

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

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I study how pricing and flows of large and small deposits respond to monetary policy. Using novel hand-collected data on posted deposit rate schedules at major U.S. banks and comprehensive regulatory data, I document that banks tier rates by deposit balance, paying higher and more policy-sensitive rates on larger balances. On average, rate pass-through for large deposits is more than double that for small deposits (0.7 versus 0.3), and the share of large deposits alone explains 15% of variation in deposit betas across banks. Despite this better pricing, large deposits flow out more strongly following monetary policy tightening and account for essentially all of the total deposit response. Risk does not explain these patterns. My results suggest that the deposits channel of monetary policy operates disproportionately through a small number of large, responsive depositors who account for a substantial share of bank funding.

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How does monetary policy transmit through the banking system? The deposits channel of monetary policy posits that banks’ market power in deposit markets allows them to keep deposit rates low when monetary policy tightens, leading to deposit outflows and a contraction in bank lending (Drechsler, Savov, and Schnabl 2017). This framework has been highly influential in finance and macroeconomics; yet, its precise workings have been the subject of an active debate (Wang et al. 2022; Drechsler et al. 2024; Granja and Paixao 2024; Begenau and Stafford 2025; Wang 2025).

In this paper, I study how the pricing and flows of large and small deposits respond to monetary policy and how this heterogeneity shapes the deposits channel. Understanding this heterogeneity is crucial because the distribution of deposits is highly right-skewed, with the largest 1% of deposit *accounts* holding 50% of deposit *balances* at U.S. commercial banks as of the first quarter of 2024. Thus, the behavior of the *average* depositor may not be representative of how total deposits of a bank or the economy *as a whole* respond to monetary policy – the total response is shaped largely by what large depositors do.

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 betas on large and small deposits – increases with the share of large deposits in the cross-section of banks in every monetary policy cycle since 1975.¹ 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 do not vary with the share of large deposits. 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 rates offered on large deposits are higher and more sensitive to policy rates than those offered on small deposits. First, I use the sparse data on larger-denomination, “relationship” and “premium”, and corporate deposit products

¹Large 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 wealth distribution – and document similar patterns for the wealthiest top 1% of households and NBFIs.

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 posted deposit rate schedules at the 32 largest U.S. banks, gathered from their websites and 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) was then 5.33%. In February 2022, right before this tightening cycle started and with the FFR at 0.08%, Wells Fargo advertised 0.02% APY on all balance tiers of savings 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 respond. 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 more than twice as much as small non-time deposits. The rotation from non-time to time deposits then roughly cancels for small deposits; for large deposits, the non-time outflow far exceeds the time-deposit inflow, producing a strong overall contraction. These flow patterns hold when monetary policy is measured as raw changes in the federal funds rate, [Romer and Romer \(2004\)](#) monetary shocks, and [Bauer and Swanson \(2023\)](#) high-frequency monetary shocks. Raw rate changes are endogenous and positively correlate with aggregate income as measured by real GDP, 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. The same finding holds within banks as well: controlling for bank fixed effects, large deposits flow out strongly following monetary tightening, while small deposits are flat.

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. Similarly, when the Fed hikes, large (uninsured) depositors may withdraw relatively more from banks because they are worried about banks' net worth (Jiang et al. 2024; Drechsler et al. 2026), and not because they are more rate-elastic. 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 show that betas on large deposits themselves, and large deposits' flow semi-elasticities to monetary shocks, do not increase with the share of large deposits in the cross-section of banks, as would be expected if risk were the dominant driver of my findings. Fourth, 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. Small and large deposits' semi-elasticities for these 5 banks are also very similar to those in the full sample: large deposits contract when the Fed tightens, while small deposits remain roughly flat. These facts suggest that risk cannot be the main driver of the deposit pricing and flow patterns I document.

Together, these findings point to small deposits being significantly more sticky than large deposits. This interpretation is consistent with who holds large deposits. 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. Larger balances also imply that 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). These forces can make large deposits more elastic with respect to deposit spreads than small deposits – and thus also push banks to offer better rates on larger balances – consistent with both the pricing and flow patterns I document.

To get a sense of how important this differential stickiness is for deposit pricing quantitatively, I benchmark 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 share of large deposits is a much

stronger predictor of deposit betas in the cross-section of banks than local deposit market concentration, explaining, on average, 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 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 within the same county-year across banks with different large-deposit inflows, excluding counties where the lending bank raises deposits. I find that banks with stronger growth of large deposits extend more small business loans, while banks losing large deposits cut such lending. This effect is stronger at small banks. These results point to 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 earning 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. The deposits channel of monetary policy thus operates disproportionately through a small number of large, responsive depositors who account for a substantial share of bank funding. 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 2026](#); [Egan et al. 2026](#)). My results imply 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.

Within this literature, a growing body of work documents that depositors are “sticky” – inattentive, inert, or financially unsophisticated ([Adams et al. 2021](#); [Fleckenstein and Longstaff 2024](#); [Yankov 2024](#); [Egan et al. 2026](#); [Lu and Wu 2026](#)). I find that this stickiness is concentrated among small retail depositors.⁴ Given that large deposits are, on average, held by agents considered more financially sophisticated and attentive (see [Section 2](#) for further discussion), my results provide further evidence that depositor stickiness shapes deposit pricing and flows in the broad cross-section of U.S. banks since 1975.

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. 2024](#); [Begenau and](#)

²Other 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”.

⁴Large deposits are also sticky – their estimated rate pass-through of about 0.7 is below 1 – but much less so than small deposits.

Stafford 2025; Wang 2025).⁵ I show that the deposits channel works primarily through large depositors: large deposits flow out following monetary tightening, while small deposits only rotate from non-time into time deposits but do not flow out overall. 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.

Third, this paper connects to the broader literature documenting that retail and large (often institutional) investors face different prices and exhibit different demand elasticities across financial markets (see Barber and Odean 2013; Lusardi and Mitchell 2014; Gabaix 2019, for reviews of the underlying frictions). Most closely related is Brown et al. (2024), who show that index fund managers price discriminate between small retail and large institutional investors, with institutional demand for index funds being considerably more elastic with respect to fees. Relatedly, 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. Similar retail vs. institutional differences have been documented for ESG funds (Baker, Egan, and Sarkar 2024), specialized ETFs (Ben-David et al. 2023), and crypto markets (Liu, Makarov, and Schoar 2023). 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 Ufieri (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. 2026; Cipriani, Eisenbach, and Kovner 2024; Jiang et al. 2024; Begenau, Landvoigt, and Elenev 2026; Blickle et al. 2025; Chang, Cheng, and Hong 2025; Kim, Kundu, and Purnanandam 2025). I contribute to

⁵This strand of research is part of the vast literature on the bank lending channel of monetary policy. 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).

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](#)).

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. 2026](#); [Lu and Wu 2026](#)). 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

⁶See 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.

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).⁸

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.⁹ 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.

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.

⁷For example, the 2022 Survey of Consumer Finances (SCF) shows that the top-1% of highest-earning households, on average, held about \$252,000 of checking deposits and \$696,000 of savings deposits, while the bottom 99% held, on average, \$14,500 and \$27,400 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).

⁸At the same time, deposits constitute a much lower *share* of wealth for the “large” depositors. Using the 2022 SCF I estimate that deposits are 30% of liquid wealth for the bottom 99% of households by wealth vs 9% for the top-1%. See Appendix E for details. Large depositors are also more likely to receive benefits from their banking relationships other than interest on deposits that might make them *a priori* more sticky (Basten and Juelsrud 2023, 2025). Thus, whether large depositors are more vs less sticky than small depositors is ultimately an empirical question that this paper addresses.

⁹This 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 the 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.

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. Differences in local market concentration cannot generate [prediction 2](#).¹⁰

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](#).

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

¹⁰[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](#).

banks (federal- and state-chartered) for the period 1975Q1-2024Q1. 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 $\text{Deposit interest expense}_{it}$ is total interest expense on deposits in domestic offices of a bank i over a reporting period t (quarter since 1983), and $\text{Deposit balance}_{i,t}$ is the interest-bearing deposits outstanding at bank i as of the end of the reporting period t .¹¹ 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 ($\leq \$250,000$ and $> \$250,000$ starting in 2009Q3). I call the deposits below the aforementioned thresholds “small”, and the deposits above “large”. I compute

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

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 1982Q2-1990Q4.¹² 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.¹³

¹¹This 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 \(2025\)](#).

¹²I 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.

¹³Some 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 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.¹⁴ [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 the 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 of local deposit market concentration. First, following [Drechsler, Savov, and Schnabl \(2017\)](#) and the subsequent literature, I compute the 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.¹⁵ See [Appendix B](#) for additional details.

Offered deposit rates: Ratewatch. My first data source on offered deposit rates is the share of deposits held by non-household sectors and the 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. [Figure A3](#) shows a strong correlation between the share of large non-time deposits and the share of transaction and savings deposits classified as not for “personal use”. The latter measure is not used in this paper because it is available only from 2014Q1 onwards, and only for the largest banks.

¹⁴The “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).

¹⁵This 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](#).

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, this dataset 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 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 the 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 the 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:

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

where $\text{Dep. exp. rate}_{i,t}$ is defined in [Section 3](#) and Short rate_t is the short rate in period t , chosen to be the effective federal funds rate.¹⁶ Total deposit expense beta is a weighted average of the small and large deposit account betas:¹⁷

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

Assuming that small and large deposit betas are approximately equal across banks¹⁸, we have that:

$$\begin{aligned} \text{Dep. exp. beta}_{i,t_0 \rightarrow t_1} &\approx \text{Dep. exp. beta}_{i,t_0 \rightarrow t_1}^{\text{Small}} \\ &+ \alpha_{i,t_0}^{\text{Large}} \left(\text{Dep. exp. beta}_{i,t_0 \rightarrow t_1}^{\text{Large}} - \text{Dep. exp. beta}_{i,t_0 \rightarrow t_1}^{\text{Small}} \right). \end{aligned} \quad (1)$$

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.

¹⁶The results are unchanged if I use 3-month Treasury yield instead.

¹⁷There is also a third “covariance” term, $(\alpha_{i,t_1}^{\text{Large}} - \alpha_{i,t_0}^{\text{Large}})(\text{Dep. exp. rate}_{i,t_1}^{\text{Large}} - \text{Dep. exp. rate}_{i,t_1}^{\text{Small}})/\Delta_{t_0,t_1} \text{SR}$. This term is empirically small and is thus ignored for simplicity.

¹⁸The results below support this assumption. See [Figure A13](#).

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.¹⁹ 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 A5. This result is not driven by local deposit market concentration (Figure A6); the results are also similar for deposit subtypes, namely savings (Figure A7) and time deposits (Figure A8). Figure A9 shows explicitly that banks with a 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):

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

where $\Delta \text{Dep. exp. rate}_{i,t-1,t+h}$ 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 $\text{Lrg. dep. share}_{i,t-1}$ 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 $\text{Lrg. dep. share}_{i,t-1}$, 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 $h = 0, 1, \dots, 8$ quarters ahead. The coefficient of interest is β^h , which captures how the

¹⁹ Figure A4 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.

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 the 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](#)).²⁰

[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 to deposit subtypes separately, namely savings and time deposits ([Figure A10](#)), and to the sample of the top-10% of banks by total assets ([Figure A11](#)).

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.

²⁰Given 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.

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 A12](#)): 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.²¹

This result shows that banks with a higher share of large deposits do *not* pay higher

²¹[Figure A12](#) 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.

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 A13](#) and [Table A7](#) show 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.²² 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 $\text{Dep. exp. beta}_{i,c}$ is the deposit beta for bank i over cycle c and $\text{Lrg. dep. share}_{i,c}$ 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 Rate-watch data are 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 A14](#) and [Table A8](#)). They also hold further back in time, before Ratewatch data become available ([Figure A15](#)). In the full sample, the average inferred small deposit beta is 0.3, while the average inferred large deposit beta is 0.7.

²²The 2022Q1-2024Q1 cycle is the exception – implied rate betas on large deposits monotonically increase over the quintiles of large-deposits-share distribution in the cross-section of banks. See [Section 6](#) for further discussion.

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 A16](#) 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, and with \$250,000 minimum balance.²³ 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, 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. When the monetary policy rate was low, Wells Fargo offered the same low rate on all savings deposits, *regardless of balance*. But when the federal funds rate went up, Wells Fargo kept rates on small deposits low, and increased rates on large deposits. Specifically, in May 2021, when the federal funds rate was at 6bps,

²³“Premium” and “relationship” deposit products are effectively just high-balance deposit products; see [Appendix D](#) for additional discussion.

Wells Fargo offered 2bps on all savings deposits, regardless of balance. But in December 2023, when the effective FFR was at 5.33%, Wells Fargo offered 0.25% on balances $\leq$ \$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 pass-through for the largest balance was thus 0.47 vs only 0.04 for the lowest balance. A similar pattern holds for TD Bank (Panel B) and for Zions Bancorporation (Panel C).²⁴ Figure A17 shows how this balance-tiered deposit pricing looked on these banks' websites.²⁵

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.²⁶

Finally, I also provide direct evidence that deposit pricing for large firms is more rate-sensitive than small-retail deposit pricing. Table A9 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 A16, 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-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,

²⁴These 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.

²⁵The 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.

²⁶The difference between the median and the mean in Figure 5 Panel B is driven by online banks that do not tier posted deposit rates.

at Bank of America, the rate on the \$100,000 corporate sweep account increased from 1.1% in July 2004 to 4.56% in September 2006, for a beta of 0.87.

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. In the comprehensive cross-section of banks, those with more large deposits exhibit higher deposit rate betas in every monetary policy cycle since 1975. [Section 6](#) shows that these pricing patterns cannot be explained by risk premia.

5. Deposit flows: Large vs small deposits

I now turn to testing [prediction 2](#), which says that the growth of large deposits is expected to be lower (higher) than the growth of small deposits 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:

$$\Delta_{t-1,t+h} \log Y = \alpha^h + \beta^h \text{MP shock}_t + \Gamma^h X_t + \varepsilon_{t+h}, \quad (3)$$

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. The deposits data are aggregated from the Call Reports over all U.S. commercial banks. 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 shock, as well as controls for real GDP growth and inflation, their lags, and indicators for quarters (to capture seasonality) and for the zero lower bound (ZLB) period. I estimate these local projections for horizons $h = 0, 1, \dots, 8$ 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 driven entirely by large deposits: large deposits decline sharply following the tightening shock, while small deposits, if anything, slightly increase. The difference between impulse responses of large and small deposits is statistically significant ([Table A10](#)). [Figure A19](#) and [Table A11](#) show that this result is robust to using high-frequency monetary policy shocks as well as to ΔFFR

directly. It also holds separately for large and small banks, as shown in [Figure A20](#).²⁷ This finding is also *not* driven by brokered deposits, which are typically thought of as wholesale funding ([Figure A21](#)). This is consistent with [prediction 2](#).

To further establish robustness of this result, in particular across time periods, [Figure A22](#) plots year-over-year real growth rates for total deposits against the year-over-year changes in the effective federal funds rate. 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, and plot their growth rates in [Figure A22](#) 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 3](#) for these dependent variables. [Figure A23](#) 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.²⁸ 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 investing in non-deposit financial products such as bonds or money market funds (or more willing to do so). This is also consistent with [prediction 2](#) – within deposits that decline following tightening monetary shocks (demand and savings), large deposits decline more than 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

²⁷[Table A13](#) shows that this relationship – stronger outflows of large deposits than small deposits in response to monetary policy – holds for all quintiles of the bank size distribution. [Table A12](#) shows that this relationship is also consistent across all quintiles of banks by the share of large deposits itself. So the results are not driven only by the banks with the highest share of large deposits – those where large (uninsured) depositors might have the strongest incentives to run ([Drechsler et al. 2026](#)). [Section 6](#) discusses this further.

²⁸The 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. \(2024\)](#).

the United States (see [Section 3](#)). This analysis 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.²⁹ I estimate local projections as in [Equation 3](#), with the dependent variable Y being, alternately, deposits of the bottom-99% of households by net worth, deposits of the 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 A24](#) plots the resulting IRFs. Consistent with the results above, 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.³⁰ 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 them around to maximize rates as much as, e.g., wealthy households.³¹ Deposits of non-depository financial businesses, on the other hand, clearly decline following monetary tightening.

I also estimate [Equation 3](#) at the bank level in panel local projections. [Table 5](#) shows the results. Panel A shows that large deposits at the *average* bank declined by 7.6% at the 2-year horizon in response to [Romer and Romer \(2004\)](#) monetary shock corresponding to a 1pp increase in the federal funds rate; small deposits do not respond (Panel B). This holds within banks too, as even-numbered columns of [Table 5](#) control for bank fixed effects. [Table A15](#) shows that this finding is also robust to alternative measures of monetary policy stance.

I briefly comment on potential endogeneity of the results in this subsection. Even

²⁹For 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 following monetary tightening, even if true “large” and “small” deposits are similarly responsive to monetary policy.

³⁰Note that the deposit flow sensitivity to monetary policy seems to increase monotonically over the net-worth percentiles. [Figure A25](#) 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.

³¹The higher deposit rates that (large) nonfinancial businesses still get, documented in [Section 4](#), may then stem from cross-selling ([Basten and Juelsrud 2025](#)).

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 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.³²

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 as well as within banks – 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.

6. Large vs uninsured: Are the results driven by risk?

The core challenge in interpreting the results presented in this paper is that large deposits tightly overlap with uninsured deposits, both conceptually and as a matter of definition.³³ 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 cor-

³²Figure A26 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.

³³Recall 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).

related with market rates, then the higher betas on large deposits could be due to risk, not higher “risk-free” rate betas. At the same time, large deposits’ higher flow elasticity to monetary policy could also reflect risk: large (uninsured) depositors could leave banks after tightening monetary shocks because these shocks lower banks’ net worth (as modeled in Jiang et al. 2024; Drechsler et al. 2026). This section shows that risk is unlikely to be the main driver behind the deposit pricing and flow patterns documented in this paper.

I first show that risk premia cannot explain the pricing differences between large and small deposits. First, Figure A27 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 A28 repeats the binscatter 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 A29).

Third, Table A7 shows that betas on large deposits do not reliably increase with the share of large deposits in the cross-section of banks, as would be expected if risk premia were the dominant source of higher betas on large deposits vs small deposits. One exception to this finding is the 2022Q1-2024Q1 tightening cycle. A proximate cause of why this cycle is different is the 2023 Regional Banking Crisis, which was driven by large (uninsured) depositors running on a set of regional banks which (a) were abnormally reliant on uninsured deposit funding, and (b) incurred big unrealized losses on their securities portfolios as the Fed hiked throughout 2022 (Cipriani, Eisenbach, and Kovner 2024; Jiang et al. 2024; Drechsler et al. 2026). I note that such runs did not occur in any other tightening cycle I study. Relatedly, as shown before in Table A12, large deposits do *not* flow out more strongly from banks with an *ex ante* higher share of large deposits when the Fed hikes, as would be expected if risk were the main driver of large deposit outflows.³⁴

³⁴In fact, Table A12 shows that semi-elasticities of large deposits with respect to monetary policy are *lower* for banks in higher quintiles of large-deposits share distribution. The decrease is essentially monotonic for all measures of monetary policy, and is not driven by bank size (Table A14). This negative relationship between large deposit flow semi-elasticity and the initial share of large deposits in the cross-section of banks is also why Section 5 does not employ panel local projections similar to Equation 2 but with $\Delta_{i,t-1,t+h} \log \text{Total deposits}$ as the dependent variable. Banks with a higher share of large deposits initially have lower semi-elasticity of large deposits themselves, thus total deposits’ semi-elasticity for such banks is roughly equal to the total

Fourth, 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:

$$\text{Fail}_{i,t+h} = \alpha + \beta \text{Lrg. dep. share}_{it} + \Gamma X_{it} + \varepsilon_{it}, \quad (4)$$

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 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 A16](#), 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:

$$\text{Fail}_{i,t+h} = \alpha + \beta_1 \text{Lrg. dep. share}_{it} + \beta_2 \text{Lrg. dep. share}_{it} \times r_t + \Gamma X_{it} + \varepsilon_{it}, \quad (5)$$

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 4](#), 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 A17](#) 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.³⁵

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 pricing results, then the relationship between deposit betas and the share of large deposits

deposits’ semi-elasticity for banks with a lower share of large deposits initially.

