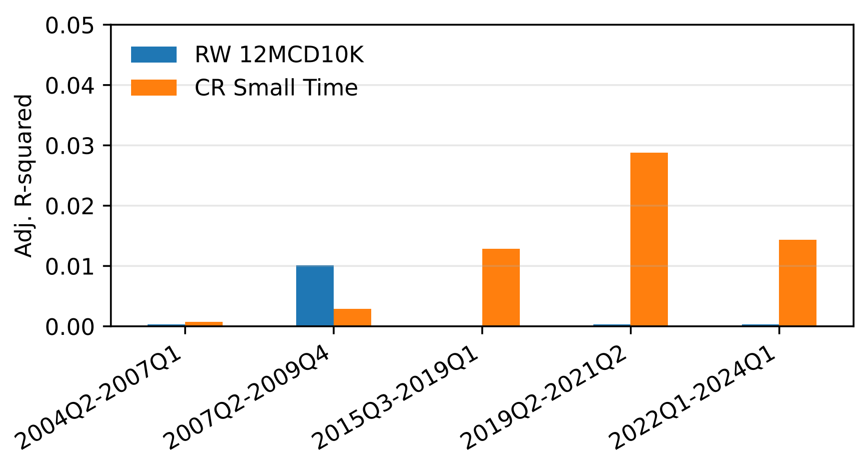
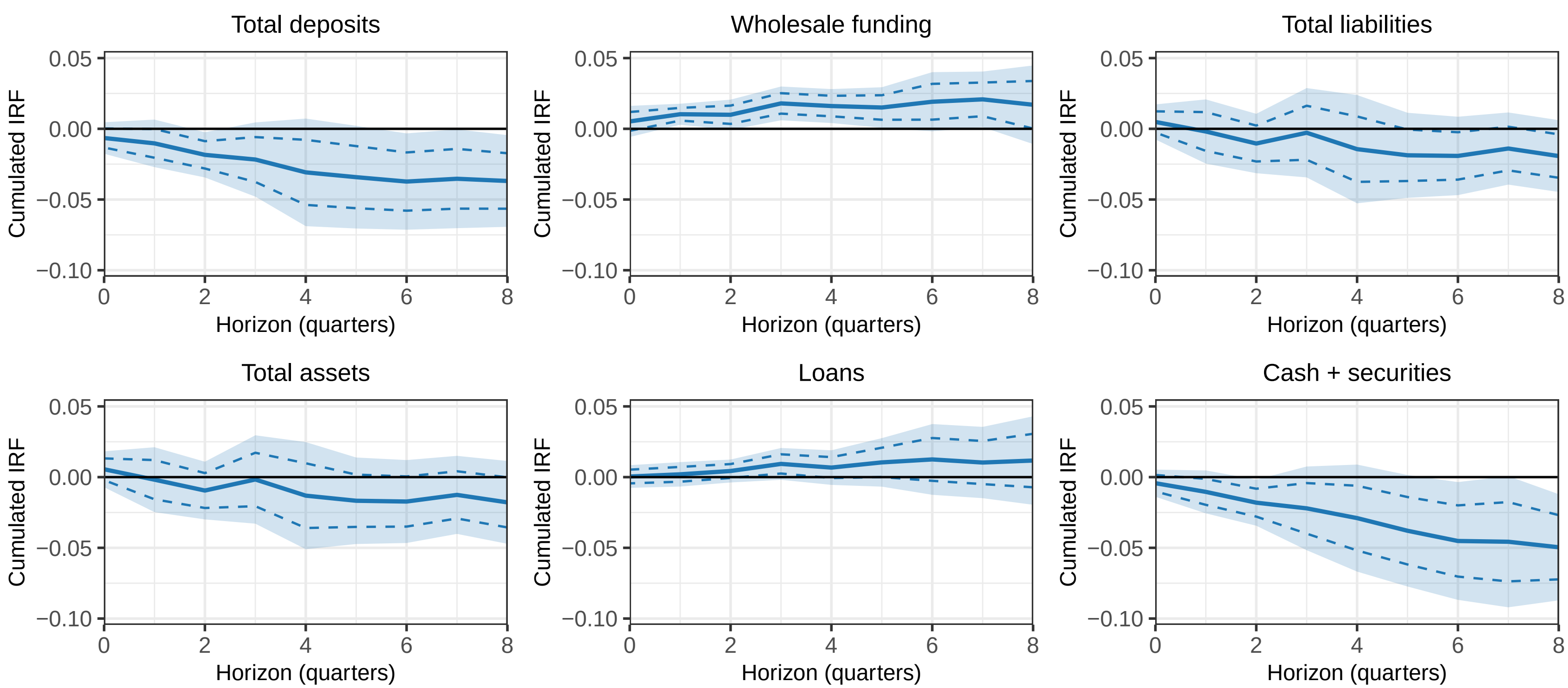


Figure A34. High-frequency monetary shocks and the balance sheet of the banking system

This figure is similar to Figure 8, but it plots IRFs to high-frequency monetary shocks of Bauer and Swanson (2023).