³⁵Relatedly, [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.

should be much weaker among the largest banks. [Figure A30](#) 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. [Figure A31](#) also shows that – even for the top-5 largest TBTF banks – large deposits flow out following monetary tightenings, while small deposits are flat, with results even stronger than the main estimates quantitatively.

7. Discussion and implications

7.1. Comparison with local deposit market concentration

This paper documents 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.³⁶ 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 A32](#) 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 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

³⁶The 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.

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 A33](#) 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 more difficult 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.³⁷

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.

7.2. 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 to [Equation 3](#) 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.

³⁷The 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 A34](#) plots R^2 for these retail deposit products separately.

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 the 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 A20 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 A35).

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 small business lending at the bank-county level.³⁸ I test whether outflows of large deposits lead banks to cut small

³⁸The 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.

business lending, controlling for county-wide loan demand:

$$\begin{aligned} \log(\text{Small bus. lending}_{i,c,t}) = & \alpha_{ic} + \delta_{ct} + \beta^L \Delta_{i,t-1,t} \text{Large deposits/Assets}_{i,t-1} \\ & + \beta^S \Delta_{i,t-1,t} \text{Small deposits/Assets}_{i,t-1} + \Gamma X_{i,t} + \epsilon_{i,c,t}, \end{aligned} \quad (6)$$

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, $\Delta_{i,t-1,t} \text{Large (Small) deposits/Assets}_{i,t-1}$ is the year-on-year growth in large (small) deposits scaled by lagged total assets, and $X_{i,t}$ is a vector of controls, including an indicator for the zero-lower-bound period, bank-level HHI, and total assets, as well as their interactions with $\Delta_{t-1,t} FFR$. The main coefficient of interest is β^L .

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 comparing small business lending within the same county-year by banks that gain more vs less large deposits overall. Still, one might be worried that this specification is mechanical: if the banks' clientele within a given county has a particularly good year, they will (a) put a lot of deposits (including large) into the bank, and (b) have very strong loan demand, even relative to clienteles of other banks in the same county. To mitigate this concern, I exclude any bank-county observations ict where bank i has a branch in county c in years $t - 1$, t , or $t + 1$. In effect, I estimate Equation 6 on the set of counties where banks do *not* raise deposits. This helps disconnect local loan demand and deposit supply.

Table 6 reports the results. β^L is consistently positive and statistically significant, even controlling for small deposits inflows. This suggests that inflows of large deposits matter for small business lending – banks expand small business lending when they get more large deposits and contract it otherwise. This is despite large deposits being more “flighty” – they are still not easily substitutable with wholesale funding. This is particularly true for small banks (those outside the top-1% of banks by assets), as shown in Table A18.

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.

7.3. Maturity transformation

[Section 4](#) shows that banks with more large deposits have more rate-sensitive deposit rates. Does this mean that the 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 the 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.³⁹ [Table A19](#) confirms this relationship in a regression framework

³⁹I 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 a higher share of large deposits tend to have a higher share of C&I loans. [Table A20](#) 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.⁴⁰

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.

7.4. 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 the 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](#)).⁴¹ Given my finding that large deposits are much more responsive to monetary policy, this compositional shift implies that the deposits channel has likely strengthened over time.

As a back-of-the-envelope calculation, I estimate that a 100bps monetary tightening is associated with about a 750bps decline in *large* deposits over two years, based on [Figure 6](#).

Zakrajšek (2018) and [Drechsler, Savov, and Schnabl \(2021\)](#).

⁴⁰The 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 \(2023\)](#).

⁴¹[Catherine, Miller, and Sarin \(2025\)](#) show that wealth inequality in the U.S. has not increased if social security is properly accounted for as an additional asset in households' wealth. The argument in this section, however, is about *financial* wealth only.

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. As the share of large, responsive deposits increased by 10 percentage points (e.g., from $\approx 40\%$ in 2000 to 50% in 2024), this likely increased the total deposits response to a 100bps monetary tightening by about 100bps over two years. My estimates also imply that this led to an additional 80-100bps contraction in lending by small banks at the 2-year horizon in response to a 100bps monetary tightening shock.⁴² 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

This paper studies how the pricing and flows of large and small deposits respond to monetary policy and how this heterogeneity shapes the deposits channel. 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. Although large deposits are largely uninsured, risk cannot fully explain these patterns. They are also not explained by local deposit market concentration. The deposits channel thus works disproportionately 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 transmission 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

⁴²The lending response is estimated by taking banks' "marginal propensity to lend" estimated in [Table 6](#) and [Table A18](#) (0.8-1) and multiplying it by the estimated deposit contraction. See also [Corell \(2025\)](#).

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 disproportionately 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. \(2024\)](#).

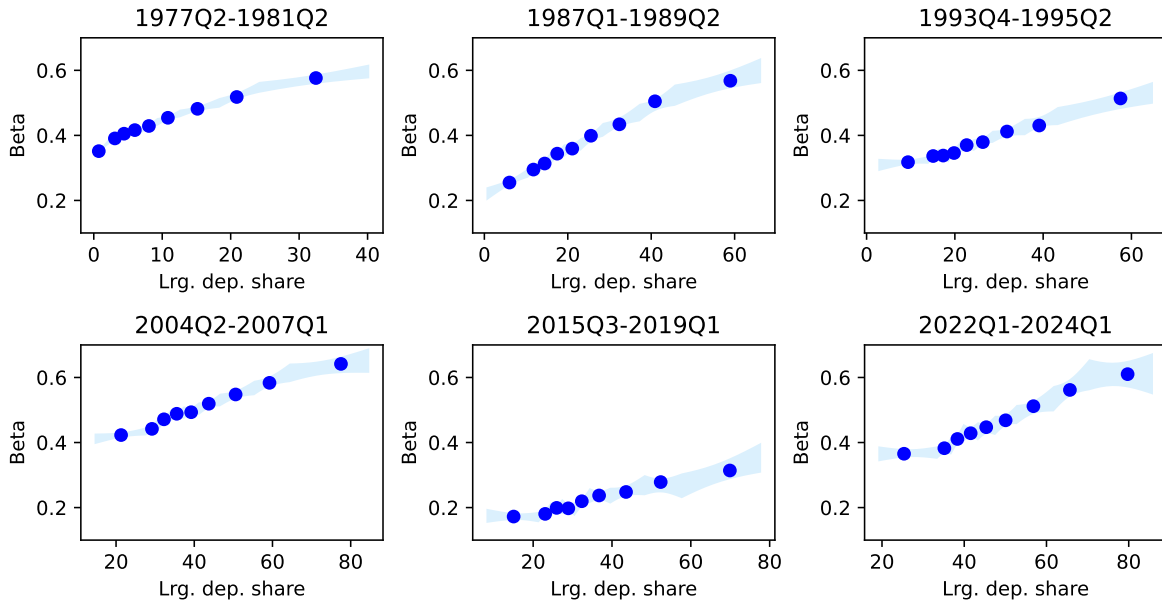


Figure 2. Impulse response of total deposit expense rates to monetary policy by share of large deposits

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

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

where $\Delta \text{Dep. exp. rate}_{i,t-1,t+h}$ 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 $\text{Lrg. dep. share}_{i,t-1}$ 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 $\text{Lrg. dep. share}_{i,t-1}$ 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 $t-1$. 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.

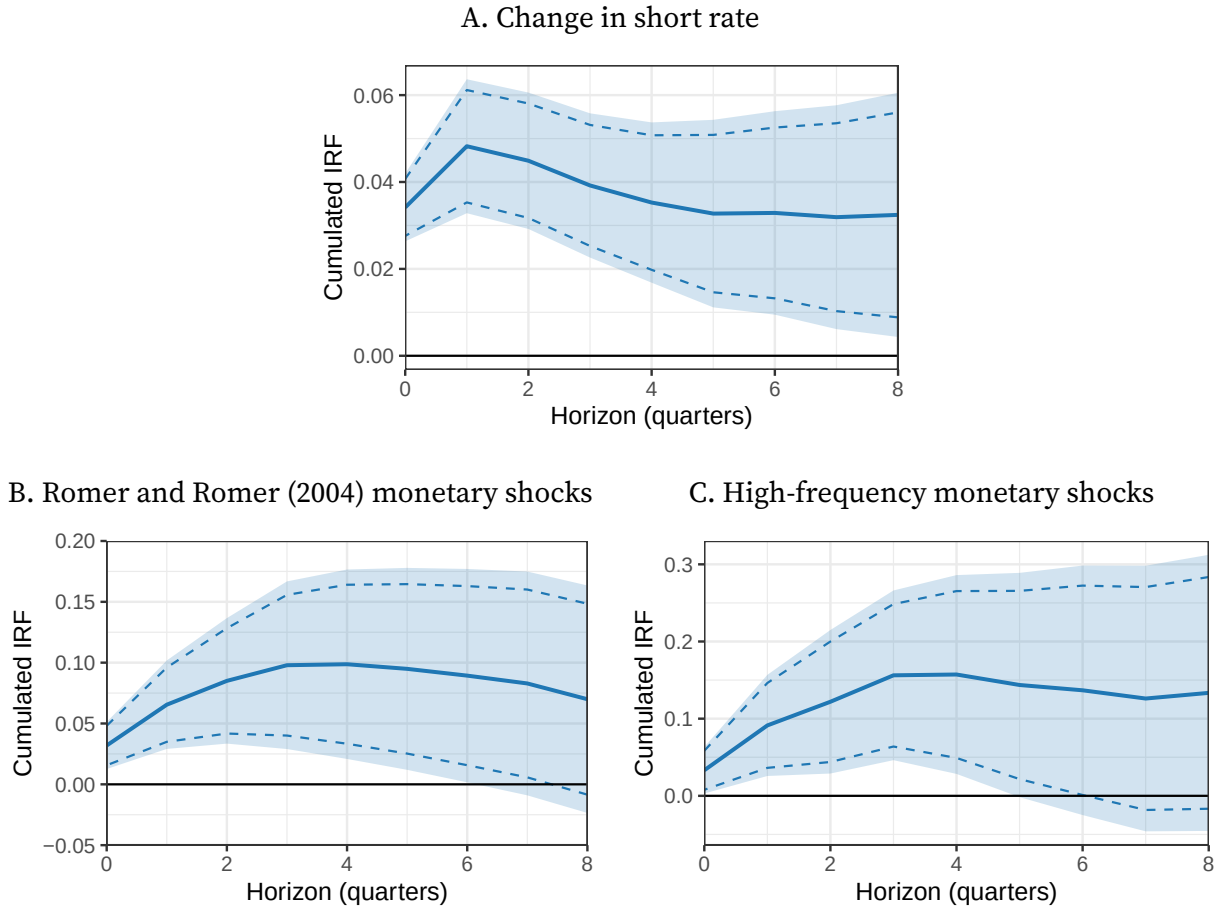


Figure 3. Call Report deposit expense betas vs Ratewatch small deposit betas by share of large deposits

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 become 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.

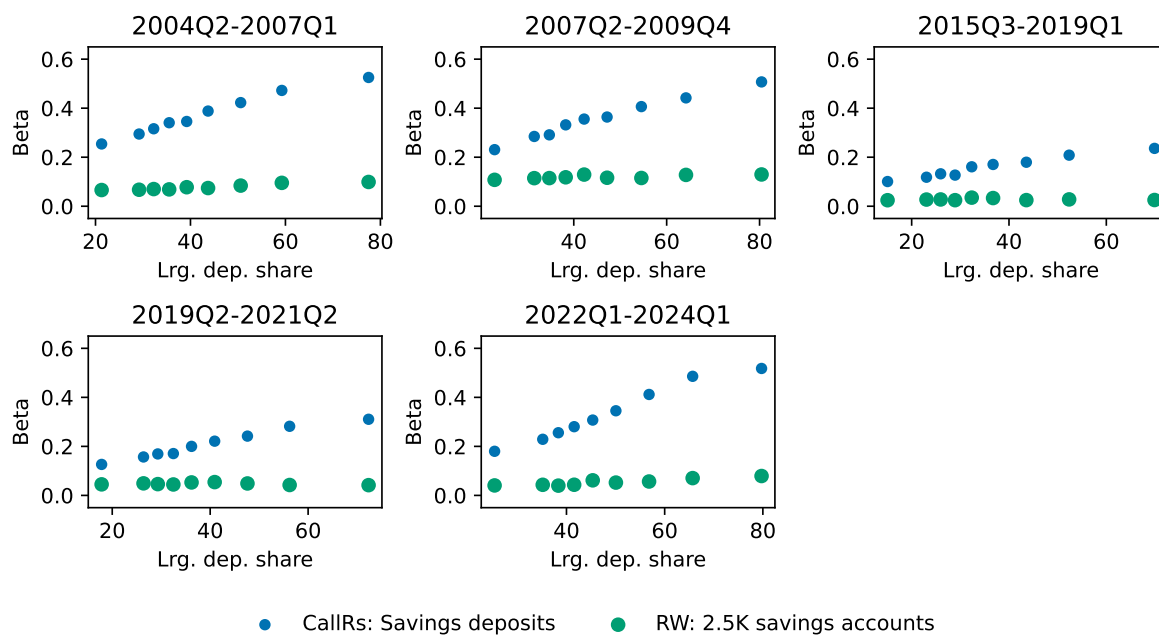


Figure 4. Inferred deposit expense betas for small and large deposits by monetary policy cycle

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 $\text{Dep. exp. beta}_{i,c}$ is the total deposit expense beta for bank i over cycle c and $\text{Lrg. dep. share}_{i,c}$ 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.

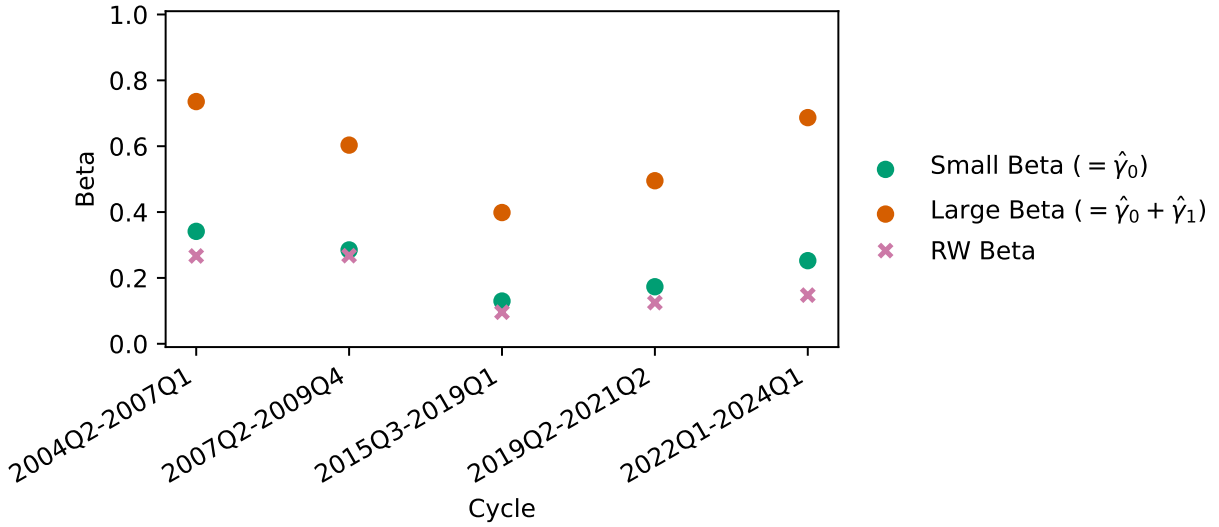
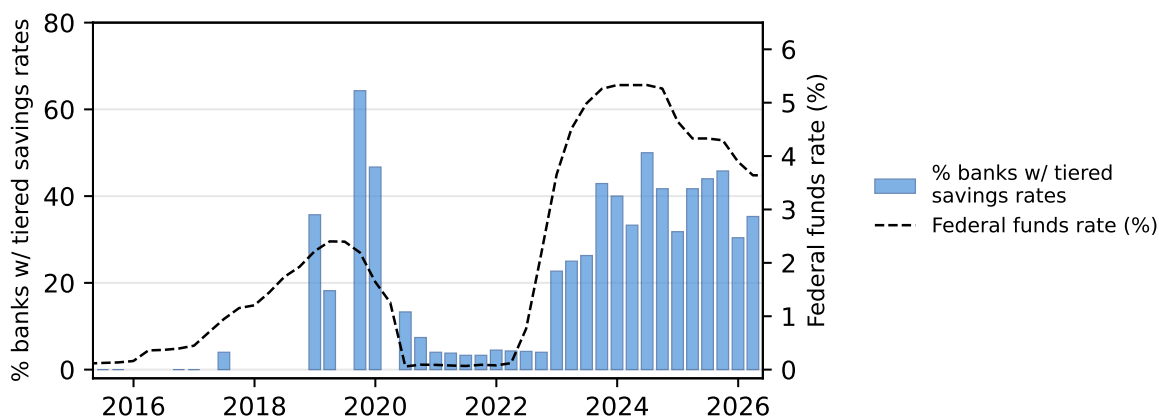


Figure 5. Tiered pricing of savings deposits across monetary policy cycles, 2015-2026

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

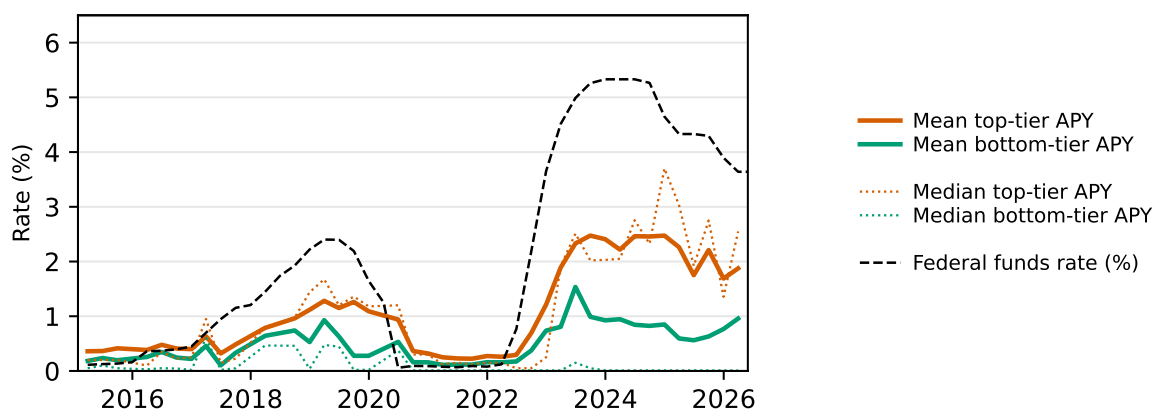


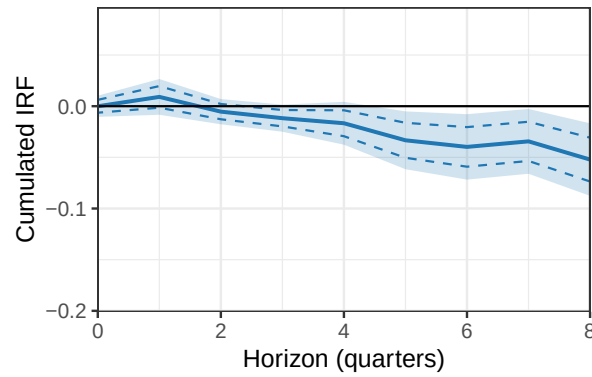
Figure 6. Aggregate deposit flow response to monetary policy shocks: Large vs small deposits

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

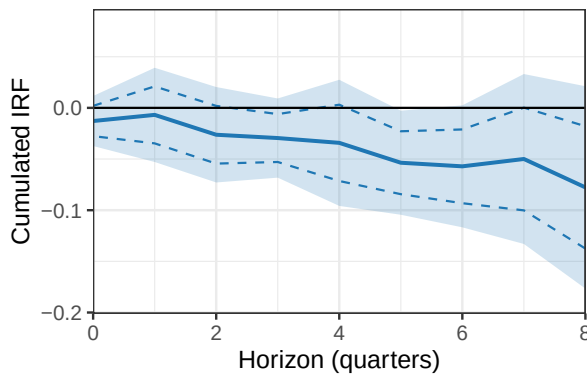
$$\Delta_{t-1,t+h} \log Y = \alpha^h + \beta^h \text{RR shock}_t + \Gamma^h X_t + \varepsilon_{t+h},$$

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 $h = 0, 1, \dots, 8$ 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.