A. All commercial banks



B. Large vs small banks

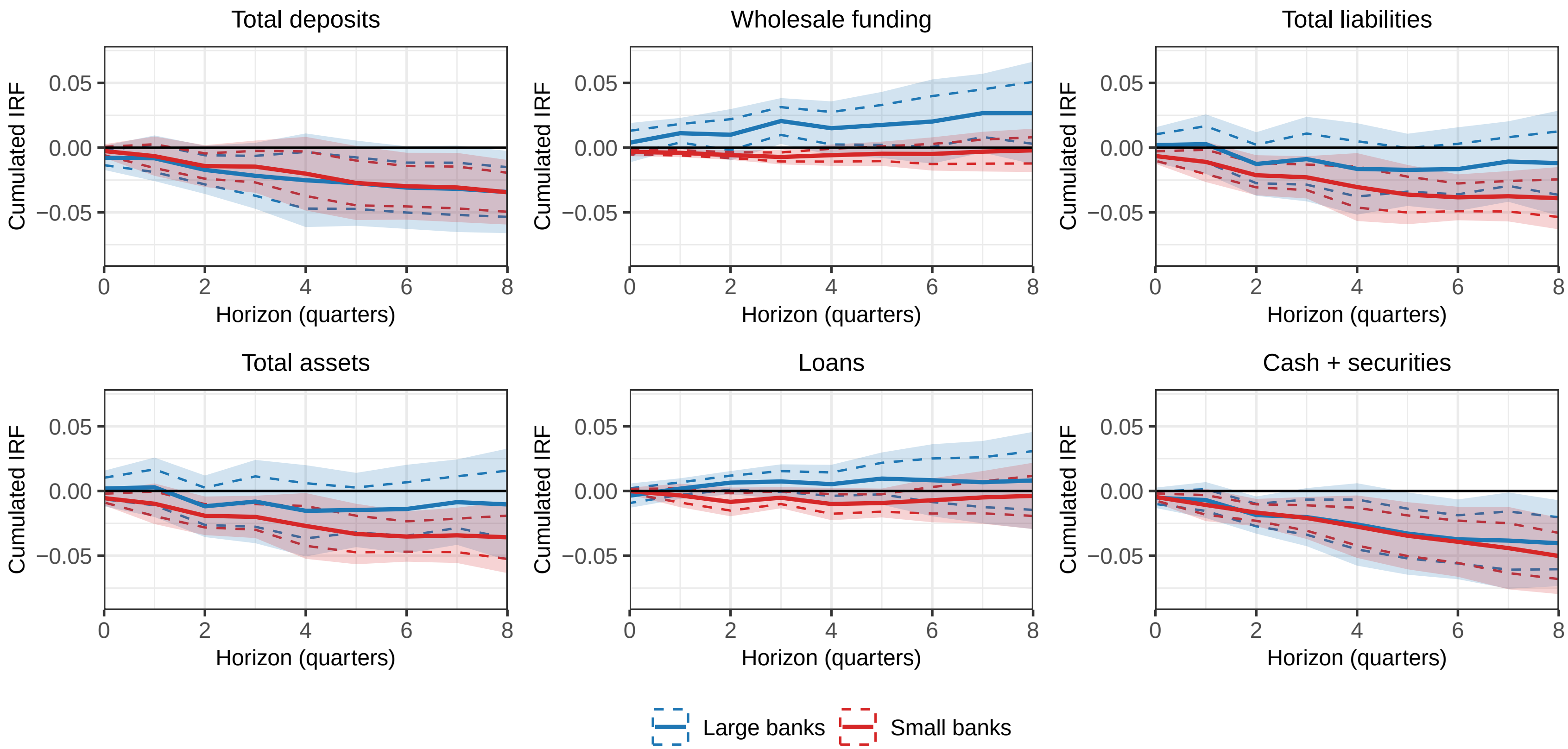
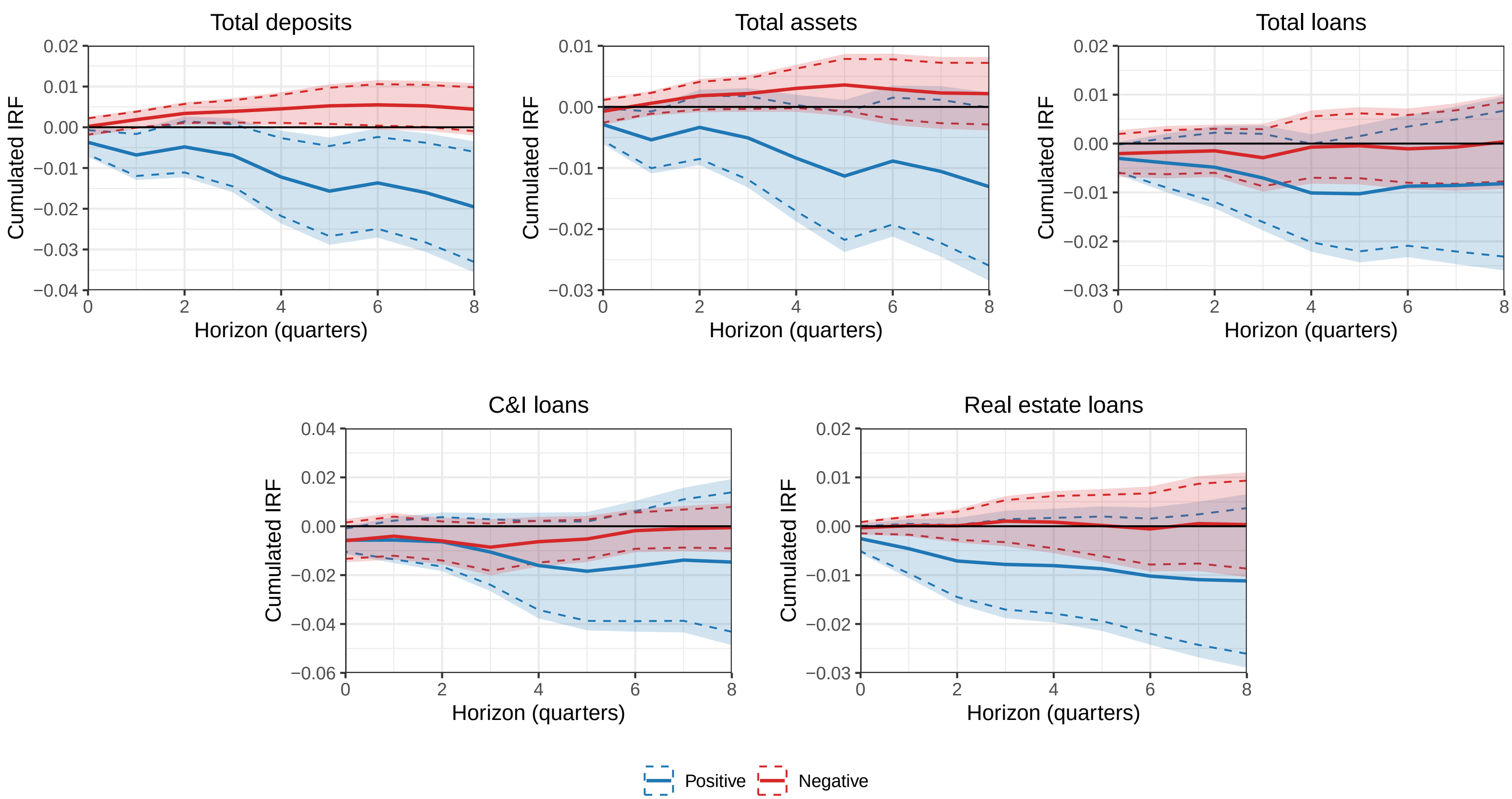


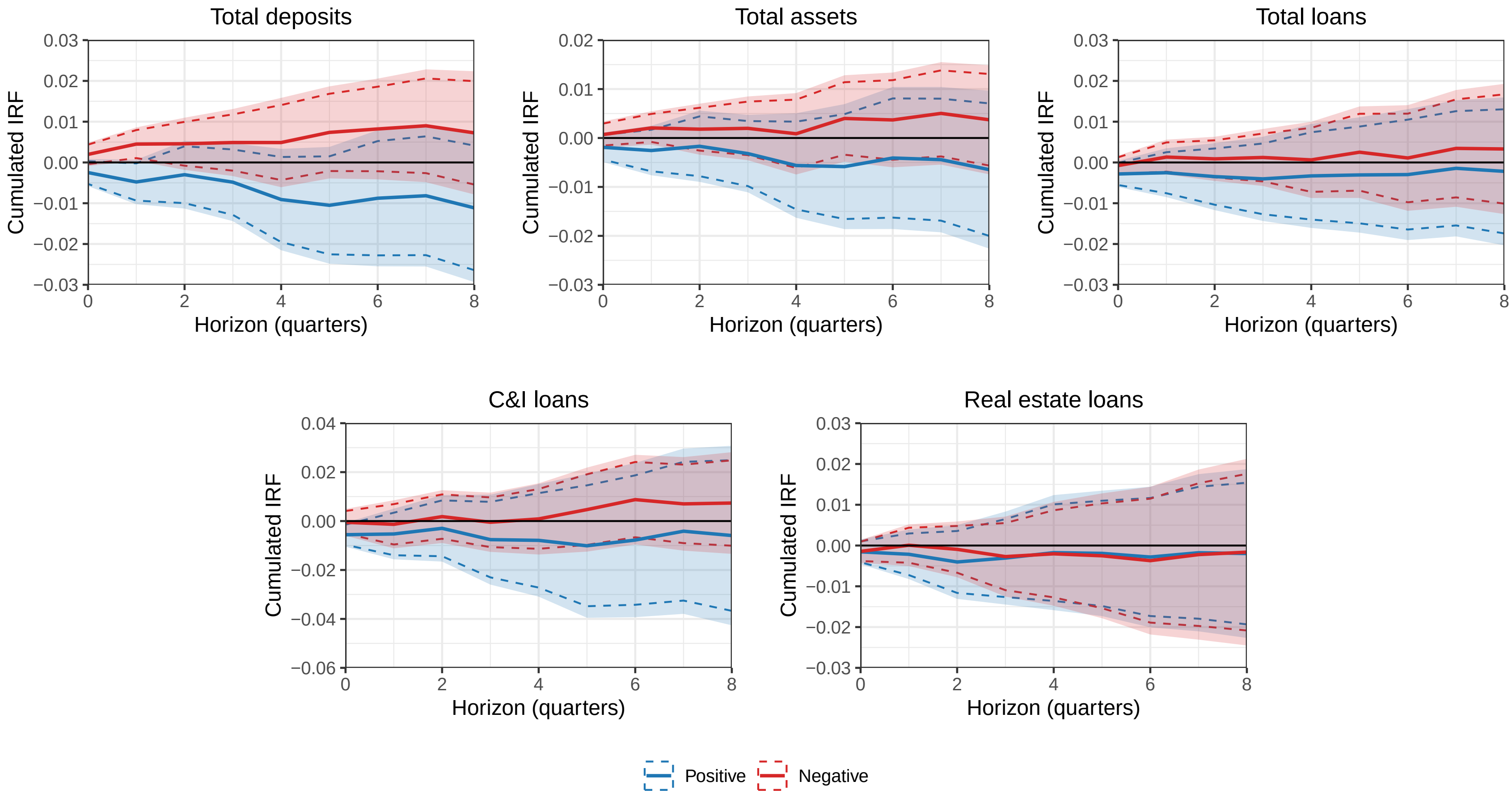
Figure A35. Balance sheet response to monetary policy in the cross-section of banks by large deposits share

This figure plots IRFs of total deposits, total assets, total loans, C&I loans, and real estate loans to monetary policy shocks, allowing for differential responses by the bank's large deposits share. The IRFs are estimated using equations as in Table 5. Within each plot, IRFs are estimated separately for positive (blue) and negative (red) shocks. Panels A, B, and C correspond to changes in the federal funds rate, Romer and Romer (2004) monetary shocks, and Bauer and Swanson (2023) high-frequency monetary shocks, respectively. The shocks are scaled to correspond to a 100bps change in the federal funds rate. Solid lines plot point estimates; dashed lines and shaded regions correspond to 90% and 95% confidence intervals based on standard errors clustered by bank and quarter.