A. Total deposits



B. Large deposits



C. Small deposits

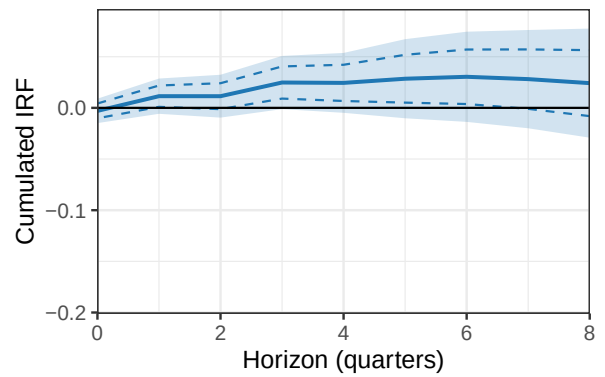
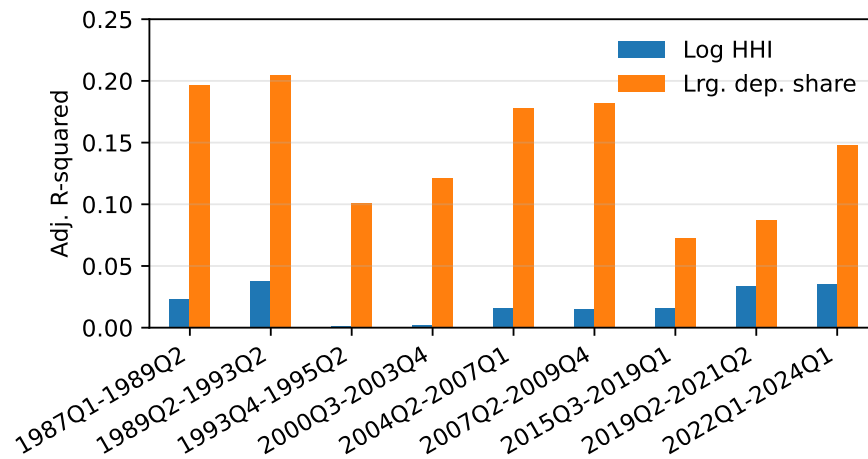


Figure 7. Large deposits share is more important than local deposit market concentration in explaining deposit pricing

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

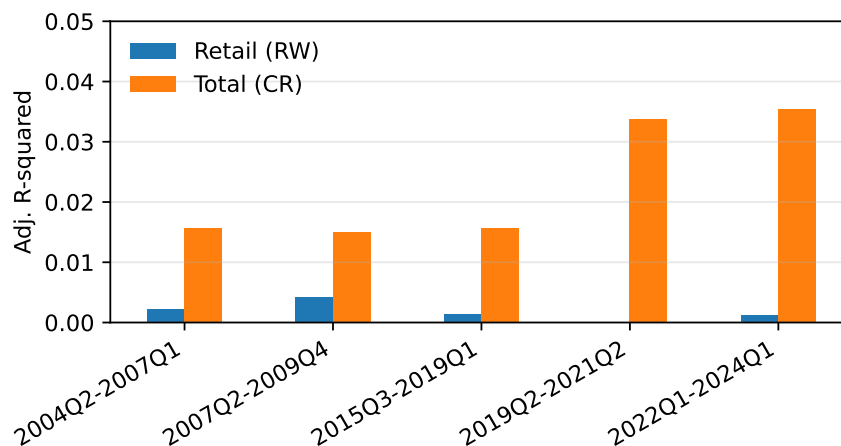
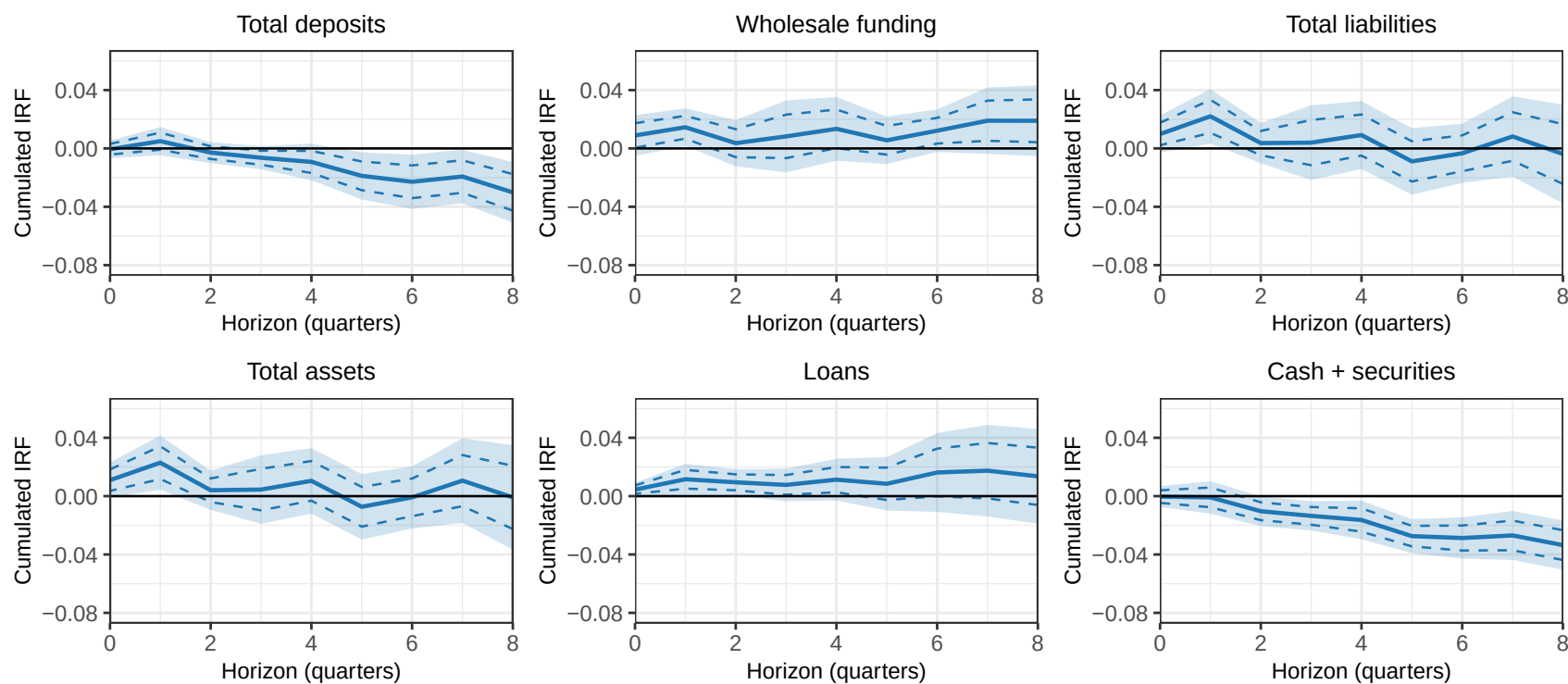


Figure 8. Monetary policy and the balance sheet of the banking system

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 3](#). 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 3](#) is $\Delta_{t-1,t+h}Y/Assets_{t-1}$. This transformation makes magnitudes of the responses of different variables comparable. Results are qualitatively similar in the standard [Equation 3](#) specification.

A. All commercial banks



B. Large vs small banks

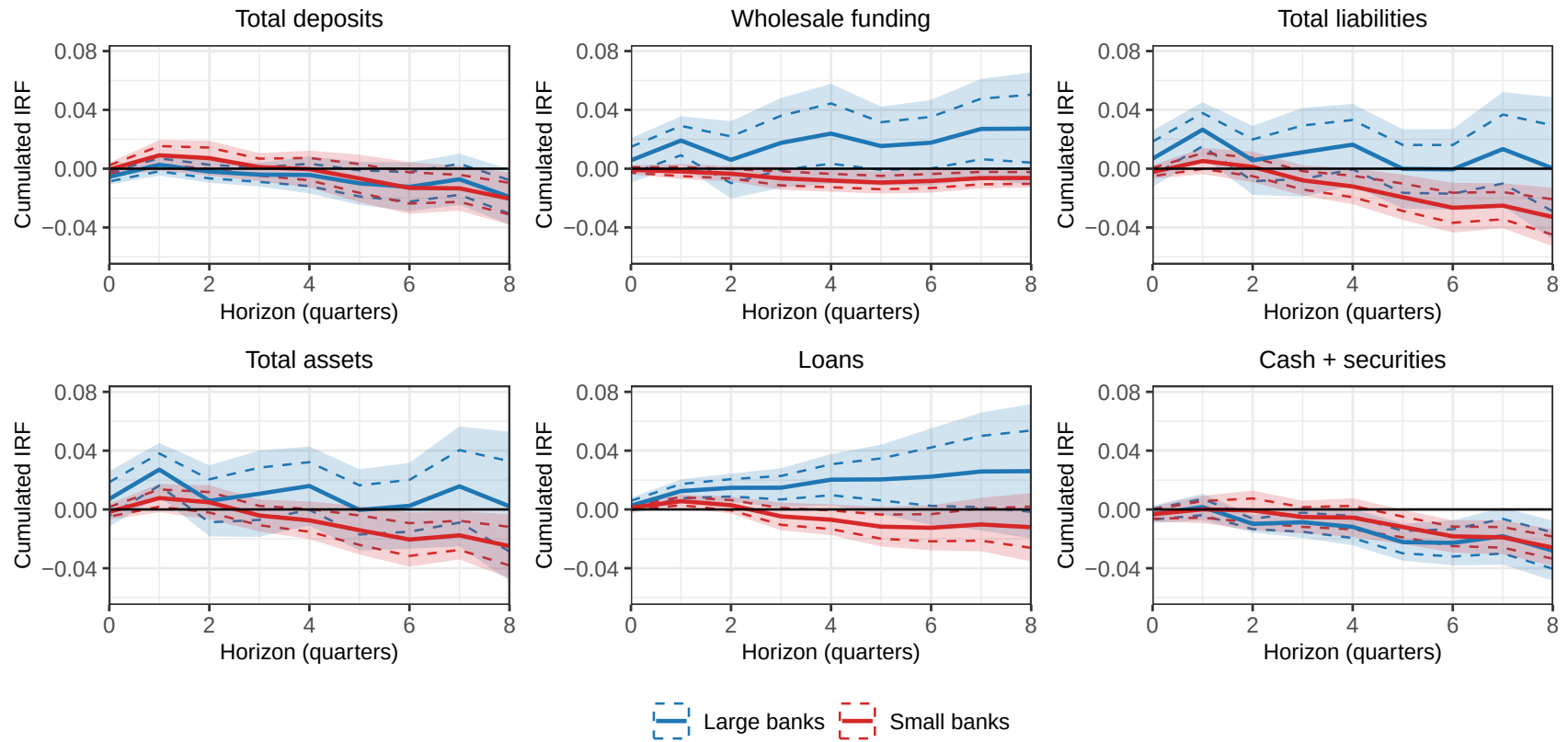


Table 1. Summary statistics

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:

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

where $\Delta \text{Dep. exp. rate}_{i,t-1,t+h}$ 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 $\text{Lrg. dep. share}_{i,t-1}$ 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 $\text{Lrg. dep. share}_{i,t-1}$ 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 these variables corresponds to an increase from the 25th to 75th percentile in their distributions 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				
	$h = 0$	$h = 2$	$h = 4$	$h = 6$	$h = 8$
$\text{Lrg. dep. share}_{i,t-1} \times \Delta \text{FFR}_t$	0.034*** (0.004)	0.045*** (0.008)	0.035*** (0.009)	0.033*** (0.012)	0.032** (0.014)
$\log(\text{HHI}_{i,t-1}) \times \Delta \text{FFR}_t$	0.003 (0.004)	-0.001 (0.008)	0.008 (0.008)	0.001 (0.009)	-0.005 (0.010)
$\log(\text{Bank age}_{i,t-1}) \times \Delta \text{FFR}_t$	-0.008*** (0.003)	-0.014* (0.007)	-0.015*** (0.005)	-0.015*** (0.005)	-0.018*** (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 $\text{Dep. exp. beta}_{i,c}$ is the total deposit expense beta for bank i over cycle c and $\text{Lrg. dep. share}_{i,c}$ 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*** (0.005)	0.285*** (0.004)	0.130*** (0.005)	0.173*** (0.006)	0.252*** (0.008)
Lrg. dep. share _{i,c}	0.394*** (0.012)	0.318*** (0.010)	0.269*** (0.016)	0.322*** (0.018)	0.434*** (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. Large deposits flow out more when the Fed tightens: Bank-level analysis

This table shows the results of estimating Equation 3 on the bank-level panel. The monetary policy shock is from Romer and Romer (2004) and is scaled so that the estimates correspond to a 100-basis-point increase in the federal funds rate. Panels A and B show the estimated impulse responses for large and small deposits, respectively. The local projections control for inflation and real GDP growth, as well as two lags of these controls and two lags of the dependent variable and the monetary policy shock. They also control for quarter indicators to account for seasonality and include bank fixed effects in even-numbered columns. The sample covers 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 the 10%, 5%, and 1% levels, respectively.

A. Large deposits						
	$h = 0$		$h = 4$		$h = 8$	
	(1)	(2)	(3)	(4)	(5)	(6)
RR shock _{<i>t</i>}	-0.019*** (0.006)	-0.020*** (0.006)	-0.061*** (0.018)	-0.063*** (0.017)	-0.076*** (0.028)	-0.078*** (0.027)
Bank FE		✓		✓		✓
Controls	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.141	0.148	0.069	0.173	0.044	0.229
N	520,701	520,455	520,701	520,455	520,701	520,455
B. Small deposits						
	$h = 0$		$h = 4$		$h = 8$	
	(1)	(2)	(3)	(4)	(5)	(6)
RR shock _{<i>t</i>}	-0.008*** (0.003)	-0.009*** (0.003)	-0.002 (0.009)	-0.007 (0.009)	0.010 (0.010)	-0.000 (0.011)
Bank FE		✓		✓		✓
Controls	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.065	0.089	0.112	0.252	0.125	0.345
N	523,691	523,442	523,691	523,442	523,691	523,442

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

This table reports estimates of

$$\log(\text{Small business lending}_{i,c,t}) = \alpha_{ic} + \delta_{ct} + \beta^L \frac{\Delta_{i,t-1,t} \text{Large deposits}}{\text{Assets}_{i,t-1}} + \beta^S \frac{\Delta_{i,t-1,t} \text{Small deposits}}{\text{Assets}_{i,t-1}} + \Gamma X_{i,t} + \epsilon_{i,c,t}.$$

The dependent variable is log small business lending by bank i in county c in year t ; the key regressors are annual changes in large and small deposits scaled by lagged total assets. All specifications include bank-county and county-year fixed effects. Columns (2) and (4) control for bank HHI and total assets and their interactions with the annual change in the federal funds rate; columns (3) and (4) also control for an indicator for the zero-lower-bound period. The sample covers 1997–2024 and excludes bank-county-year observations ict where the bank i has a branch in that county c in years $t - 1$, t or $t + 1$. This exclusion ensures that the relationship is estimated only on counties where banks do *not* raise deposits, further mitigating endogeneity of loan demand.

	(1)	(2)	(3)	(4)
$\Delta \text{Large deposits}_{i,t} / \text{Assets}_{i,t-1}$	0.365 (0.260)	0.535** (0.257)	0.609** (0.262)	0.871*** (0.243)
$\Delta \text{Small deposits}_{i,t} / \text{Assets}_{i,t-1}$	0.530** (0.243)	0.658*** (0.237)	0.798*** (0.264)	0.940*** (0.250)
Controls		✓		✓
ZLB			✓	✓
N	663,937	663,937	635,796	635,796
Within R^2	0.002	0.019	0.006	0.045

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 :

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

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:

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

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:

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

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:

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

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

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 :⁴³

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

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

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

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 :

$$-\frac{\partial D_{Hi}}{\partial s_{Hi}} \frac{s_{Hi}}{D_{Hi}} > -\frac{\partial D_{Li}}{\partial s_{Li}} \frac{s_{Li}}{D_{Li}}. \quad (\text{A7})$$

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

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

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:

$$\pi = \max_s \alpha_L D_L(s) s + \alpha_H D_H(s) s,$$

⁴³I follow DSS (2017) and let $\lambda \rightarrow 0$ 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 $s_L > s_H$. $\square$

Under price discrimination, spreads are set as:

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

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

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

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,

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

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:⁴⁴

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

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:*

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

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

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

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

$$-\frac{\partial D_L}{\partial f} \frac{1}{D_L} < -\frac{\partial D_H}{\partial f} \frac{1}{D_H}. \quad (\text{A14})$$

⁴⁴Again, I let $\lambda \rightarrow 0$ 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.⁴⁵

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:*

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

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.

⁴⁵The 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 are 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 a 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 a 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 $\tilde{D}_t^j = D_t^j + DI_t^j$ 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

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

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 A23](#)).

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 U.S. 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 in 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”⁴⁶. 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

⁴⁶<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 the provided latitude and longitude of bank branches (and geocode these for the 1975-1993 historical SOD data), together with MSA maps from the National 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 York⁴⁷ 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)⁴⁸. 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.