A. Change in the federal funds rate



B. Romer and Romer (2004) monetary shocks



C. High-frequency monetary shocks

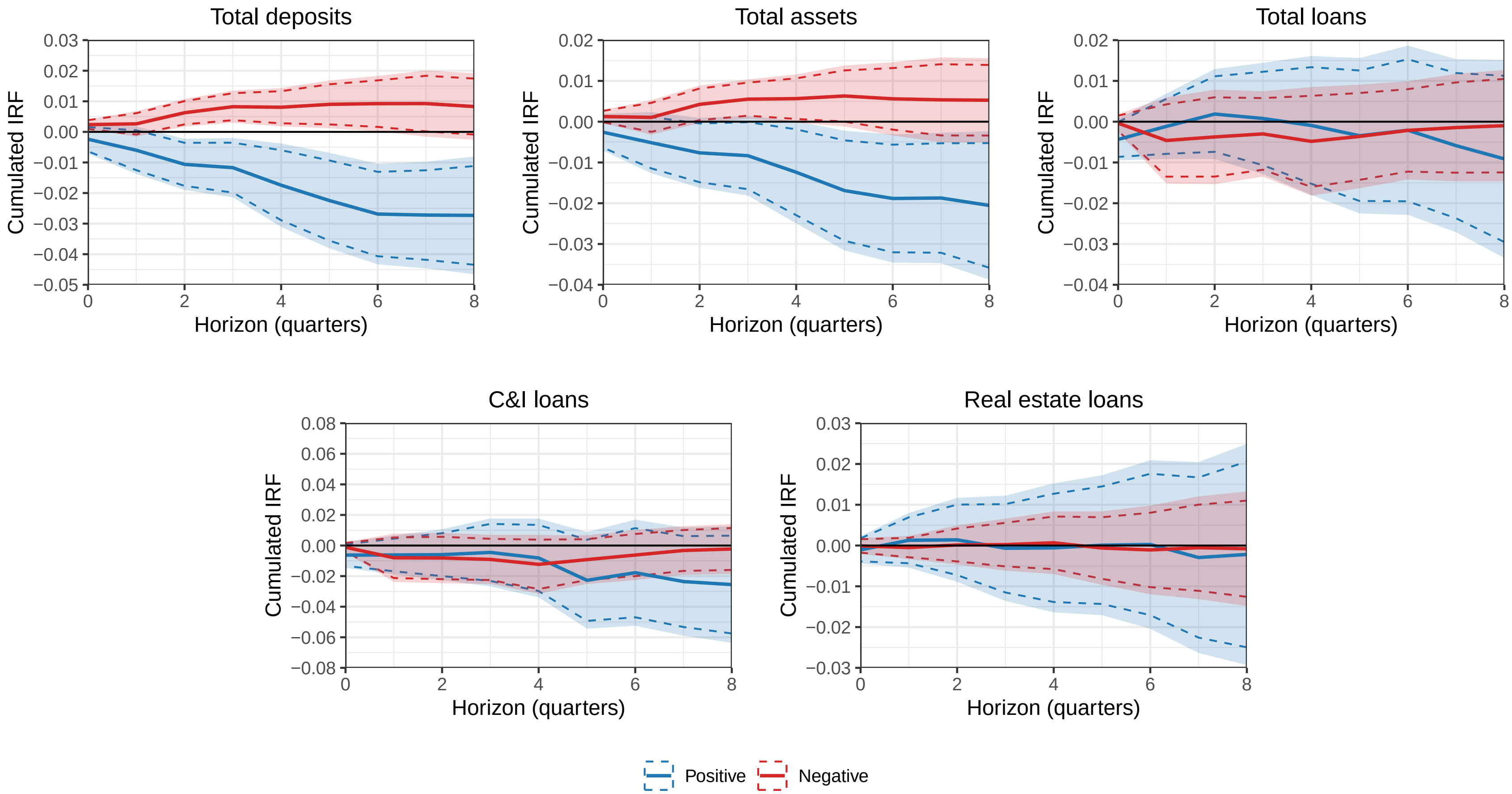


Figure A36. Interest expense, interest income, and net interest margin: Response to monetary policy by large deposits share

This figure plots impulse response functions (IRFs) of interest expense rates, interest income rates, and net interest margins (NIM) to monetary policy shocks, estimated using the following local projections:

$$\Delta Y_{i,t-1,t+h} = \alpha_t^h + \beta^h \Delta \text{FFR}_t \times \text{Lrg. dep. share}_{i,t-1} + \Gamma^h X_{i,t} + \varepsilon_{i,t+h},$$

where $\Delta Y_{i,t-1,t+h}$ is change in either the interest expense rate, interest income rate, or NIM for bank i over the horizon h, and ΔFFR_t is change in the short rate from $t-1$ to t. Other variables are as in Equation 2. Interest income rate is calculated as total interest income divided by total assets, interest expense rate is total interest expense divided by total assets, and NIM is the difference between the two. The figure plots the estimates of β^h along with 90% (dashed blue lines) and 95% (shaded blue area) confidence intervals based on standard errors double clustered by bank and time. The share of large deposits is standardized such that a one-unit change in this variable corresponds to an increase from 25th to 75th percentile in its distribution within each quarter. The sample is all U.S. commercial banks over the period 1985Q1-2024Q1.

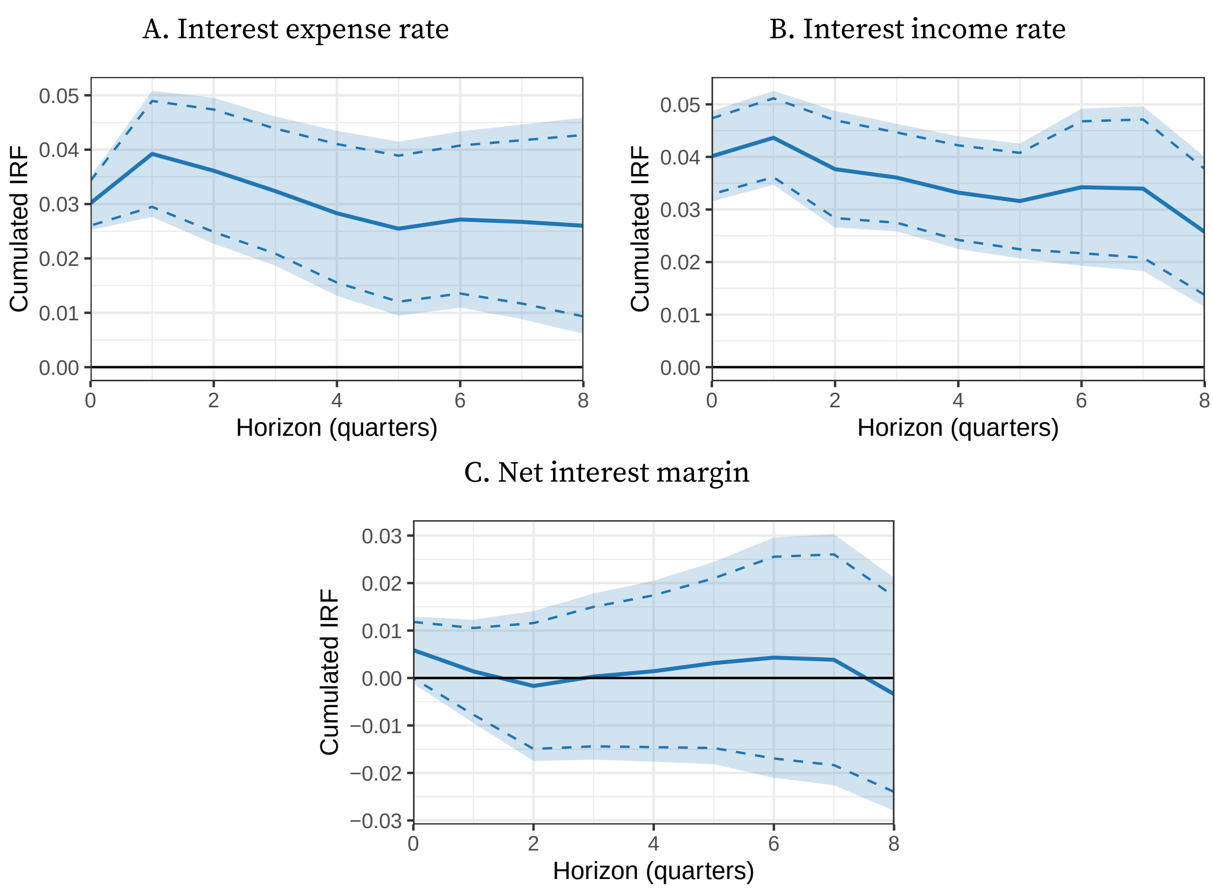


Figure A37. NIM by large deposits share: Romer & Romer (2004) shocks

This figure is similar to Figure A36 but for Romer and Romer (2004) monetary shocks as the monetary policy variable.