⁴⁷https://www.newyorkfed.org/research/banking_research/crsp-frb

⁴⁸Scheuch, 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). 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 `rx1.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 URL pattern, filter to status-200 responses, and download the raw archived bytes via the

`web.archive.org/web/tsid_/url` endpoint.⁴⁹

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 that no longer exist on the live site:

⁴⁹When 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.

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.⁵⁰

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.⁵¹

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.⁵² 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 A18** shows screenshots of posted CD rates

⁵⁰<https://www.cnbc.com/select/best-premium-checking-accounts/>
<https://www.wellsfargo.com/premier/>
<https://account.chase.com/sapphire/brand>

⁵¹<https://web.archive.org/web/20230912032915/https://www.pnc.com/en/rates/money-market/95120/NA>

⁵²<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. Deposits as a share of liquid wealth in the SCF

I use the 2022 Survey of Consumer Finances (SCF) Dataset. I classify households using the SCF's net-worth percentile categories into the top 1% and bottom 99%. Deposits are defined as

$$\text{Deposits} = \text{Checking} + \text{Savings} + \text{Money market deposit accounts} + \text{CDs}.$$

The SCF savings category includes conventional savings accounts and a small number of tax-preferred accounts, such as health savings and Coverdell or 529 education accounts.⁵³ CDs are time certificates of deposit.

I define gross liquid wealth as the sum of the SCF's liquid-assets aggregate, CDs, non-money-market mutual funds, directly held stocks, directly held bonds, and U.S. savings bonds. The liquid-assets aggregate comprises checking and savings accounts; money market accounts, including both money market deposit accounts and money market mutual funds; brokerage call accounts; and prepaid debit cards. This measure excludes retirement accounts, cash-value life insurance, other managed and financial assets, all nonfinancial assets, and does not subtract debt.

The SCF provides five implicates to account for multiple imputation. For each implicate m and wealth group g , I calculate the ratio of survey-weighted group totals,

$$s_g^m = \frac{\sum_{i \in g} w_i D_i}{\sum_{i \in g} w_i L_i},$$

where D_i is deposits of household i , L_i is gross liquid wealth of household i , and w_i is the SCF survey weight. I then average s_g^m across the five implicates. Thus, the reported statistic measures the fraction of each group's total liquid wealth held as deposits. The resulting estimates are 30.37% for the bottom 99% and 9.24% for the top 1%.

⁵³<https://www.federalreserve.gov/publications/files/scf23.pdf>

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.

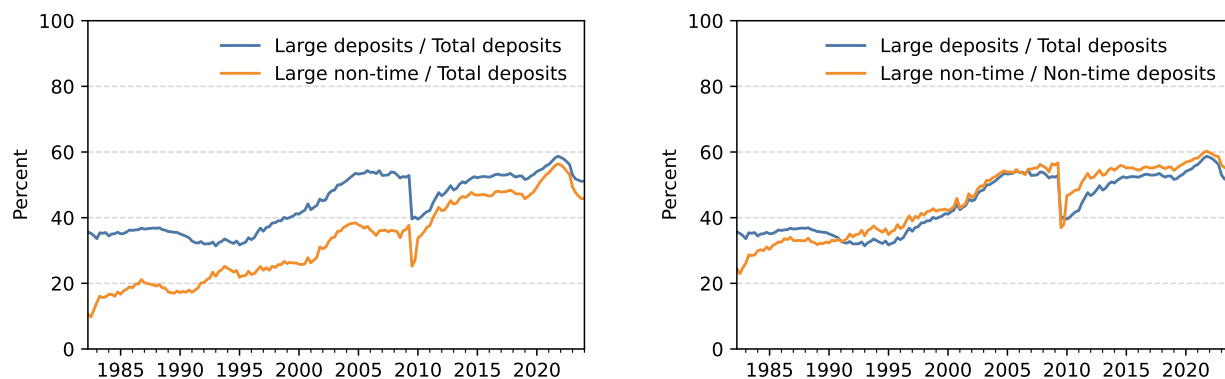
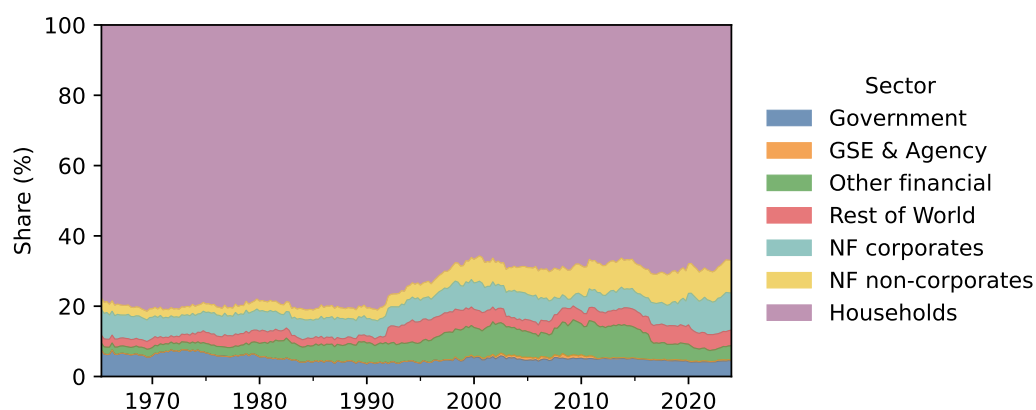


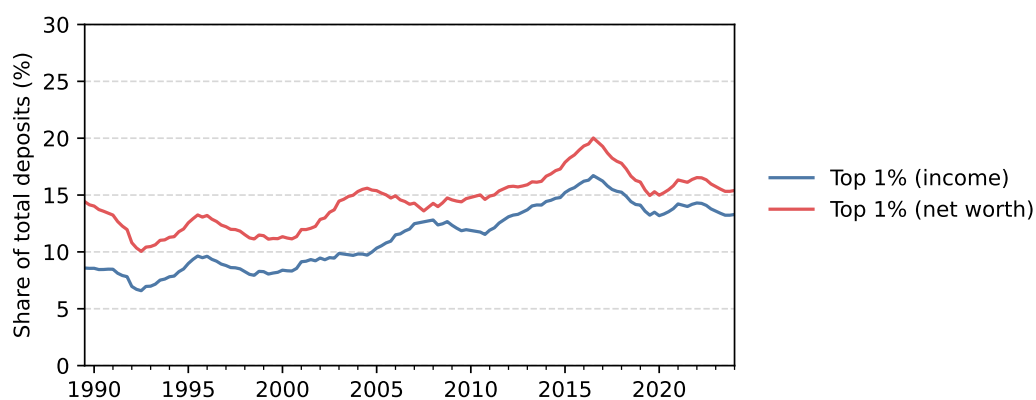
Figure A2. Sectoral composition of deposits, the top-1% household share, and the large-deposit share

Panel A plots the 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 the 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

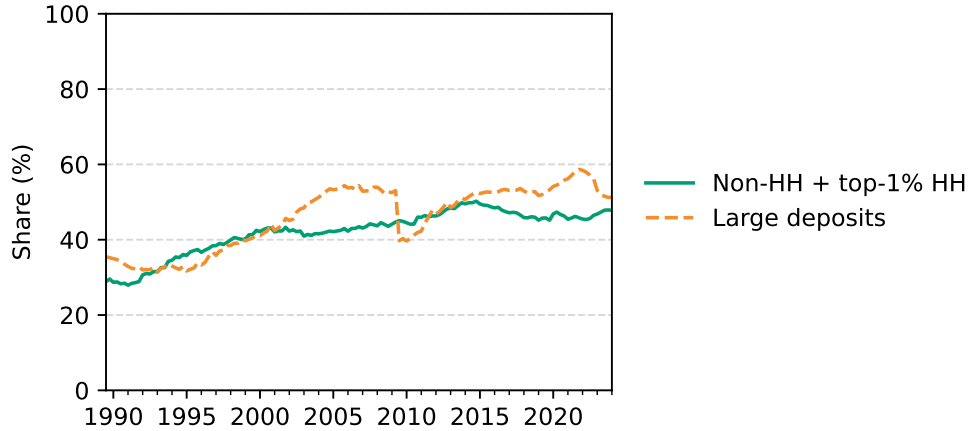


Figure A3. Banks with more large non-time deposits hold more non-personal transaction and savings deposits

This figure plots a pooled binscatter of the non-personal share of transaction and savings deposits against the share of large non-time deposits. Both shares are demeaned by their year-quarter-specific cross-sectional averages. Bank-quarter observations are then grouped into 20 equal-sized bins using the pooled distribution of the time-adjusted large non-time deposit share. The dots represent the average of each time-adjusted share within each bin after adding back the unconditional average of the year-quarter-specific means. The sample is 2014Q1-2024Q1, banks with \$1 billion in assets or more (this is the set of banks that reported deposits for personal use).

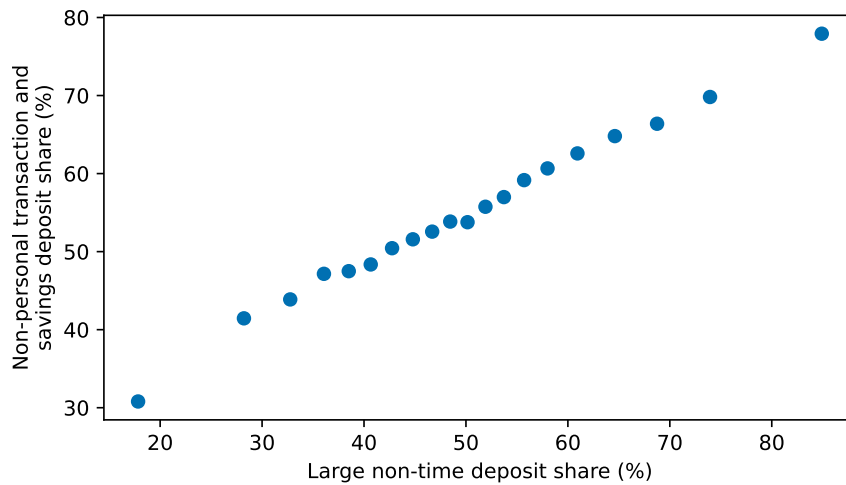


Figure A4. Effective federal funds rate and monetary policy cycles

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.

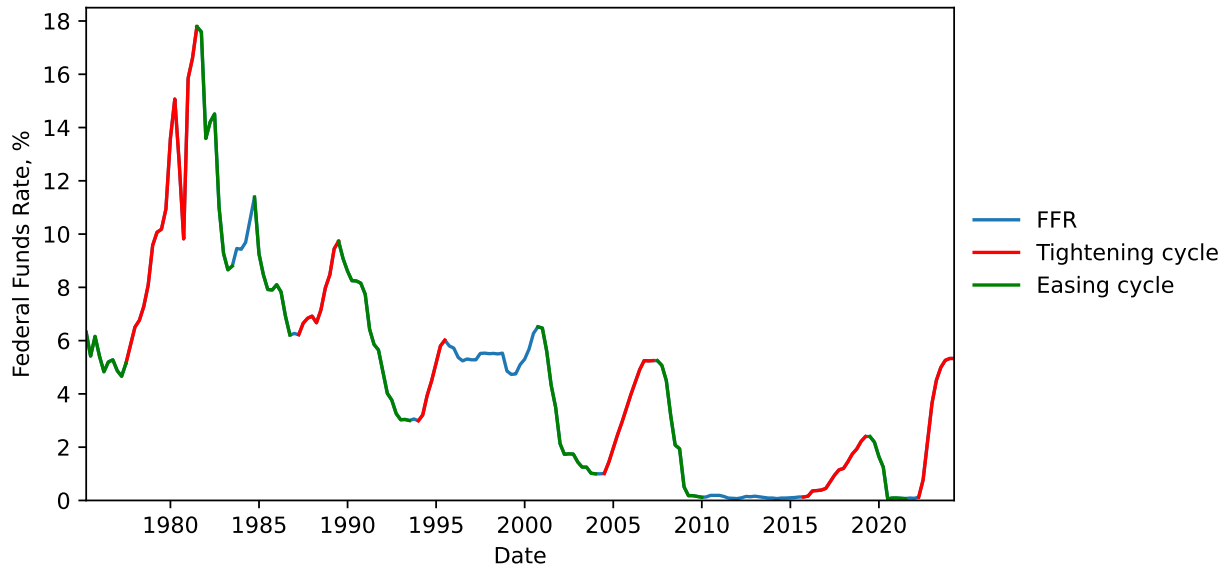


Figure A5. Deposit expense betas by share of large deposits: Easing cycles

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.

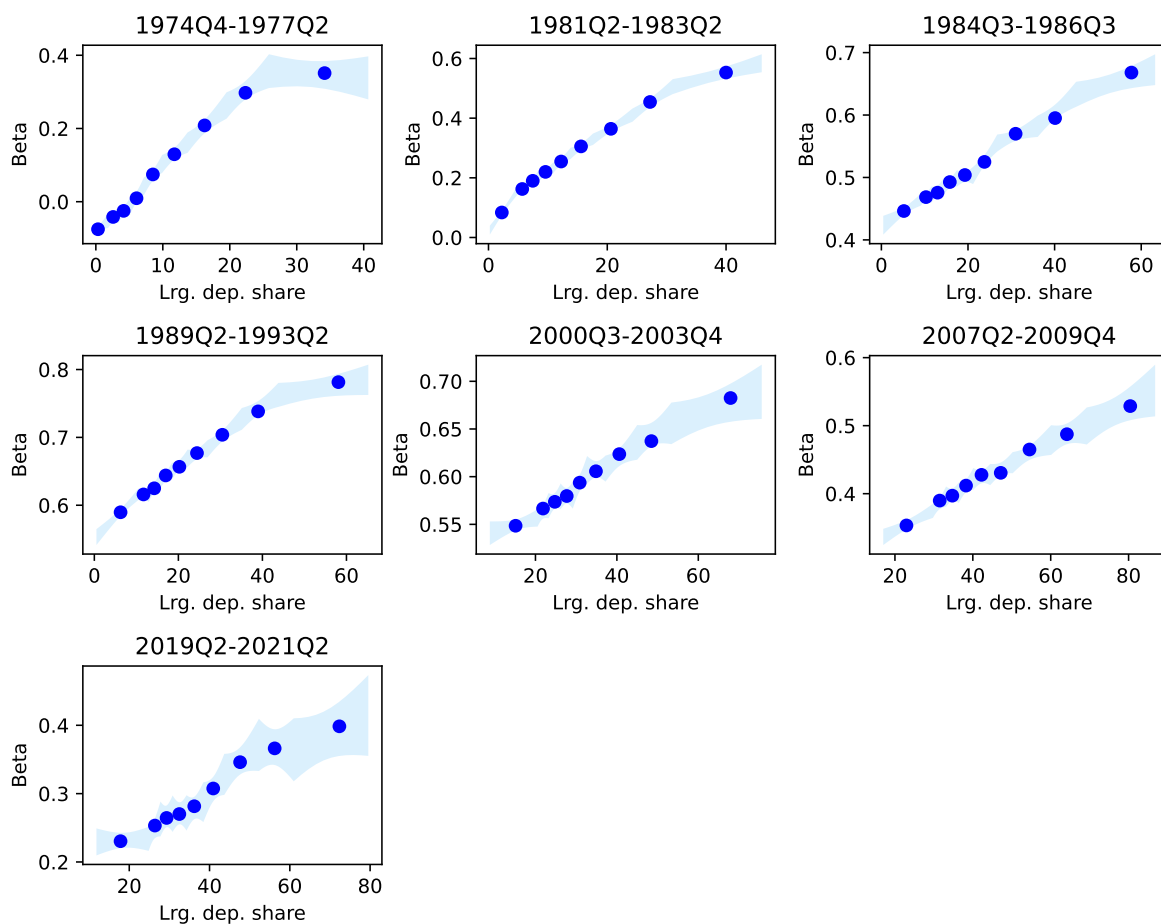


Figure A6. Deposit expense betas by share of large deposits: Controlling for local deposit market concentration and age

This figure is similar to [Figure 1](#) and [Figure A5](#), but controls for bank age and local deposit market concentration as measured by HHI.

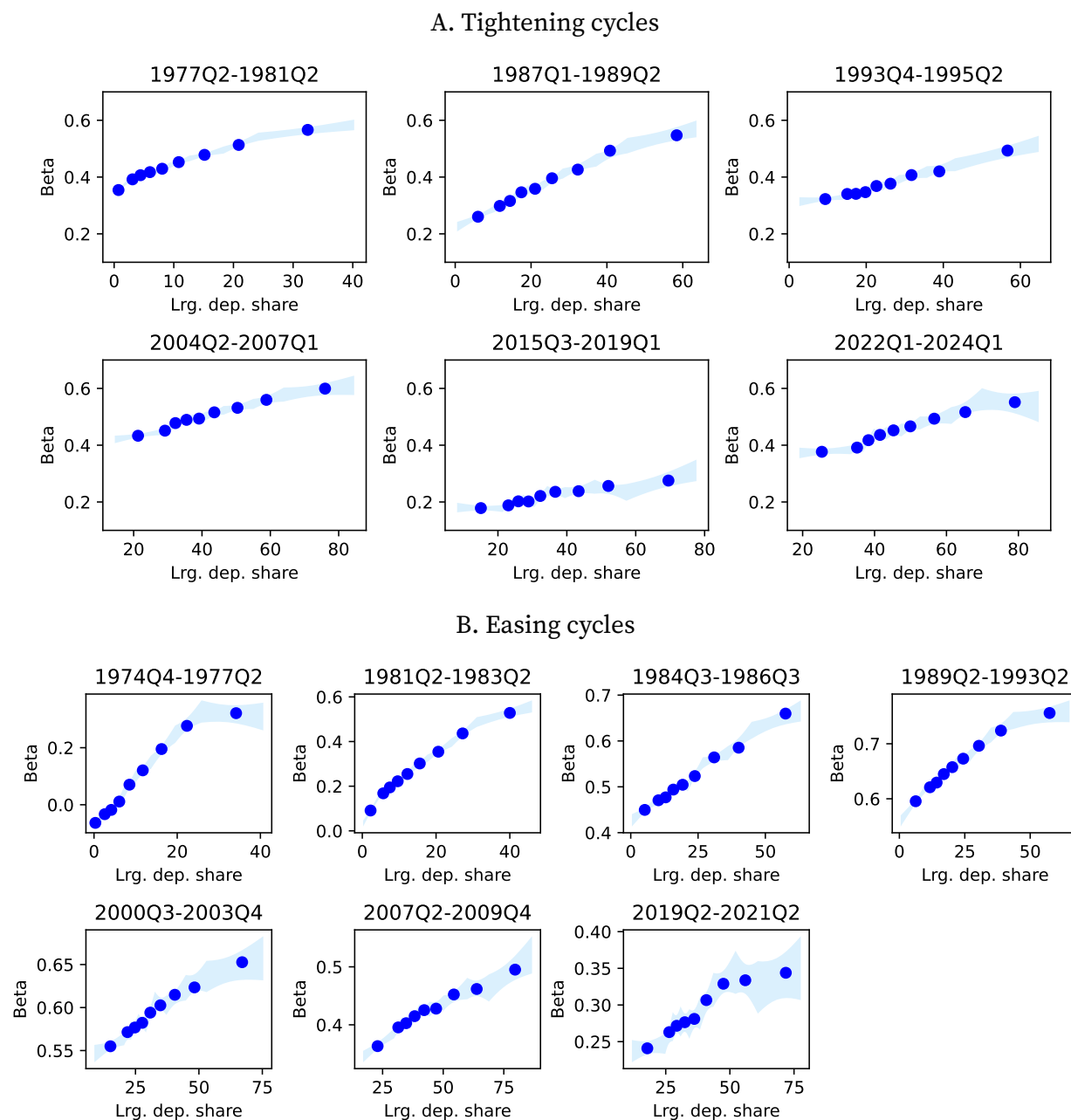


Figure A7. Savings deposit expense betas by share of large deposits

This figure is similar to [Figure 1](#) and [Figure A5](#), 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.

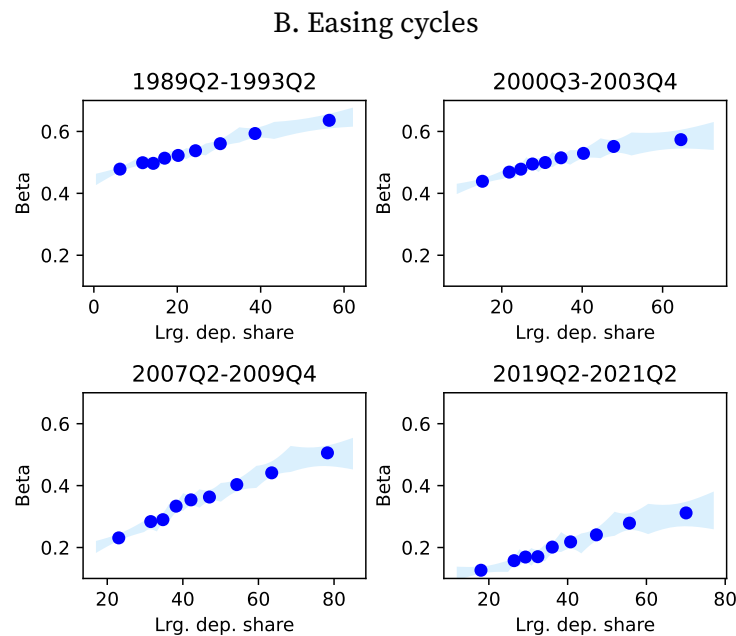
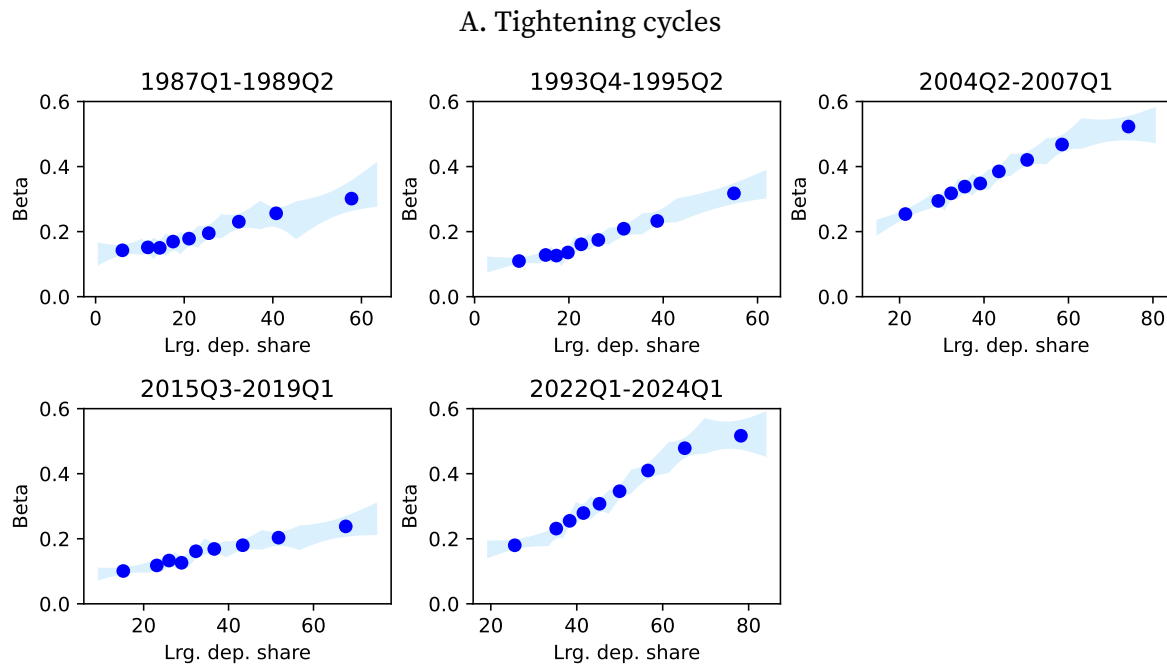
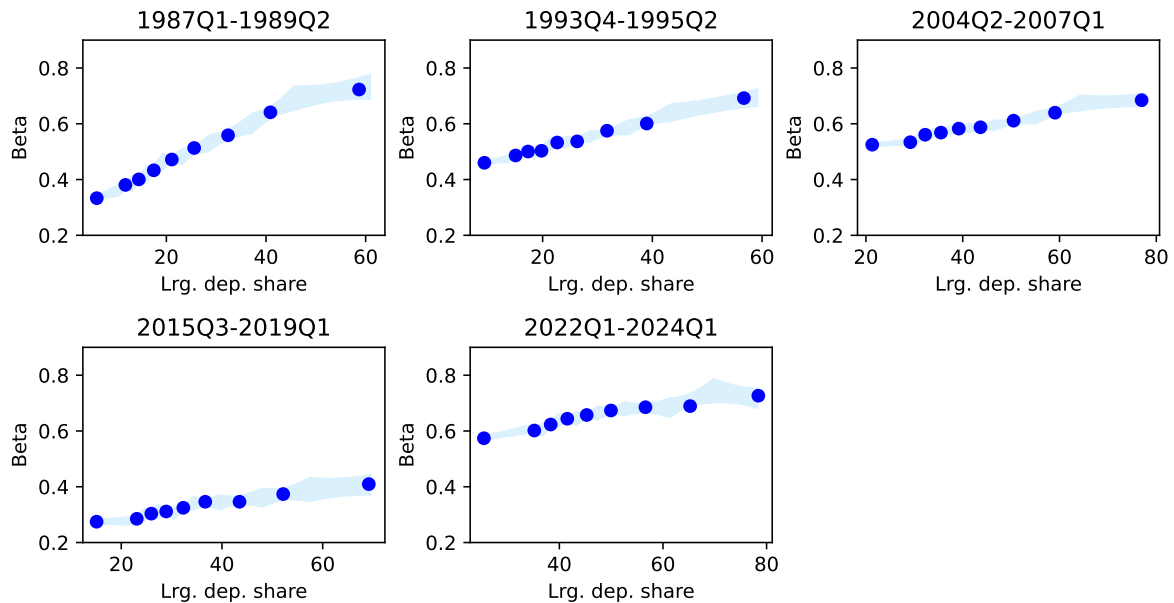


Figure A8. Time deposit expense betas by share of large deposits

This figure is similar to [Figure 1](#) and [Figure A5](#), 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

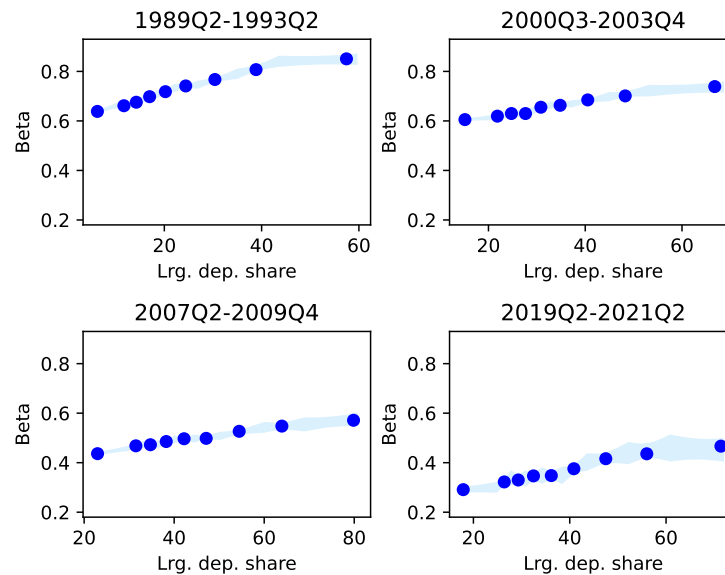


Figure A9. Total deposit expense rates at the start and end of tightening cycles by share of large deposits

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. The 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.

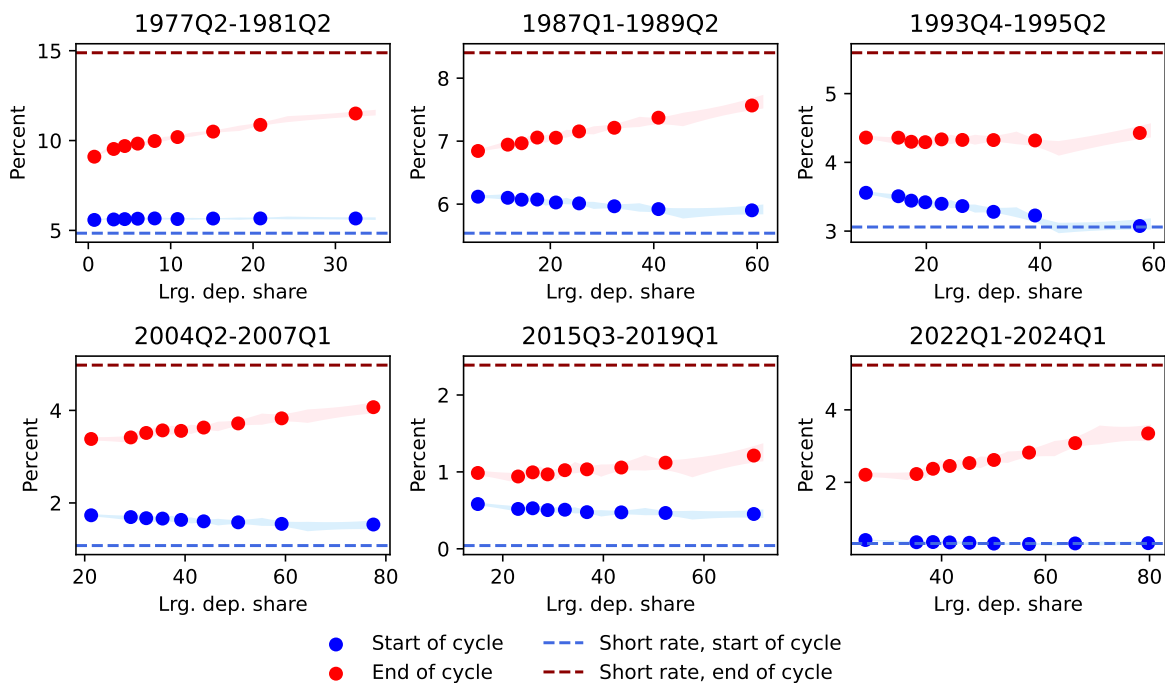


Figure A10. Impulse response of deposit expense rates to a federal funds rate change by share of large deposits: Core, savings, and time deposits

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).

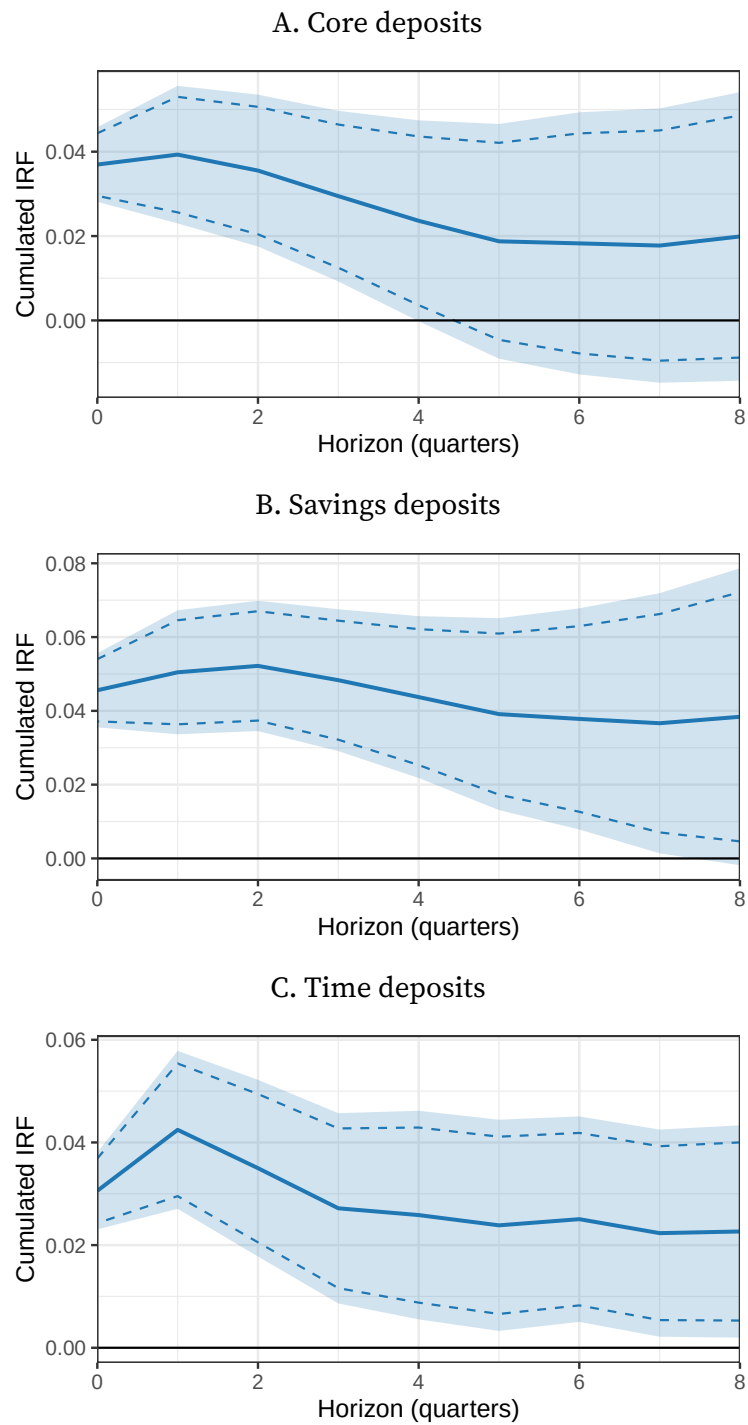
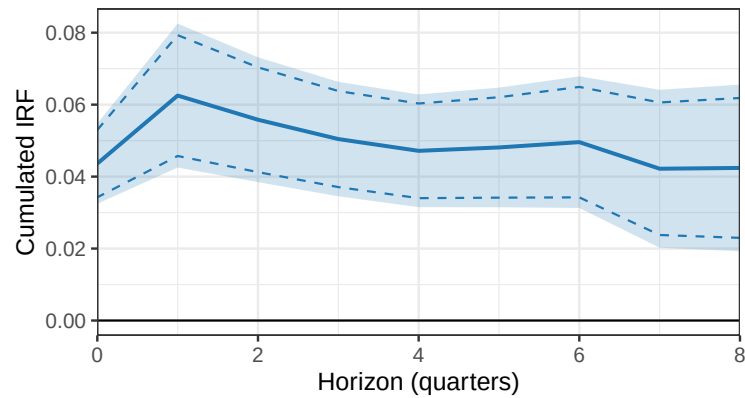


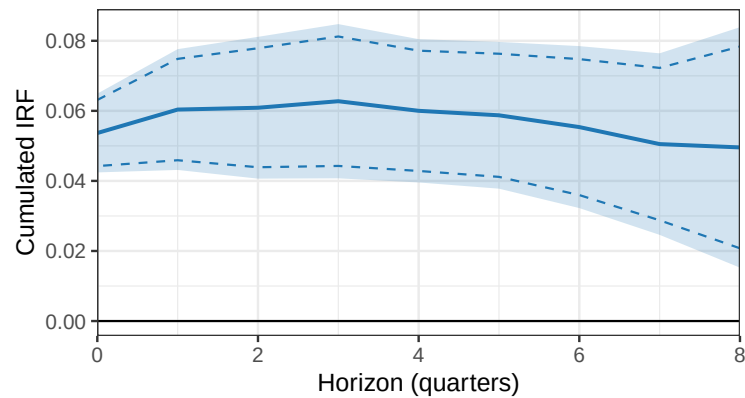
Figure A11. Impulse response of deposit expense rates to a federal funds rate change by share of large deposits: Top-10% sample

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 they are 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

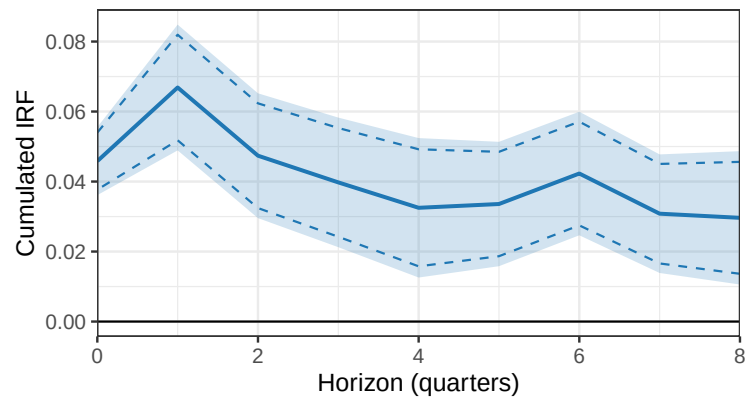
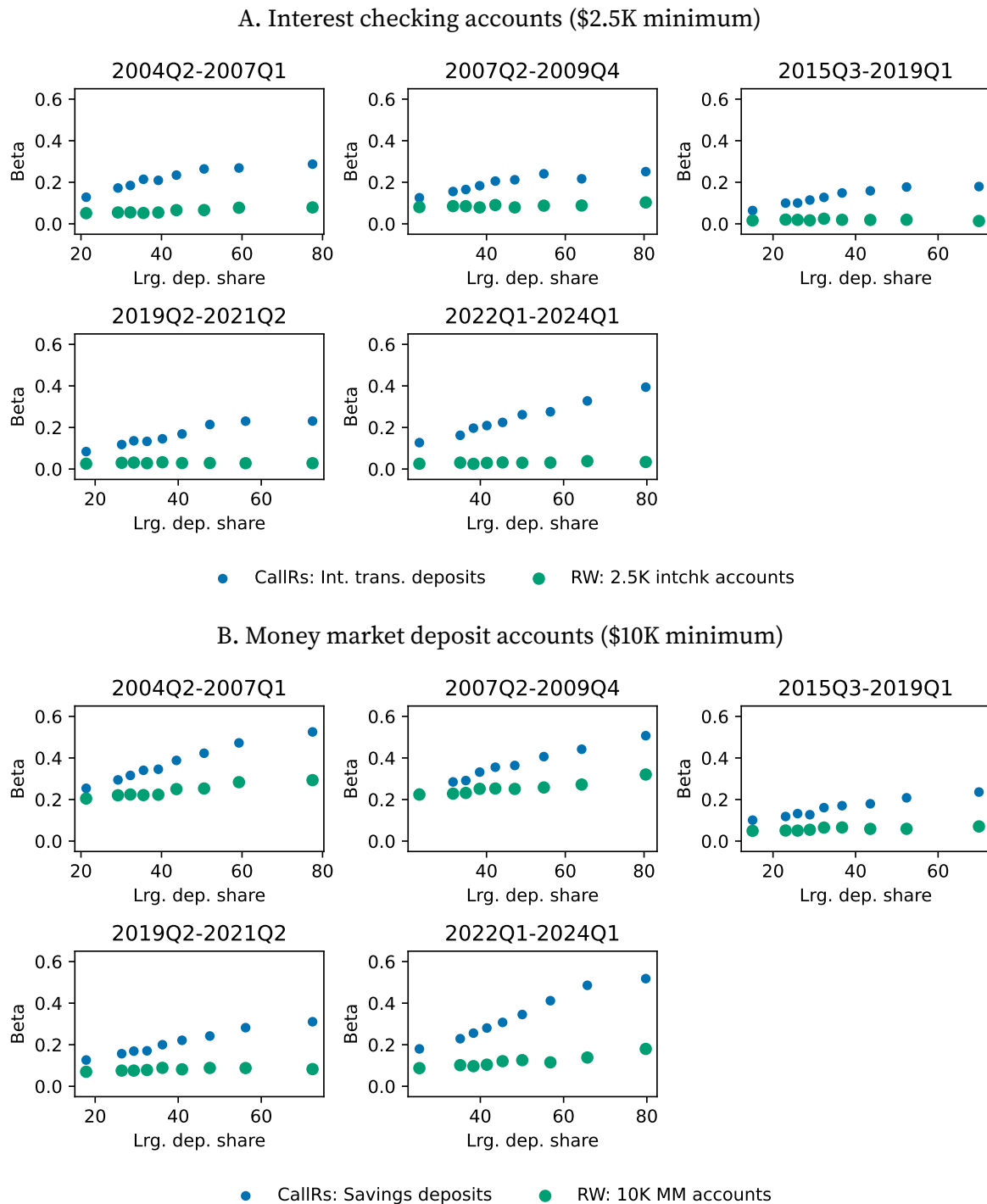


Figure A12. Call Report deposit expense betas vs Ratewatch small deposit betas by share of large deposits: Additional retail deposit products

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).