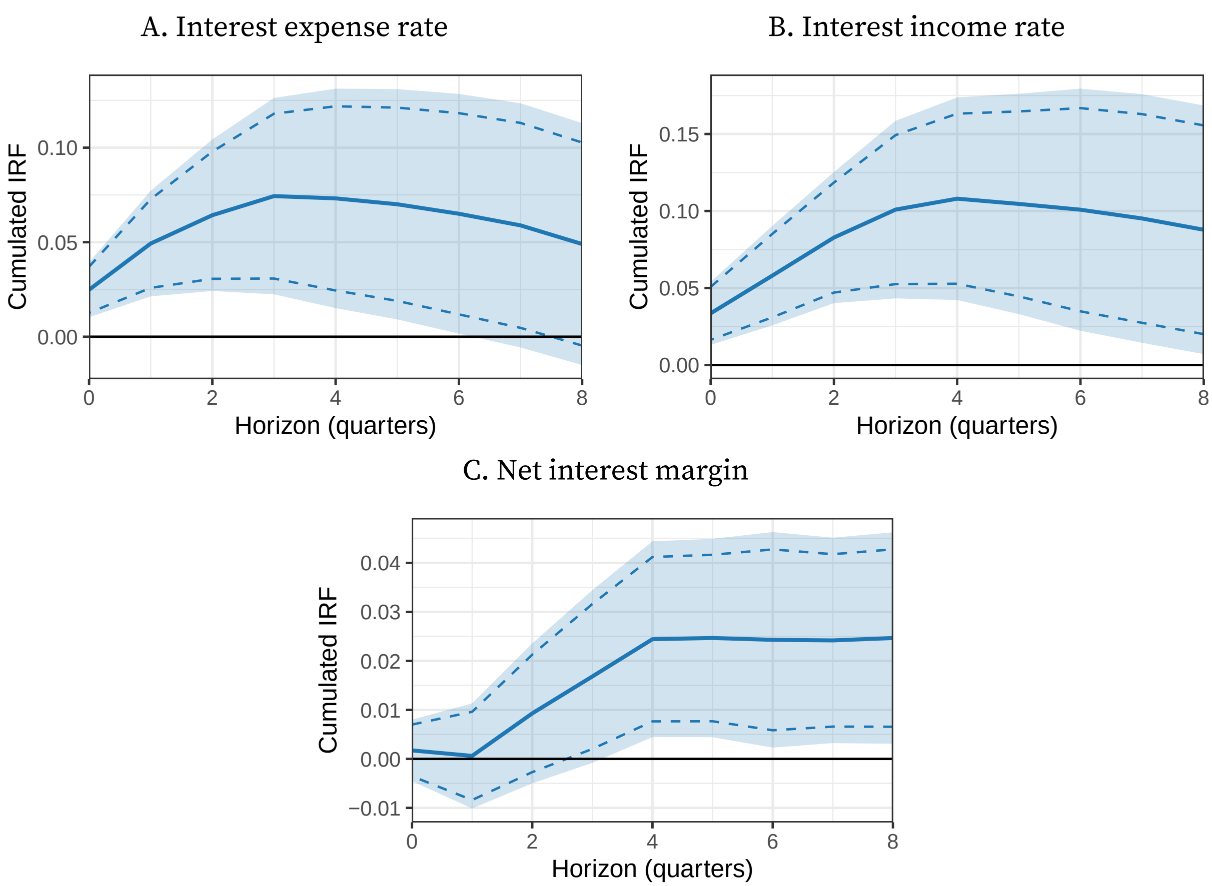


Figure A38. Banks with more large deposits hold shorter-maturity assets

This figure plots a binscatter of asset maturity against the share of large deposits in the cross-section of banks. The banks are grouped into bins by large deposits share at the following percentiles: [0%, 25%), [25%, 30%), ..., [95%, 100%]. The dots represent the average asset maturity and the average share of large deposits within each bin. The sample is all U.S. commercial banks over the period 1982Q2-2024Q1, averaged over time for each bank.

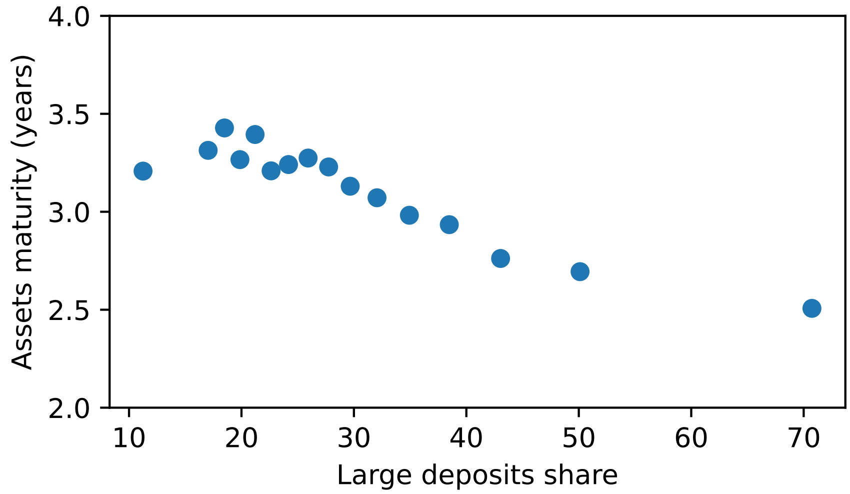


Figure A39. Banks with more large deposits hold more C&I loans

This figure plots a binscatter of commercial and industrial (C&I) loans to total loans ratio against the share of large deposits in the cross-section of banks. The banks are grouped into bins by large deposits share at the following percentiles: [0%, 25%), [25%, 30%), ..., [95%, 100%]. The dots represent the average C&I loans to total assets ratio and the average share of large deposits within each bin. The sample is all U.S. commercial banks over the period 1982Q2-2024Q1, averaged over time for each bank.

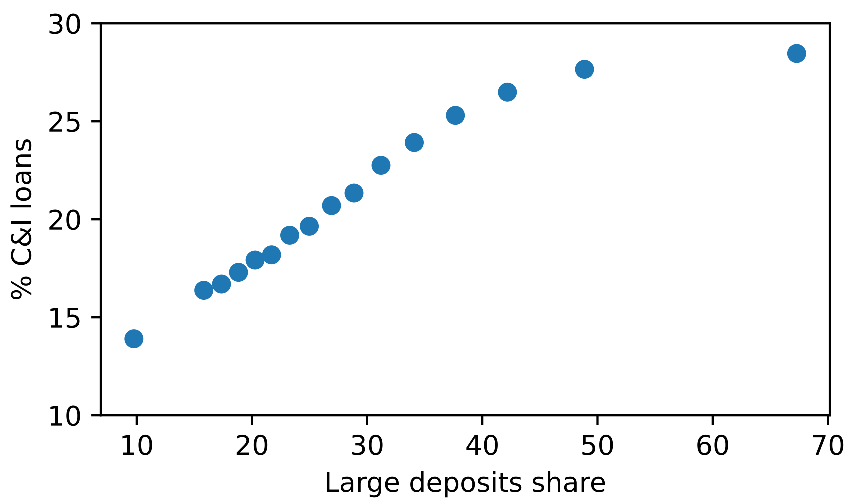


Table A1. Average deposit holdings by income distribution

This table reports the distribution of deposits across income groups. The data are from the Survey of Consumer Finances (SCF), 1989-2022 (triennial surveys). The table reports average checking, savings, and certificate of deposits (CD) holdings for the bottom 99% and top 1% of households by income.