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

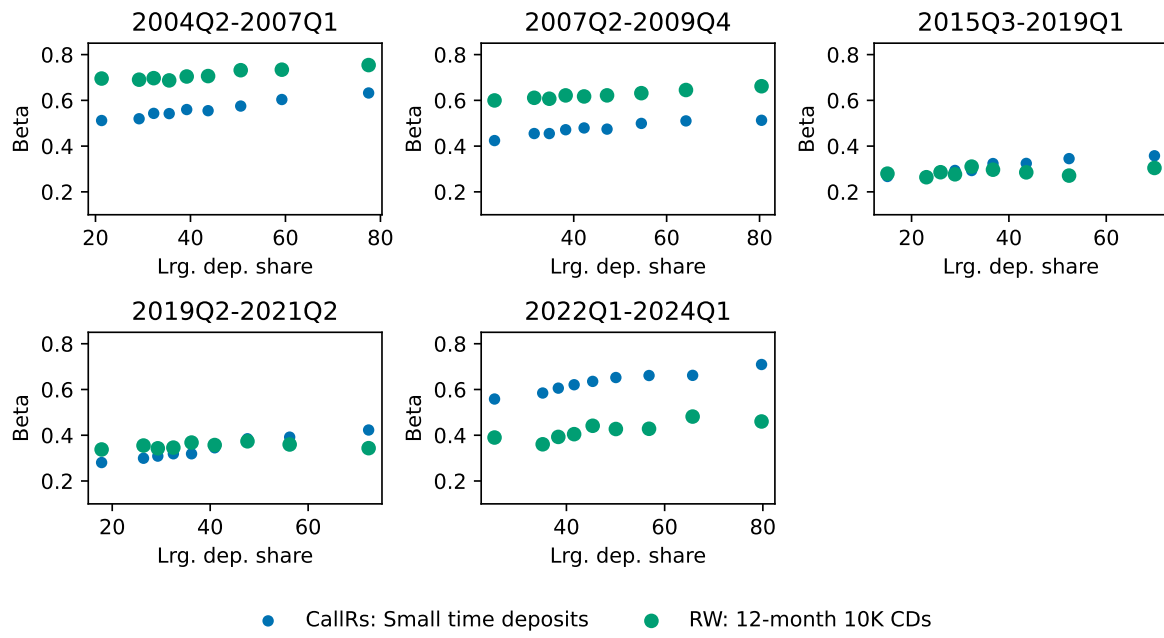


Figure A13. Small and large savings deposit rate betas

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 $\text{Dep. exp. beta}_{i,t_0 \rightarrow t_1}$ on savings deposits computed from Call Reports, share of large deposits computed from Call Reports α_{i,t_0}^{Large} , and rate beta on small savings deposits computed from Ratewatch $\text{Dep. beta}_{i,t_0 \rightarrow t_1}^{Small}$, as:

$$\text{Dep. beta}_{i,t_0 \rightarrow t_1}^{Large} = \frac{\text{Dep. exp. beta}_{i,t_0 \rightarrow t_1} - (1 - \alpha_{i,t_0}^{Large}) \text{Dep. beta}_{i,t_0 \rightarrow t_1}^{Small}}{\alpha_{i,t_0}^{Large}}.$$



Figure A14. 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).

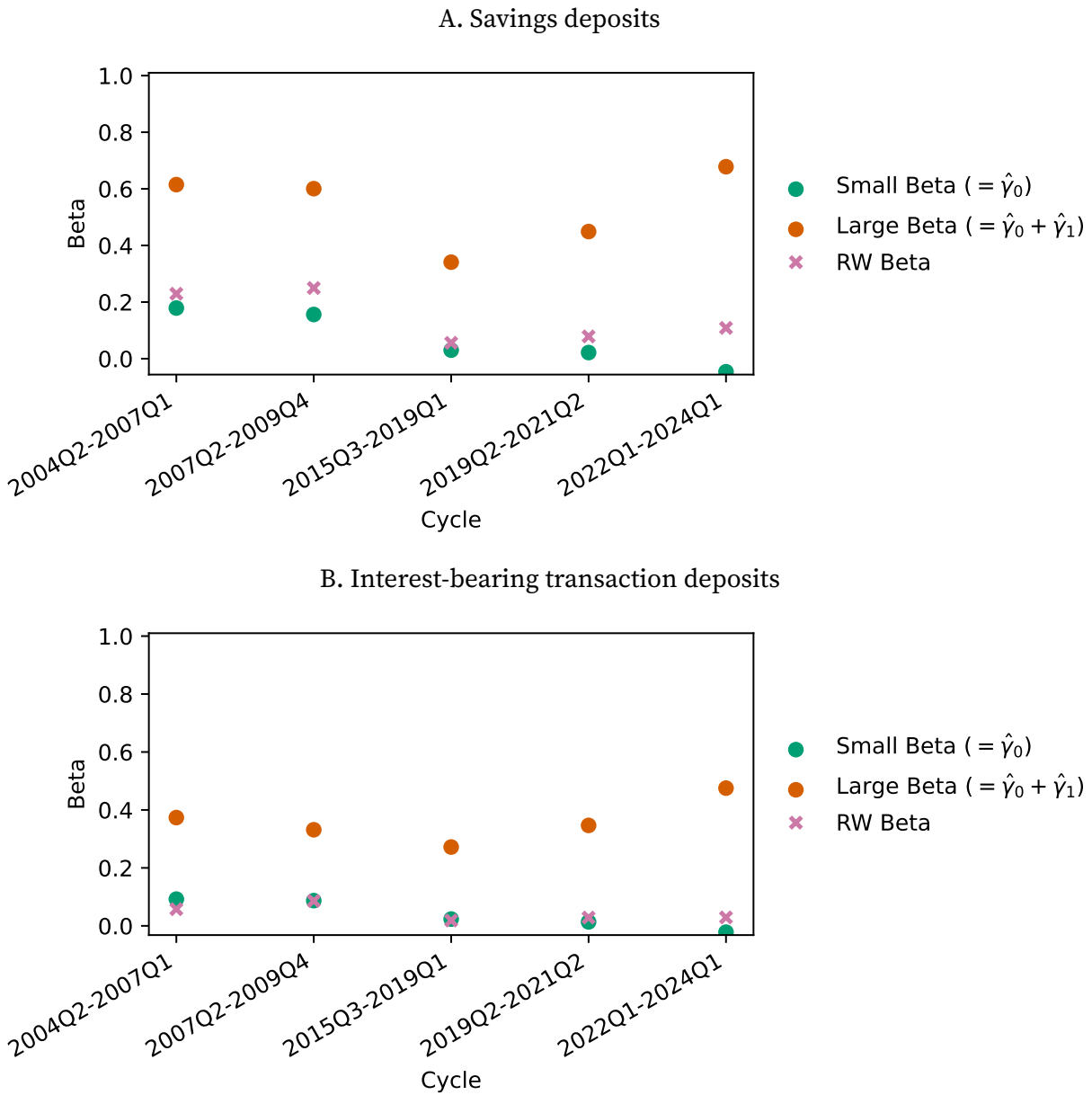


Figure A15. Inferred deposit expense betas for small and large deposits by monetary policy cycle: 1984-2024

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.

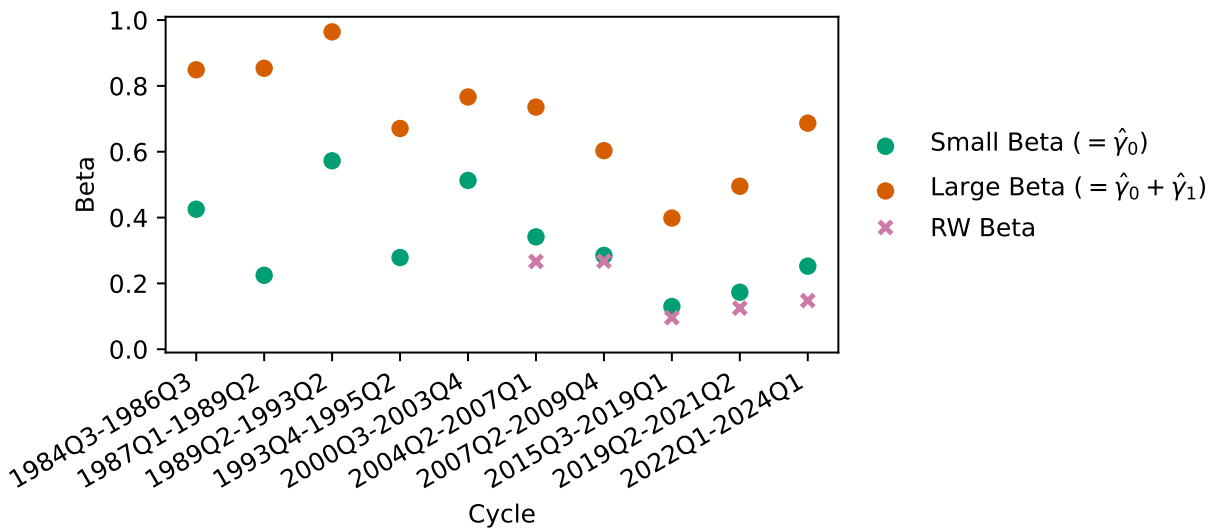
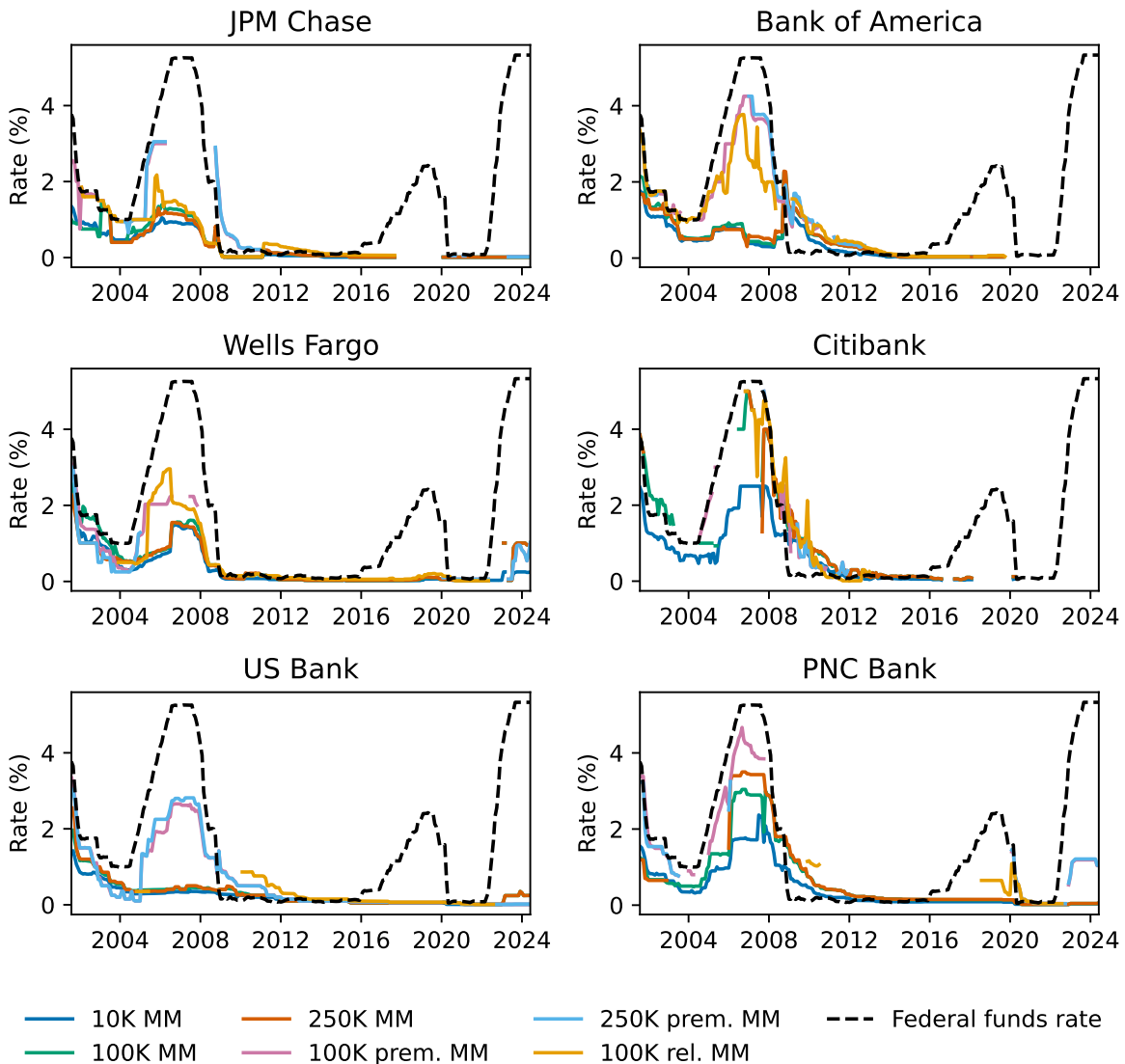


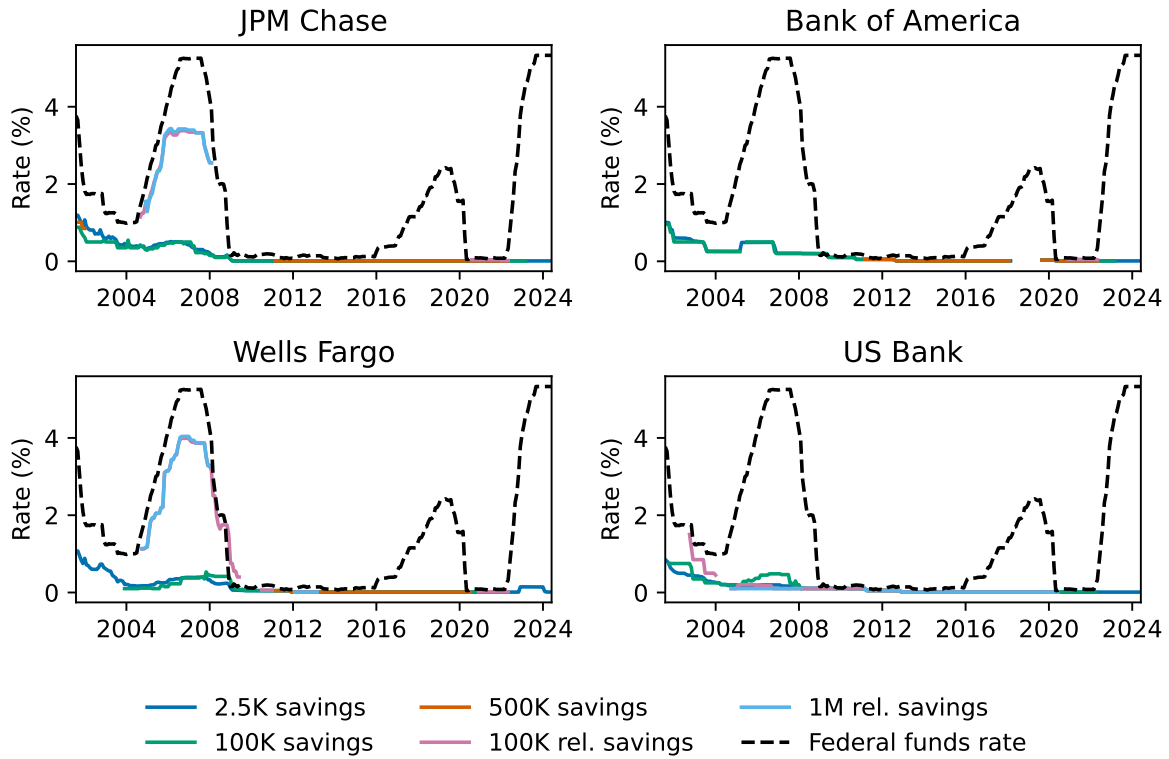
Figure A16. Rates on small and large deposit products at select banks

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 \$100,000 and \$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

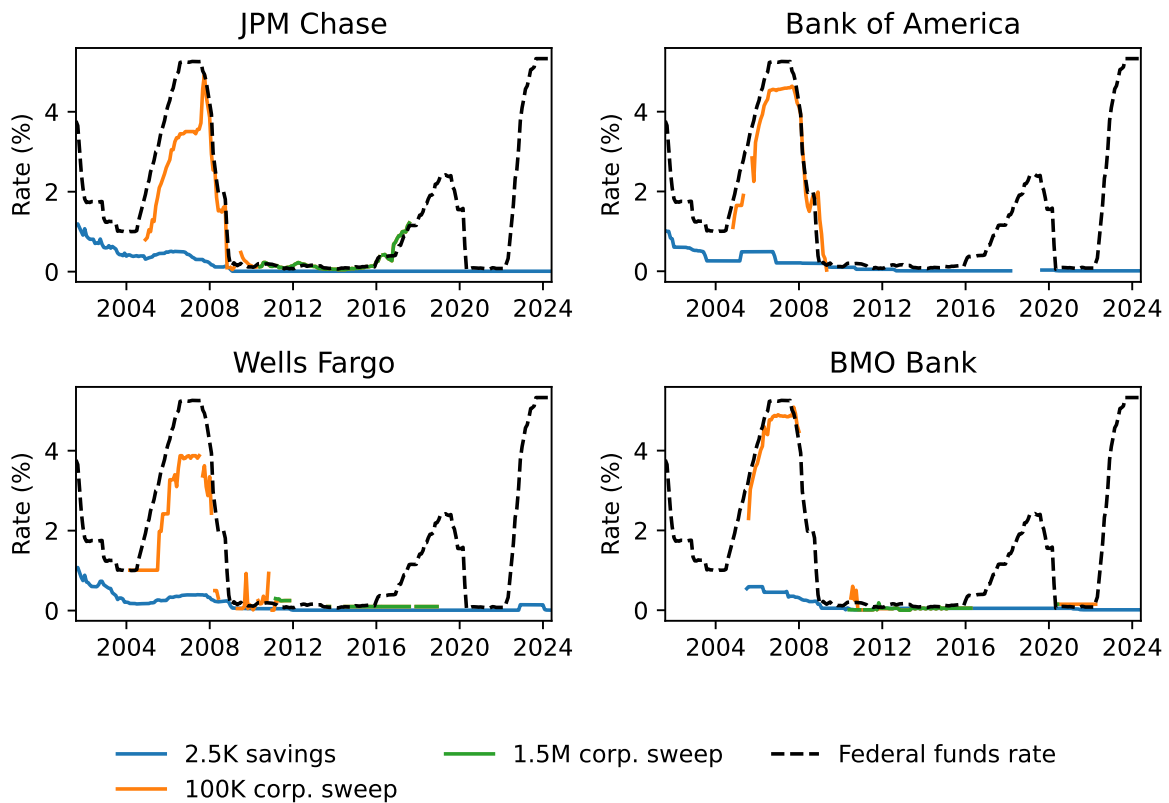


Figure A17. Screenshots of posted savings and MMDA rates at select banks

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 rate¹ that increases with your balance.

Rates effective as of: 10/02/2024

Displaying rates for: Idaho

BALANCE	Interest Rate ¹	Variable APY ²
\$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 Market³ account offers our highest interest rates for a Money Market account³.

Rates effective as of: 10/02/2024

Displaying rates for: Idaho

BALANCE	Interest Rate ¹	Variable APY ²
\$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 A18. 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

<i>APY</i>	<i>MIN</i>	<i>MAX</i>	<i>ACCOUNT NAME</i>
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 A19. 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.

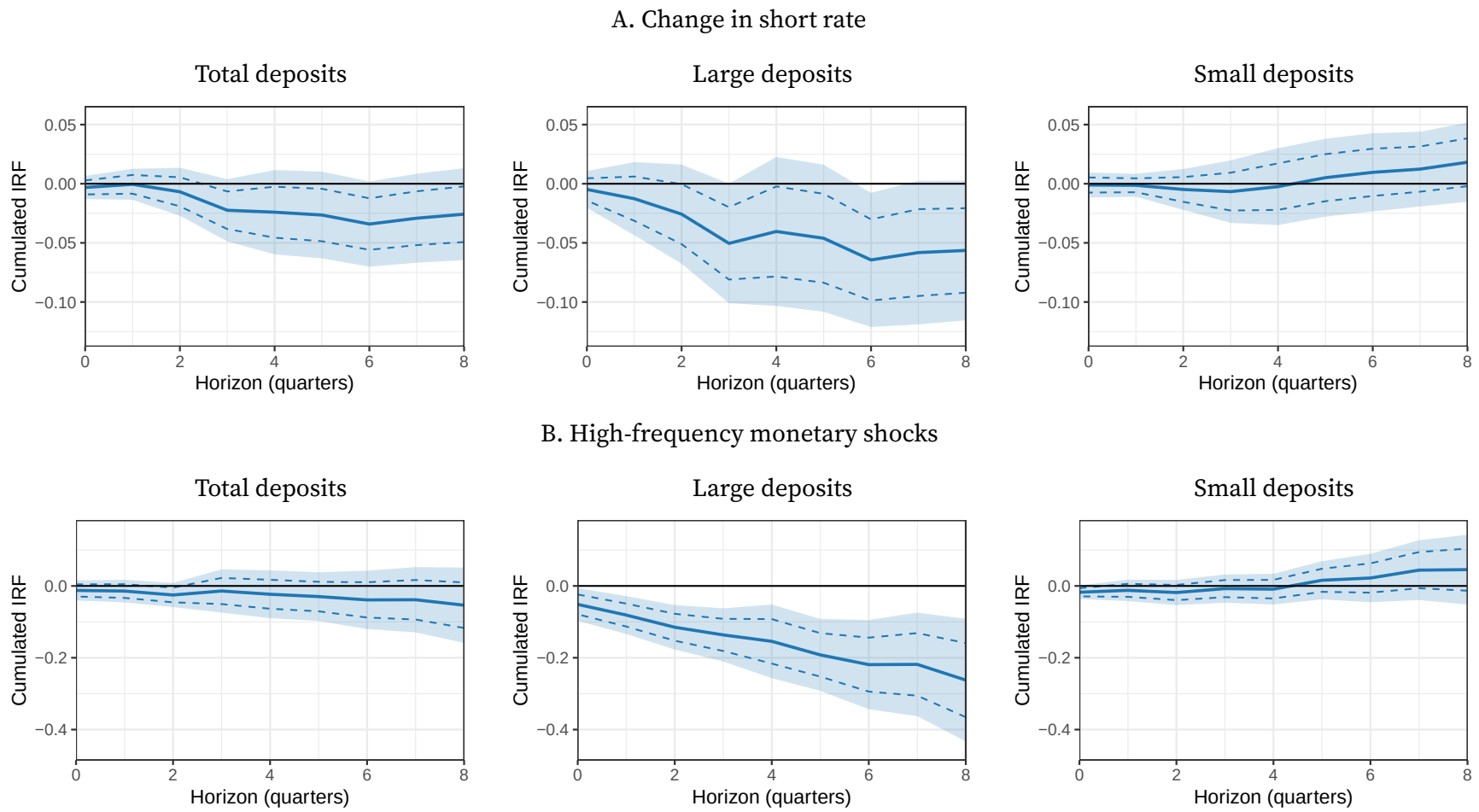
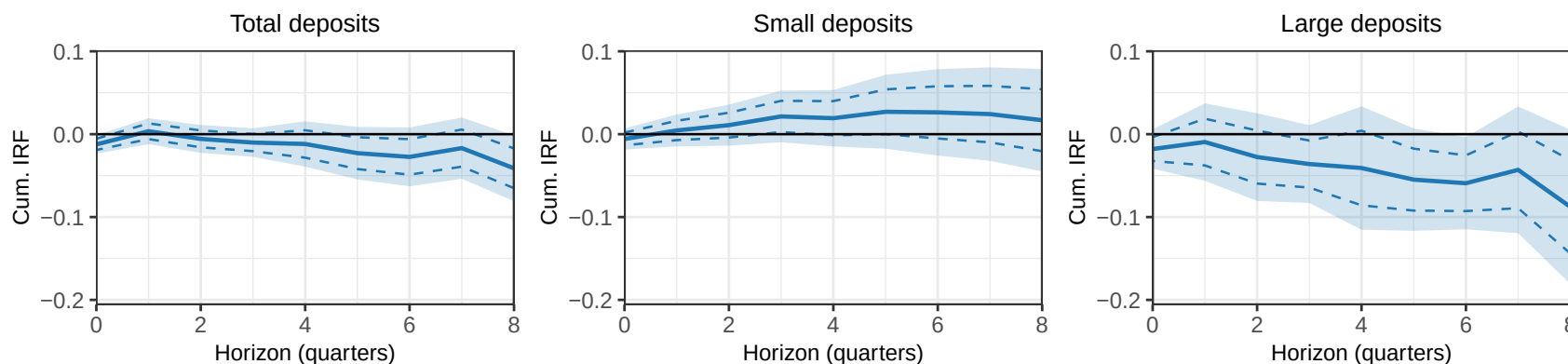


Figure A20. Large vs small deposits' response to monetary policy shocks by bank size

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)

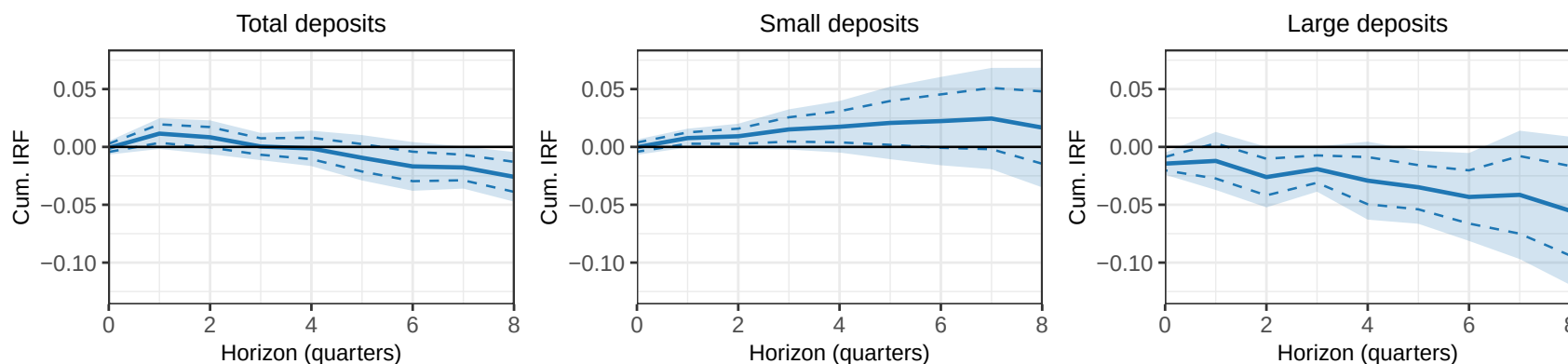
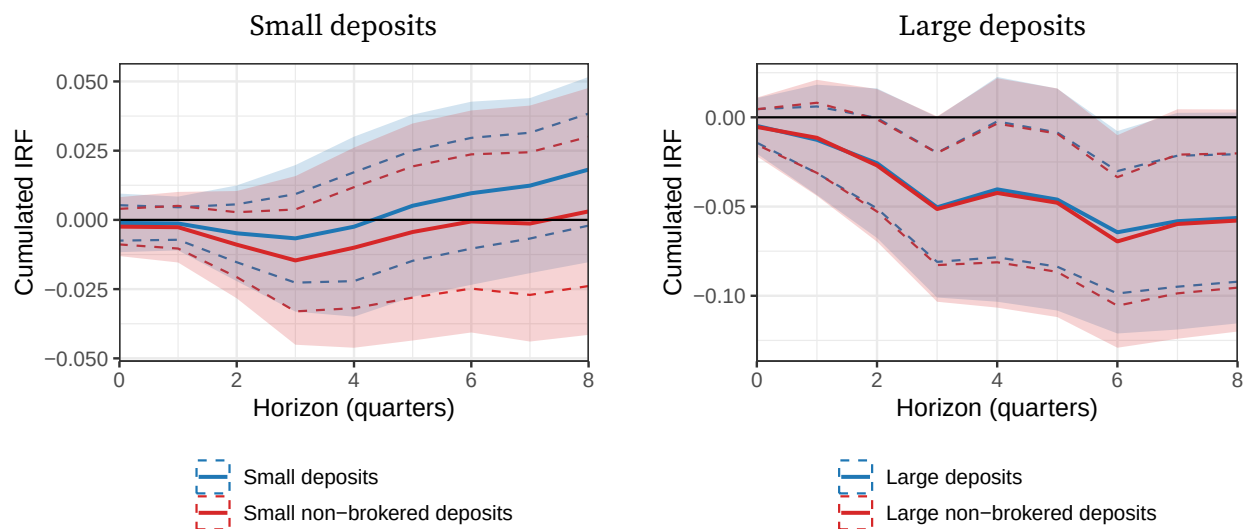


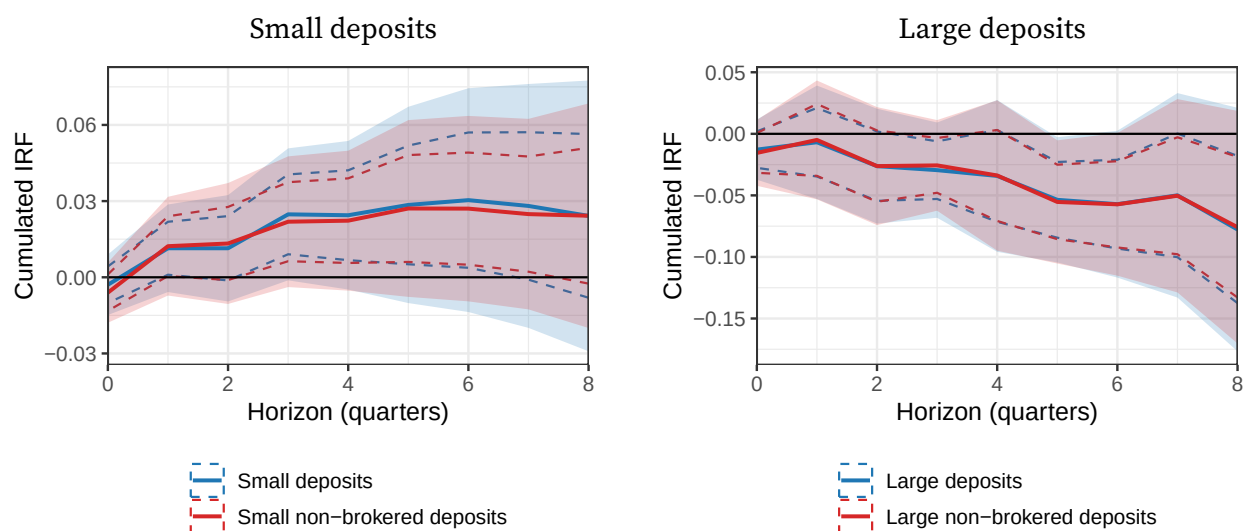
Figure A21. Brokered deposits do not drive small vs large deposits' flow response to monetary policy shocks

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).

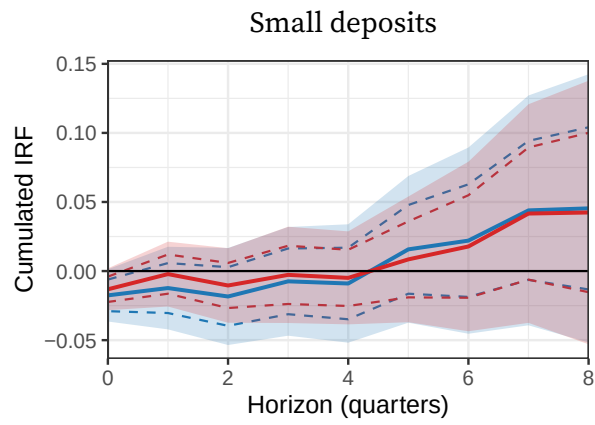
A. Change in short rate



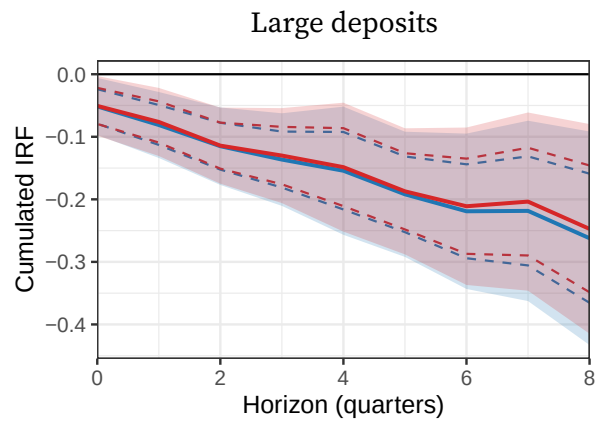
B. Romer and Romer (2004) monetary shocks



C. High-frequency monetary shocks



Small deposits
Small non-brokered deposits



Large deposits
Large non-brokered deposits

Figure A22. Deposit growth decomposed: Small vs large deposits

This figure plots year-on-year log-growth in real total deposits (blue line) and splits 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).

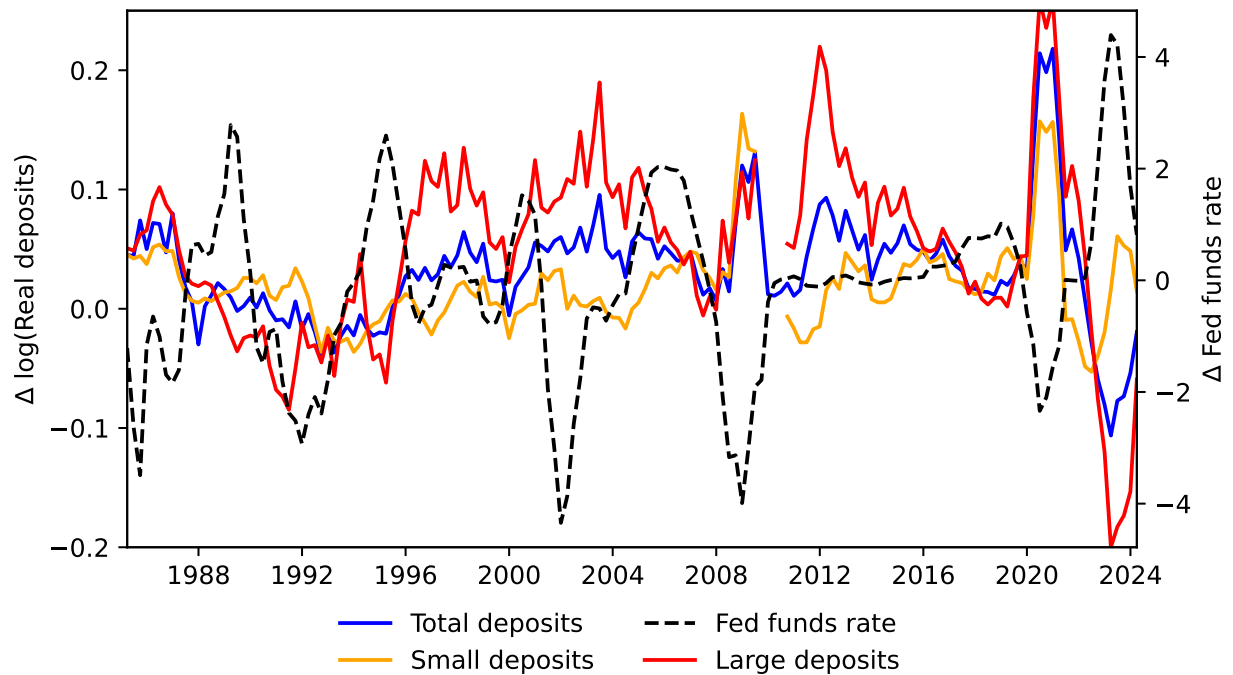
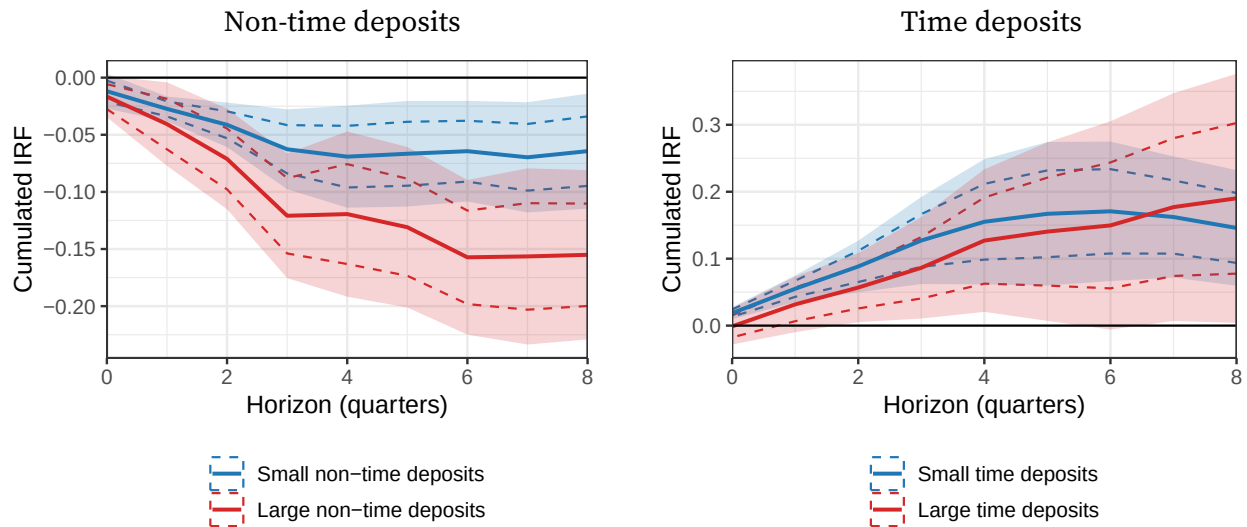