Year	Checking		Savings		CDs	
	Bottom 99%	Top 1%	Bottom 99%	Top 1%	Bottom 99%	Top 1%
1989	5,351	69,152	6,334	40,857	13,876	143,462
1992	4,161	48,540	6,225	34,716	11,126	42,880
1995	4,599	64,572	5,138	54,664	8,889	123,837
1998	5,387	58,217	7,694	48,275	9,951	66,312
2001	6,043	68,952	7,829	47,596	9,371	54,442
2004	7,260	68,677	10,072	104,511	10,153	88,262
2007	5,721	104,948	9,192	104,073	11,139	180,219
2010	6,874	94,170	11,519	129,755	10,413	175,951
2013	8,166	217,225	11,299	174,466	5,444	96,666
2016	9,713	183,565	15,374	405,956	5,308	81,623
2019	10,437	197,603	14,789	191,477	7,358	180,042
2022	14,502	252,095	18,448	400,711	5,127	132,515

Table A2. Coverage of hand-collected deposit rate data

This table reports coverage of the deposit rate data hand-collected from each bank's website (for current rates) and from Internet Archive's Wayback Machine snapshots (for historical rates) for the top-30 U.S. banks by total assets. Column 2 lists which of the four product categories—Savings, MMDA, CD, and Business (business savings and business MMDA combined)—are observed at each bank. Column 3 reports the year-month of the earliest and latest snapshots. Column 4 is the number of unique snapshot dates, and Column 5 is the total number of product-snapshot observations.

Bank	Products	Time coverage	*N* snapshots	*N* obs
Ally Bank	Savings, MMDA, CD	2010-06 – 2026-01	101	4,333
Bank of America	Savings, MMDA, CD, Business	2013-10 – 2026-03	77	2,835
BB&T	Savings, MMDA, CD, Business	2014-04 – 2021-07	14	292
BMO Bank	Savings, MMDA, CD, Business	2014-05 – 2026-02	40	1,057
Capital One	Savings, MMDA, CD, Business	2013-08 – 2026-02	67	901
Citibank	Savings, MMDA, CD	2009-06 – 2025-10	58	1,975
Citizens Bank	Savings, MMDA, CD, Business	2015-09 – 2026-01	44	1,240
Discover Bank	Savings, MMDA, CD	2013-10 – 2026-03	82	1,263
Fifth Third Bank	Savings, MMDA, CD	2014-06 – 2025-12	32	955
First Horizon Bank	Savings, MMDA, CD	2015-06 – 2025-12	22	415
First Republic Bank	Savings, MMDA, CD, Business	2014-08 – 2023-12	17	586
First-Citizens Bank	Savings, MMDA, CD	2015-03 – 2026-01	67	710
Goldman Sachs (Marcus)	Savings, CD	2016-08 – 2026-03	60	448
HSBC Bank USA	Savings, CD	2013-12 – 2025-10	31	659
Huntington National Bank	Savings, MMDA, CD	2015-09 – 2026-02	64	1,931
JPMorgan Chase	Savings, MMDA, CD, Business	2014-04 – 2026-03	58	5,537
KeyBank	Savings, MMDA, CD, Business	2014-04 – 2026-03	36	5,010
M&T Bank	Savings, MMDA, CD	2014-06 – 2025-10	32	386
PNC Bank	Savings, MMDA, CD	2014-04 – 2026-02	45	5,033
Regions Bank	Savings, MMDA, CD, Business	2014-08 – 2026-02	22	1,031
Santander Bank	Savings, MMDA, CD, Business	2015-04 – 2025-10	24	316
Silicon Valley Bank	MMDA	2019-08 – 2022-01	8	32
SunTrust Bank	Savings, CD	2015-04 – 2022-01	12	130
Synchrony Bank	Savings, MMDA, CD	2014-06 – 2026-03	65	1,761
Synovus Bank	MMDA, CD	2020-12 – 2025-07	15	69
TD Bank	Savings, MMDA, CD, Business	2013-10 – 2025-12	25	1,918
Truist Bank	Savings, MMDA, CD	2022-09 – 2026-02	6	49
U.S. Bank	Savings, MMDA, CD, Business	2018-12 – 2026-02	46	1,761
USAA Federal Savings Bank	Savings, CD	2014-08 – 2025-06	46	2,346
Webster Bank	Savings, MMDA, CD, Business	2013-12 – 2025-12	19	500
Wells Fargo	Savings, MMDA, CD, Business	2014-08 – 2026-03	106	2,244
Zions Bank	Savings, MMDA, CD, Business	2014-08 – 2026-03	28	2,323

Table A3. Correlation between large deposits share and other bank characteristics

This table reports Pearson correlation coefficients between the share of large deposits and other bank characteristics, namely share of deposits in total assets, share of savings and time deposits in total deposits, log total assets, book equity ratio, return on assets (ROA), log of the Herfindahl-Hirschman Index (HHI) of deposits, and log bank age, computed in the cross-section of banks for the last quarter of the years 1985, 1990, 1995, ..., 2020, and 2024Q1.

Variable	1985	1990	1995	2000	2005	2010	2015	2020	2024
Deposits / Assets	-0.24	-0.34	-0.31	-0.22	-0.20	-0.23	-0.18	-0.14	-0.14
Savings deposits / Total deposits	-0.02	0.06	0.09	0.22	0.29	0.37	0.29	0.30	0.17
Time deposits / Total deposits	-0.12	-0.16	-0.30	-0.22	-0.20	-0.40	-0.37	-0.35	-0.28
Loans / Assets	0.22	0.08	-0.07	-0.07	0.04	-0.14	-0.10	-0.04	-0.13
Liquid assets / Assets	-0.26	-0.16	-0.05	-0.07	-0.13	0.12	0.07	0.04	0.10
Log(Assets)	0.32	0.35	0.31	0.29	0.35	0.33	0.39	0.41	0.28
Book equity / Assets	-0.04	0.04	0.02	0.09	0.14	0.20	0.17	0.11	0.17
ROA	-0.05	-0.04	0.05	0.10	0.06	0.09	0.19	0.18	0.20
Log(HHI)	-0.27	-0.20	-0.13	-0.14	-0.17	-0.09	-0.09	-0.16	-0.11
Log(Age)	-0.42	-0.33	-0.29	-0.38	-0.46	-0.25	-0.31	-0.36	-0.31

Table A4. Transition matrix of large deposits share

This table reports the transition matrix of the share of large deposits. The share of large deposits is categorized into 5 equal bins (quintiles) based on its distribution across banks in each quarter. The table reports the probabilities of transitioning from one bin to another over different horizons: 1 quarter, 1 year, and 5 years. The data are for all U.S. commercial banks over the period 1982Q2-2024Q1.

A. Horizon: 1 quarter

From To	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Quintile 1	0.86	0.12	0.01	0.00	0.00
Quintile 2	0.12	0.72	0.14	0.01	0.00
Quintile 3	0.01	0.14	0.71	0.13	0.01
Quintile 4	0.00	0.01	0.13	0.76	0.09
Quintile 5	0.00	0.00	0.01	0.09	0.90

B. Horizon: 1 year

From To	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Quintile 1	0.76	0.19	0.03	0.01	0.01
Quintile 2	0.18	0.57	0.21	0.03	0.01
Quintile 3	0.03	0.20	0.55	0.20	0.02
Quintile 4	0.01	0.04	0.20	0.61	0.14
Quintile 5	0.01	0.01	0.02	0.15	0.81

C. Horizon: 5 years

From To	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Quintile 1	0.58	0.26	0.10	0.04	0.02
Quintile 2	0.24	0.38	0.25	0.10	0.03
Quintile 3	0.09	0.24	0.35	0.25	0.06
Quintile 4	0.04	0.10	0.25	0.41	0.20
Quintile 5	0.02	0.03	0.08	0.22	0.65

Table A5. Monetary policy cycles

This table lists the monetary policy tightening and easing cycles identified in Figure A3, as well as their duration in quarters and change in the federal funds rate (FFR) during each cycle. The cycles are defined as periods when the federal funds rate increases from a local trough to a local peak (tightening) or decreases from a local peak to a local trough (easing). The table reports the start and end dates of each cycle.

Cycle	Type	Length (Quarters)	FFR Change (pp)
1974M09-1977M06	Easing	11	-1.15
1977M06-1981M06	Tightening	16	12.63
1981M06-1983M06	Easing	8	-8.99
1984M09-1986M09	Easing	8	-5.18
1987M03-1989M06	Tightening	9	3.51
1989M06-1993M06	Easing	16	-6.73
1993M12-1995M06	Tightening	6	3.03
2000M09-2003M12	Easing	13	-5.52
2004M06-2007M03	Tightening	11	4.24
2007M06-2009M12	Easing	10	-5.13
2015M09-2019M03	Tightening	14	2.27
2019M06-2021M06	Easing	8	-2.33
2022M03-2024M03	Tightening	8	5.21

Table A6. Local projections of deposit expense rate on monetary policy and share of large deposits: Using monetary policy shocks

This table is similar to Table 2 but instruments changes in the federal funds rate with monetary policy shocks. Panel A uses Romer and Romer (2004) monetary shocks; Panel B uses Bauer and Swanson (2023) high-frequency monetary shocks; both are scaled to correspond to a 100bps change in the federal funds rate. Other variables are as in Equation 2. Standard errors are double clustered by bank and time. *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

A. Romer & Romer (2004) monetary policy shocks

	Horizon, quarters				
	$h = 0$	$h = 2$	$h = 4$	$h = 6$	$h = 8$
Lrg. dep. share$_{i,t-1}$ × RR shock$_t$	0.032***	0.085***	0.099**	0.089**	0.070
	(0.010)	(0.026)	(0.040)	(0.045)	(0.048)
log(HHI$_{i,t-1}$) × RR shock$_t$	-0.004	-0.007	0.008	0.011	0.005
	(0.004)	(0.008)	(0.011)	(0.013)	(0.014)
log(Bank age$_{i,t-1}$) × RR shock$_t$	-0.009*	-0.024**	-0.025	-0.028	-0.026
	(0.005)	(0.012)	(0.016)	(0.019)	(0.023)
Time FE	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓
N	859,816	859,816	859,816	859,816	859,816
Within R^2	0.045	0.063	0.068	0.071	0.080

B. High-frequency monetary policy shocks

	Horizon, quarters				
	$h = 0$	$h = 2$	$h = 4$	$h = 6$	$h = 8$
Lrg. dep. share$_{i,t-1}$ × HF shock$_t$	0.033**	0.122**	0.157**	0.137*	0.133
	(0.015)	(0.047)	(0.066)	(0.082)	(0.091)
log(HHI$_{i,t-1}$) × HF shock$_t$	0.003	-0.012	-0.015	-0.009	-0.012
	(0.009)	(0.017)	(0.024)	(0.029)	(0.032)
log(Bank age$_{i,t-1}$) × HF shock$_t$	-0.007	-0.023	-0.045	-0.038	-0.016
	(0.008)	(0.023)	(0.028)	(0.034)	(0.041)
Time FE	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓
N	919,249	919,249	919,249	919,249	919,249
Within R^2	0.038	0.049	0.055	0.063	0.080

Table A7. Inferred deposit expense betas for small and large deposits: Deposit subtypes

This table is similar to Table 3, but for savings deposits (Panel A) and interest-bearing transaction deposits (Panel B).

A. Savings deposits

	Cycle				
	2004Q2 - -2007Q1	2007Q2 - -2009Q4	2015Q3 - -2019Q1	2019Q2 - -2021Q2	2022Q1 - -2024Q1
Constant$_c$	0.179***	0.156***	0.030***	0.022***	-0.046***
	(0.007)	(0.005)	(0.005)	(0.006)	(0.010)
Lrg. dep. share$_{i,c}$	0.436***	0.444***	0.311***	0.428***	0.724***
	(0.017)	(0.012)	(0.014)	(0.016)	(0.021)
RW Beta	0.229	0.250	0.056	0.079	0.109
Small Beta	0.179	0.156	0.030	0.022	-0.046
Large Beta	0.615	0.601	0.341	0.449	0.678
R^2	0.102	0.203	0.111	0.174	0.267
Observations	6942	6517	5213	4755	4402

B. Interest-bearing transaction deposits

	Cycle				
	2004Q2 - -2007Q1	2007Q2 - -2009Q4	2015Q3 - -2019Q1	2019Q2 - -2021Q2	2022Q1 - -2024Q1
Constant$_c$	0.092***	0.087***	0.023***	0.014*	-0.022**
	(0.006)	(0.005)	(0.006)	(0.007)	(0.011)
Lrg. dep. share$_{i,c}$	0.281***	0.245***	0.249***	0.333***	0.497***
	(0.017)	(0.013)	(0.018)	(0.021)	(0.024)
RW Beta	0.058	0.086	0.019	0.029	0.029
Small Beta	0.092	0.087	0.023	0.014	-0.022
Large Beta	0.374	0.332	0.272	0.347	0.475
R^2	0.046	0.059	0.046	0.075	0.115
Observations	6844	6381	5127	4699	4336

Table A8. Select examples of *business* balance-tiered savings deposit pricing

This table is similar to Table 4, but for posted business savings and money market deposit accounts (MMDA) at three large U.S. banks: Wells Fargo (Panel A), U.S. Bank (Panel B), and Zions Bancorporation (Panel C). The rates are hand-collected from each bank's website (for current rates) and from Internet Archive's Wayback Machine snapshots (for historical rates). Panel A shows rates on Wells Fargo's Business Platinum Savings; Panel B shows rates on U.S. Bank's Platinum Business MMA; Panel C shows rates on Zions Bank's Business MMA. The right column reports the effective federal funds rate (FFR) on each date for reference.

A. Wells Fargo

Date	Rates (APY)	FFR, %
2016-12-06	0.05% on \$0-\$25K, 0.06% on >\$25K	0.41
2018-05-18	0.05% on \$0-\$25K, 0.06% on \$25K-\$100K, 0.1% on >\$100K	1.70
2020-12-10	0.01% on all balances	0.09
2022-10-07	0.01% on all balances	3.08
2023-01-30	0.25% on \$0-\$100K, 1.01% on \$100K-\$500K, 1.5% on \$500K-\$1M, 2.0% on >\$1M	4.33
2024-05-25	0.25% on \$0-\$100K, 1.01% on \$100K-\$500K, 2.0% on \$500K-\$1M, 2.5% on >\$1M	5.33
2024-09-19	0.05% on all balances	4.83
2025-03-28	0.01% on all balances	4.33

B. U.S. Bank

Date	Rates (APY)	FFR, %
2018-12-18	0.05% on \$0-\$5K, 0.06% on \$5K-\$50K, 0.2% on \$50K-\$100K, 0.25% on \$100K-\$250K, 0.3% on \$250K-\$500K, 0.5% on \$500K-\$1M, 0.6% on >\$1M	2.20
2019-12-16	0.06% on \$0-\$50K, 0.2% on \$50K-\$100K, 0.25% on \$100K-\$250K, 0.3% on \$250K-\$500K, 0.4% on \$500K-\$3M, 0.6% on >\$3M	1.56
2020-09-28	0.01% on \$0-\$100K, 0.05% on >\$100K	0.09
2023-02-04	0.01% on \$0-\$25K, 1.76% on \$25K-\$50K, 1.88% on \$50K-\$250K, 2.06% on >\$250K	4.58
2023-09-29	0.05% on \$0-\$25K, 4.6% on \$25K-\$500K, 4.86% on >\$500K	5.33
2024-06-20	0.05% on \$0-\$25K, 4.34% on >\$25K	5.33
2025-02-07	0.05% on \$0-\$25K, 3.56% on >\$25K	4.33

C. Zions

Date	Rates (APY)	FFR, %
2017-04-08	0.1% on $1K-$100K, 0.15% on >$100K	0.91
2019-09-20	0.2% on $1K-$5K, 0.3% on $5K-$25K, 0.35% on $25K-$100K, 0.45% on $100K-$250K, 0.5% on >$250K	1.90
2020-09-23	0.02% on $1K-$25K, 0.05% on $25K-$100K, 0.08% on $100K-$250K, 0.1% on >$250K	0.09
2021-06-18	0.02% on $1K-$25K, 0.03% on $25K-$100K, 0.04% on $100K-$250K, 0.05% on >$250K	0.10
2022-12-02	0.11% on $1K-$5K, 0.15% on $5K-$25K, 0.2% on $25K-$100K, 0.3% on $100K-$250K, 0.4% on >$250K	3.83
2023-03-26	0.25% on $1K-$5K, 0.3% on $5K-$25K, 0.55% on $25K-$100K, 0.75% on $100K-$250K, 1.0% on >$250K	4.83
2023-09-29	0.55% on $1K-$5K, 0.75% on $5K-$25K, 1.0% on $25K-$250K, 1.21% on >$250K	5.33
2024-09-09	0.25% on $1K-$100K, 0.95% on >$100K	5.33
2025-05-21	0.2% on $1K-$100K, 0.5% on $100K-$250K, 0.6% on $250K-$500K, 0.65% on $500K-$1M, 0.7% on >$1M	4.33

Table A9. Large deposits share does not predict elevated risk of bank failures

This table reports the results of the following regressions:

$$\text{Fail}_{i,t+h} = \alpha + \beta \text{Lrg. dep. share}_{it} + \Gamma X_{it} + \varepsilon_{it},$$

where $\text{Fail}_{i,t+h}$ is an indicator variable equal to 1 if bank i fails within h years of time t, and 0 otherwise; $\text{Lrg. dep. share}_{it}$ is the share of large deposits at bank i at t; and X_{it} is a vector of control variables including log total assets, log bank age, dummies for quartiles of bank's past 3-year asset growth, and past 3-year GDP growth. Average failure rate at a given horizon (in percent) is reported below the table as "Mean of dep. var.". The data are annual (as of end of the year) for all U.S. commercial banks, 1985-2024. Standard errors are Driscoll-Kraay with bandwidth 2. *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

	Fail in the next h years		
	$h = 1$	$h = 3$	$h = 5$
Lrg. dep. share	-0.01303**	-0.00489	0.01761
	(0.00642)	(0.01901)	(0.02942)
N	360,622	360,622	360,622
Adj. R^2	0.006	0.011	0.018
Mean of dep. var.	0.36	1.37	2.20

Table A10. Large deposits share does not predict elevated risk of bank failures, also when interacted with monetary policy shocks

This table reports the results of the following regressions:

$$\text{Fail}_{i,t+h} = \alpha + \beta_1 \text{Lrg. dep. share}_{it} + \beta_2 \text{Lrg. dep. share}_{it} \times r_t + \Gamma X_{it} + \varepsilon_{it},$$

where $\text{Fail}_{i,t+h}$ is an indicator variable equal to 1 if bank i fails within h years of time t, and 0 otherwise; $\text{Lrg. dep. share}_{it}$ is the share of large deposits at bank i at t; r_t is either change in the federal funds rate (Panel A) or Romer and Romer (2004) monetary shock (Panel B); and X_{it} is a vector of control variables including log total assets, log bank age, dummies for quartiles of bank's past 3-year asset growth, and past 3-year GDP growth. X_{it} also includes 4 lags of r_t; these lags as well as r_t itself are all interacted with the large deposits share, log total assets, and log bank age. Average failure rate at a given horizon (in %) is reported below the table as "Mean of dep. var.". The data are quarterly for all U.S. commercial banks, 1985Q1-2024Q1. Standard errors are Driscoll-Kraay with bandwidth 8. *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

A. Interacted with change in short rate

	Fail in the next h years		
	h = 1	h = 3	h = 5
Lrg. dep. share	-0.01191**	-0.00445	0.01821
	(0.00532)	(0.01551)	(0.02381)
Lrg. dep. share × ΔSR	0.00124	-0.01788*	-0.02867*
	(0.00384)	(0.00938)	(0.01589)
N	1,449,826	1,449,826	1,449,826
Adj. R^2	0.007	0.013	0.020
Mean of dep. var.	0.36	1.37	2.20

B. Interacted with Romer and Romer (2004) monetary shocks

	Fail in the next h years		
	$h = 1$	$h = 3$	$h = 5$
Lrg. dep. share	-0.01194*	0.00323	0.03241
	(0.00618)	(0.01945)	(0.03012)
Lrg. dep. share × RR shock	-0.00536	-0.02627*	-0.02410
	(0.00567)	(0.01346)	(0.01877)
N	1,347,958	1,347,958	1,347,958
Adj. R^2	0.007	0.013	0.020
Mean of dep. var.	0.36	1.37	2.20

Table A11. Local projections of deposit flows by select bank characteristics: Combined positive and negative monetary shocks

This table is similar to Table 5, but the change in the federal funds rate, ΔFFR_t, is not split into positive and negative parts. All other specification details are as in Table 5.

	Horizon, quarters				
	$h = 0$	$h = 2$	$h = 4$	$h = 6$	$h = 8$
Lrg. dep. share$_{i,t-1} \times \Delta\text{FFR}_t$	-0.000	0.002	0.001	0.001	-0.000
	(0.001)	(0.001)	(0.002)	(0.003)	(0.003)
log(HHI)$_{i,t-1} \times \Delta\text{FFR}_t$	-0.001**	0.000	-0.001	0.004*	0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Time FE	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓
N	804,769	804,769	804,769	804,769	804,769
Within R^2	0.125	0.161	0.168	0.177	0.173

Table A12. Local projections of deposit flows by select bank characteristics: Alternative monetary policy measures

This table is similar to Table 5, but it uses monetary policy shocks in place of ΔFFR. Panel A uses Romer and Romer (2004) narrative monetary shocks, while Panel B uses Bauer and Swanson (2023) high-frequency monetary shocks. As in Table 5, each shock is split into a positive (tightening) and negative (easing) part, and each part is interacted with the lagged share of large deposits and lagged log of local deposit market HHI. Both shocks are scaled to 100bps change in the federal funds rate.

A. Romer and Romer (2004) shocks

	Horizon, quarters				
	$h = 0$	$h = 2$	$h = 4$	$h = 6$	$h = 8$
Lrg. dep. share$_{i,t-1}$ × RR shock$_t^+$	-0.002	-0.003	-0.009	-0.009	-0.011
	(0.002)	(0.004)	(0.006)	(0.009)	(0.009)
Lrg. dep. share$_{i,t-1}$ × RR shock$_t^-$	0.002	0.005	0.005	0.008	0.007
	(0.001)	(0.003)	(0.006)	(0.006)	(0.008)
log(HHI)$_{i,t-1}$ × RR shock$_t^+$	-0.002	-0.002	-0.006	-0.005	-0.005
	(0.002)	(0.003)	(0.004)	(0.006)	(0.007)
log(HHI)$_{i,t-1}$ × RR shock$_t^-$	-0.003**	-0.002	-0.001	0.008	0.004
	(0.001)	(0.003)	(0.004)	(0.005)	(0.006)
Time FE	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓
N	699,571	699,571	699,571	699,571	699,571
Within R^2	0.128	0.170	0.180	0.190	0.187

B. High-frequency shocks

	Horizon, quarters				
	$h=0$	$h=2$	$h=4$	$h=6$	$h=8$
Lrg. dep. share$_{i,t-1}$ × HF shock$_t^+$	-0.002	-0.011**	-0.017**	-0.027***	-0.027***
	(0.002)	(0.004)	(0.007)	(0.008)	(0.010)
Lrg. dep. share$_{i,t-1}$ × HF shock$_t^-$	0.002***	0.006***	0.008**	0.009**	0.008
	(0.001)	(0.002)	(0.003)	(0.005)	(0.006)
log(HHI)$_{i,t-1}$ × HF shock$_t^+$	0.004	-0.001	-0.003	-0.009	-0.004
	(0.003)	(0.004)	(0.007)	(0.007)	(0.009)
log(HHI)$_{i,t-1}$ × HF shock$_t^-$	-0.000	0.003*	0.004**	0.009***	0.008**
	(0.001)	(0.002)	(0.002)	(0.003)	(0.004)
Time FE	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓
N	804,769	804,769	804,769	804,769	804,769
Within R^2	0.125	0.161	0.168	0.177	0.174

Table A13. Pre-trend tests for difference-in-differences evidence on retail deposit pricing

This table reports the results of testing for pre-treatment differences between treatment and control markets. Estimates come from the following regression:

$$Y_{i,t} = \sum \delta_{c(i),t} + \sum \gamma_i + \sum_{j=1}^{3} \beta_j D_{c(i),t-j} \times \text{Treated}_i + \varepsilon_{i,t},$$

where $Y_{i,t}$ is either deposit market HHI, APY on select deposit products, or deposit betas, $D_{c(i),t-j}$ are dummies for 1, 2, and 3 years before the treatment for cohort $c(i)$, and Treated_i is an indicator for whether market i is in the treatment group. i indexes deposit markets-merger pairs and $c(i)$ indexes the cohort of the merger. See Appendix E for additional detail. Standard errors are clustered at the banking market level. *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

	HHI		APYs				Betas			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	HHI	Log HHI	Checking	Savings	MMDA	CD	Checking	Savings	MMDA	CD
D_{t-1} × Treated	-15.19	-0.0153	-0.0188	0.00585	-0.135	-0.0231	0.0401	0.0436	-0.0156	0.174
	(76.32)	(0.0472)	(0.0596)	(0.0683)	(0.0988)	(0.0692)	(0.0498)	(0.0776)	(0.0604)	(0.171)
D_{t-2} × Treated	-12.99	-0.00379	-0.00631	0.0157	-0.0625	-0.0757	0.0198	0.0186	-0.0144	0.0918
	(56.71)	(0.0350)	(0.0517)	(0.0564)	(0.0701)	(0.0611)	(0.0424)	(0.0769)	(0.0544)	(0.153)
D_{t-3} × Treated	-17.52	-0.00738	-0.0157	-0.00838	-0.0660	-0.0332	-0.0184	-0.0325	-0.0786	0.0455
	(44.61)	(0.0268)	(0.0482)	(0.0524)	(0.0576)	(0.0570)	(0.0517)	(0.0781)	(0.0576)	(0.149)
Observations	1315	1315	1314	1314	1314	1315	1314	1314	1314	1315
F-stat	0.0984	0.153	0.170	0.257	0.933	1.051	1.459	1.226	0.871	1.091
p-val	0.961	0.927	0.916	0.856	0.427	0.373	0.229	0.303	0.458	0.355
Cohort-Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Merger FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table A14. Retail deposit pricing and market concentration: Evidence from bank mergers

This table reports the results of the difference-in-differences regression following Wooldridge (2025):

$$Y_{i,t} = \sum \delta_{c(i),t} + \sum \gamma_i + \sum_{c,t>c(i)} \beta_{c(i),t} \text{Post}_{c(i),t} \times \text{Treated}_i + \varepsilon_{i,t},$$

where $Y_{i,t}$ is either deposit market HHI (Panel A), APY on select deposit products (Panel B), or deposit betas (Panel C), $c(i)$ indexes the cohort of the merger, t indexes time (year), and i indexes deposit market-merger pair. $\text{Post}_{c(i),t}$ is an indicator for whether t is after the merger in cohort $c(i)$, and Treated_i is an indicator for whether market i is in the treatment group. The table reports the coefficient on the interaction term $\text{Post}_{c(i),t} \times \text{Treated}_i$, aggregated to a single effect using cohort counts. Panels B and C report results for APYs and betas on the following retail deposit products: "checking" (interest-bearing checking accounts with minimum balance $2,500), "savings" (savings accounts with minimum balance $2,500), "MMDA" (money market accounts with minimum balance $10,000) and "CD" (12-month CDs with minimum balance $10,000). Standard errors are clustered at the banking market level. *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

A. Market concentration

	(1) HHI	(2) Log HHI
Post × Treated	-109.4**	-0.0808***
	(44.94)	(0.0239)
N	2786	2786
Cohort-Year FE	✓	✓
Merger FE	✓	✓

B. Rates on select deposit products

	(1) Checking	(2) Savings	(3) MMDA	(4) CD
Post × Treated	0.0246	-0.0131	0.0285	0.0175
	(0.0292)	(0.0285)	(0.0324)	(0.0229)
N	2783	2783	2785	2786
Cohort-Year FE	✓	✓	✓	✓
Merger FE	✓	✓	✓	✓

C. Deposit betas

	(1) Checking	(2) Savings	(3) MMDA	(4) CD
Post × Treated	-0.00780	0.0483	0.0751	-0.0358
	(0.0385)	(0.0713)	(0.0904)	(0.160)
N	2783	2783	2785	2786
Cohort-Year FE	✓	✓	✓	✓
Merger FE	✓	✓	✓	✓

Table A15. CRA small business lending: Alternative monetary policy measures

This table is similar to Table 6, but it uses monetary policy shocks instead of ΔFFR. Panel A uses Romer and Romer (2004) narrative monetary shocks, while Panel B uses Bauer and Swanson (2023) high-frequency monetary shocks. As in Table 6, each shock is split into a positive (tightening) and negative (easing) part, and each part is interacted with the lagged share of large deposits. Note: in this table I do not rescale the shocks to match 100bps monetary tightening since the small business lending data are annual and require aggregation of shocks, introducing additional noise.

A. Romer and Romer (2004) shocks

	Small banks		Large banks	
	(1)	(2)	(3)	(4)
RR $\text{shock}_t^+ \times \text{Lrg. dep. share}_{i,t-1}$	-0.115**	-0.161***	0.129	0.078
	(0.057)	(0.059)	(0.156)	(0.156)
RR $\text{shock}_t^- \times \text{Lrg. dep. share}_{i,t-1}$	0.021	0.051*	-0.080	-0.056
	(0.034)	(0.030)	(0.110)	(0.108)
Controls		✓		✓
County × Year FE	✓	✓	✓	✓
County × Bank FE	✓	✓	✓	✓
N	365,134	365,134	225,995	225,995
Within R^2	0.005	0.023	0.007	0.025

B. Bauer and Swanson (2023) shocks

	Small banks		Large banks	
	(1)	(2)	(3)	(4)
BS $\text{shock}_t^+ \times \text{Lrg. dep. share}_{i,t-1}$	-0.406**	-0.529**	-0.451	-0.533
	(0.199)	(0.207)	(0.400)	(0.347)
BS $\text{shock}_t^- \times \text{Lrg. dep. share}_{i,t-1}$	0.008	0.046	0.268*	0.281**
	(0.083)	(0.075)	(0.154)	(0.137)
Controls		✓		✓
County × Year FE	✓	✓	✓	✓
County × Bank FE	✓	✓	✓	✓
N	365,134	365,134	225,995	225,995
Within R^2	0.003	0.020	0.006	0.030

Table A16. Banks with more large deposits hold shorter-maturity assets

This table reports the results of the following regression:

$$\text{Assets maturity}_{it} = \alpha_t + \beta_t \text{Lrg. dep. share}_{it} + \Gamma_t X_{it} + \varepsilon_{it},$$

where Assets maturity$_{it}$ is the average maturity (in years) of total assets at bank i at time t; Lrg. dep. share$_{it}$ is the share of large deposits at bank i at time t; and X_{it} is a vector of control variables including log total assets, log HHI, log bank age, and equity-to-assets ratio. The data are as of the end of the year for select years (1990, 1995, 2005, 2015, 2023) for all U.S. commercial banks; the sample starts in 1990 because maturity reporting in the Call Reports begins around that date. Assets maturity is winsorized at the 1%/99% level by date. Heteroskedasticity-robust standard errors are in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

	1990		1995		2005		2015		2023	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Large deposit share	-0.016***	-0.014***	-0.014***	-0.015***	-0.027***	-0.030***	-0.027***	-0.030***	-0.035***	-0.029***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	12,070	12,052	9,905	9,825	7,938	7,807	6,161	6,143	4,554	4,538
R-squared	0.047	0.104	0.034	0.097	0.058	0.124	0.026	0.064	0.035	0.074

Table A17. Banks with more large deposits hold more C&I loans

This table reports the results of the following regression:

$$\text{C\&I loan share}_{it} = \alpha_t + \beta_t \text{Lrg. dep. share}_{it} + \Gamma_t X_{it} + \varepsilon_{it},$$

where C&I loan share$_{it}$ is the share of commercial and industrial loans in total loans at bank i at time t; Lrg. dep. share$_{it}$ is the share of large deposits at bank i at time t; and X_{it} is a vector of control variables including log total assets, log HHI, log bank age, and equity-to-assets ratio. The data are as of the end of the year for select years (1985, 1995, 2005, 2015, 2023) for all U.S. commercial banks. Heteroskedasticity-robust standard errors are in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

	1985		1995		2005		2015		2023	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Large deposit share	0.441***	0.301***	0.321***	0.269***	0.171***	0.156***	0.223***	0.198***	0.156***	0.113***
	(0.010)	(0.011)	(0.016)	(0.017)	(0.012)	(0.014)	(0.011)	(0.015)	(0.016)	(0.019)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	14,165	14,143	10,475	10,401	7,894	7,775	6,122	6,105	4,520	4,505
R-squared	0.202	0.268	0.126	0.177	0.063	0.080	0.110	0.126	0.043	0.058