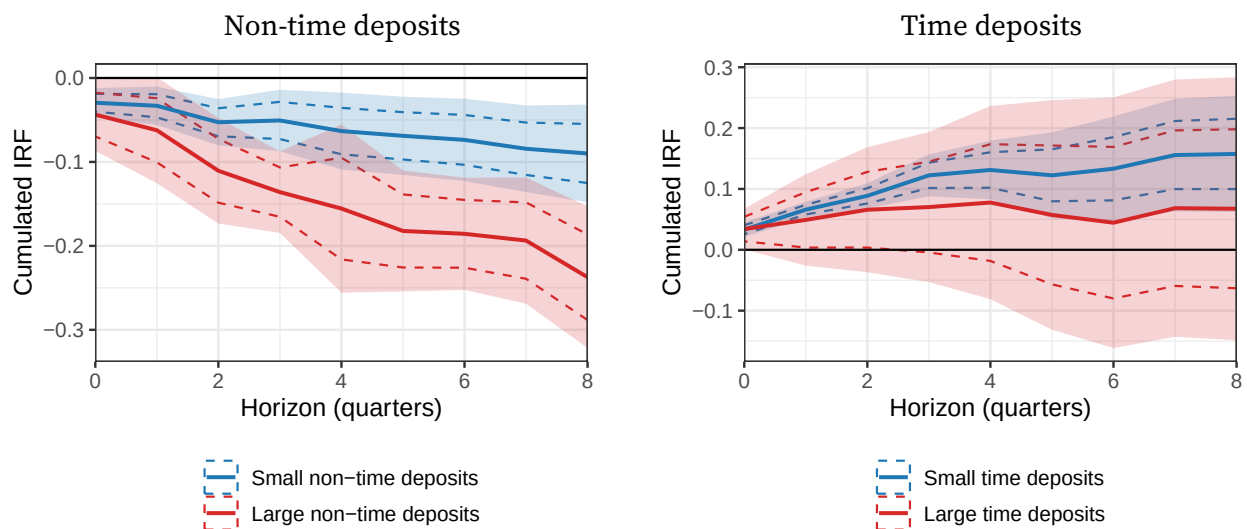
Figure A23. Time vs non-time deposits response to monetary policy shocks

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

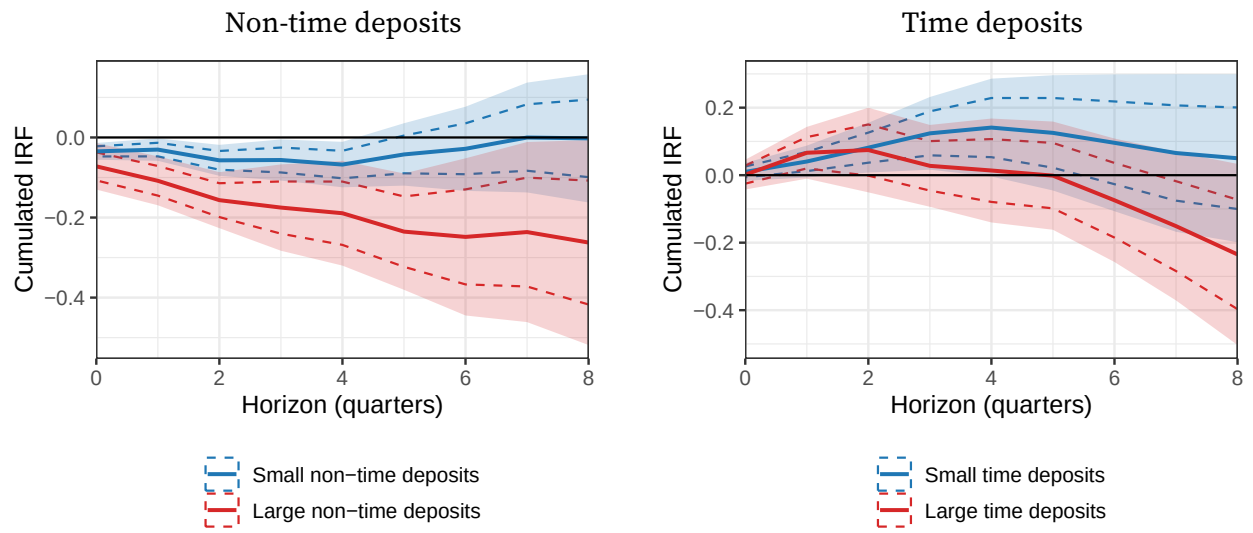


Figure A24. Deposit flow response to monetary policy by sector

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.

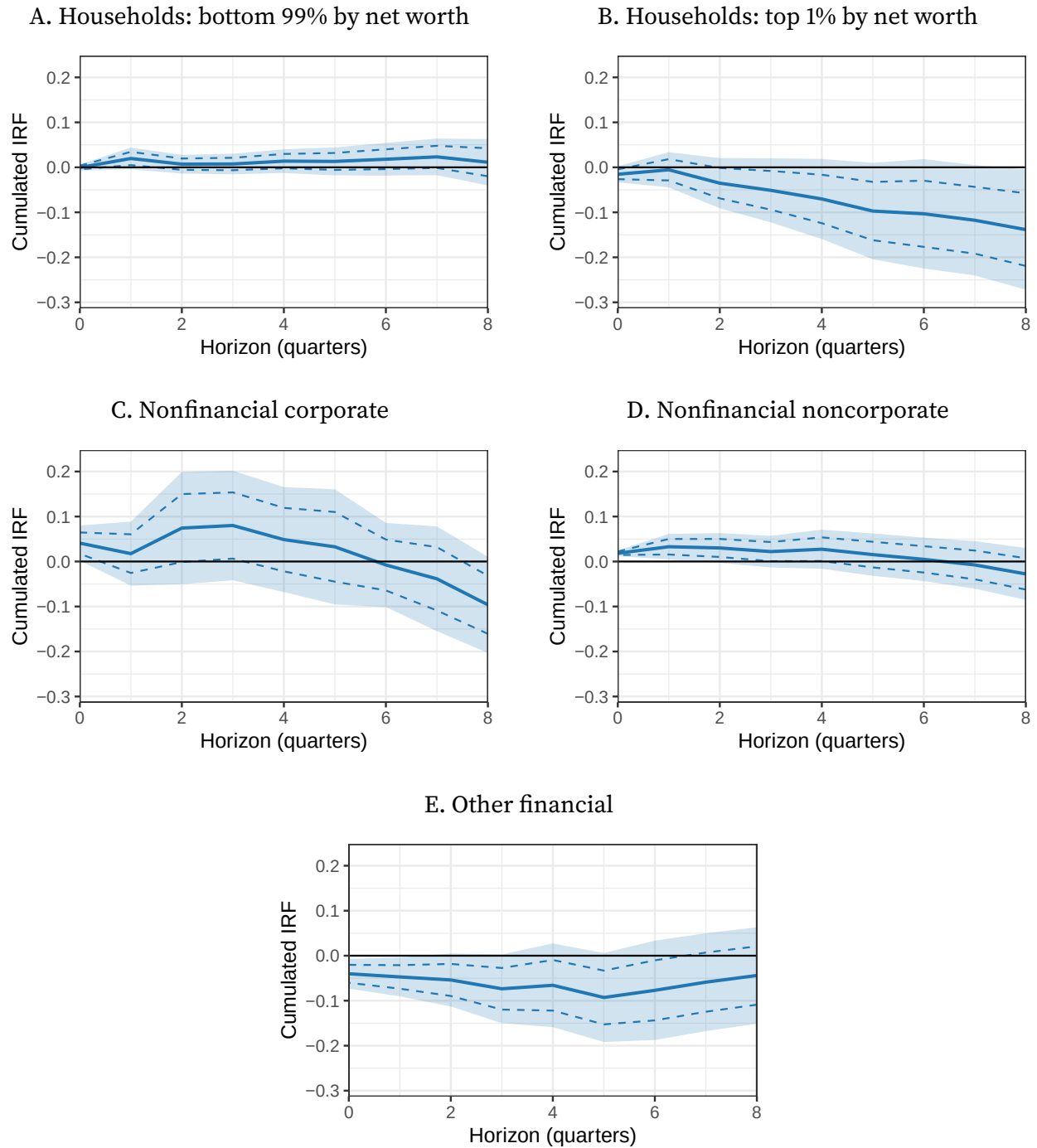


Figure A25. Household deposit flow response to monetary policy by net-worth group

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.

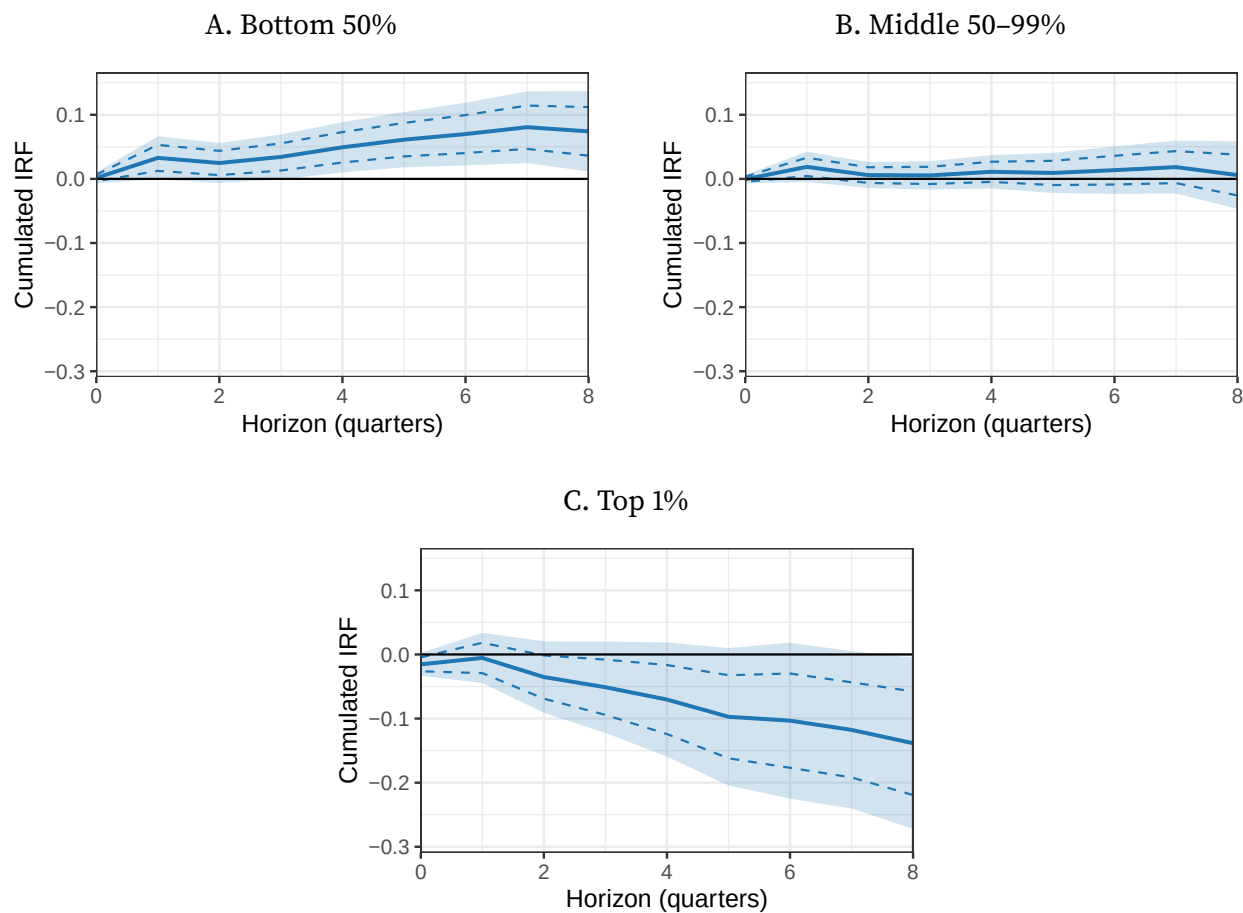


Figure A26. Real GDP response to monetary policy shocks

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.

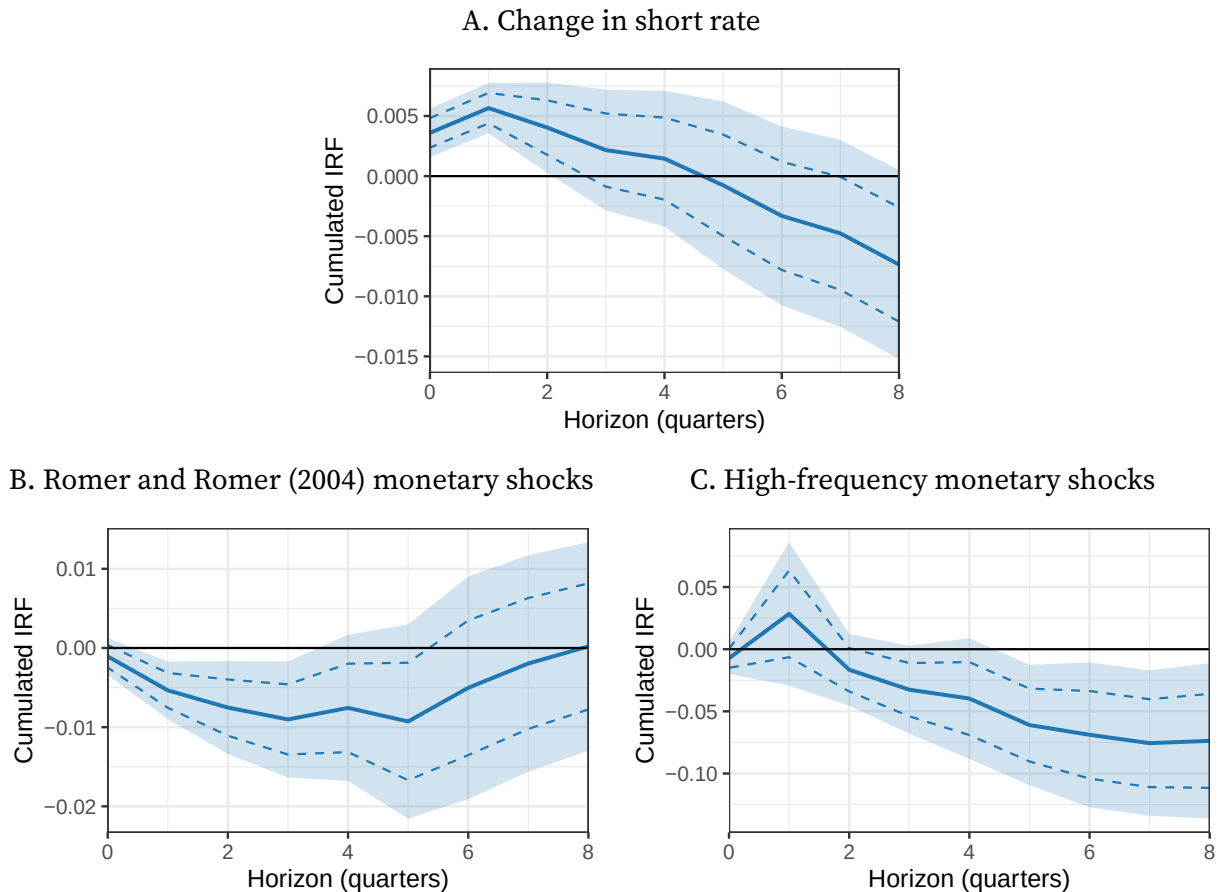
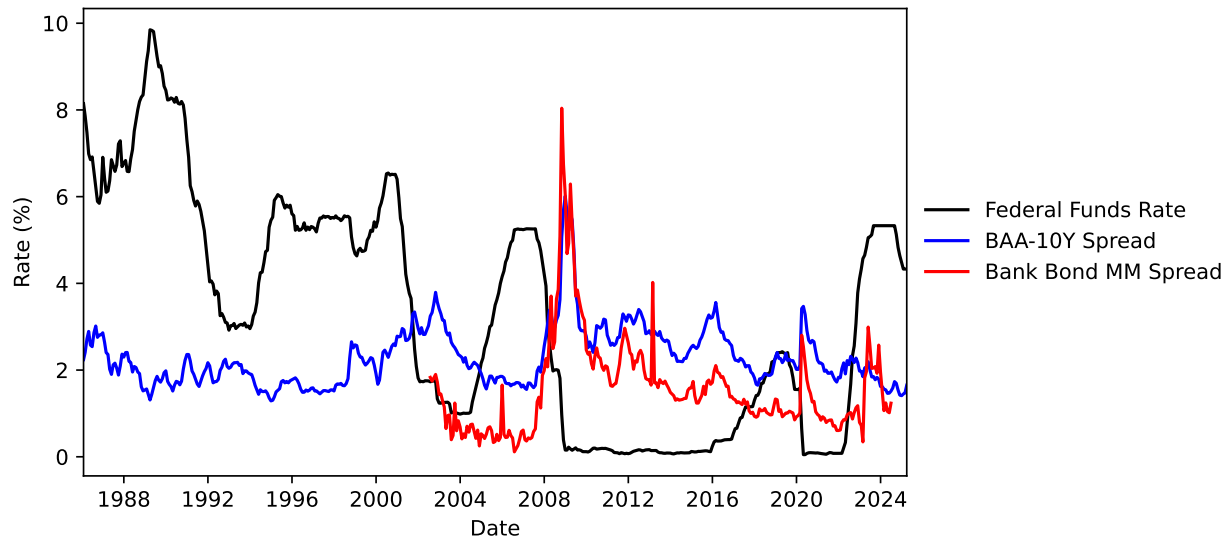


Figure A27. Baa corporate bond spread and bank bond spreads, 1985-2024

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 A28. 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.

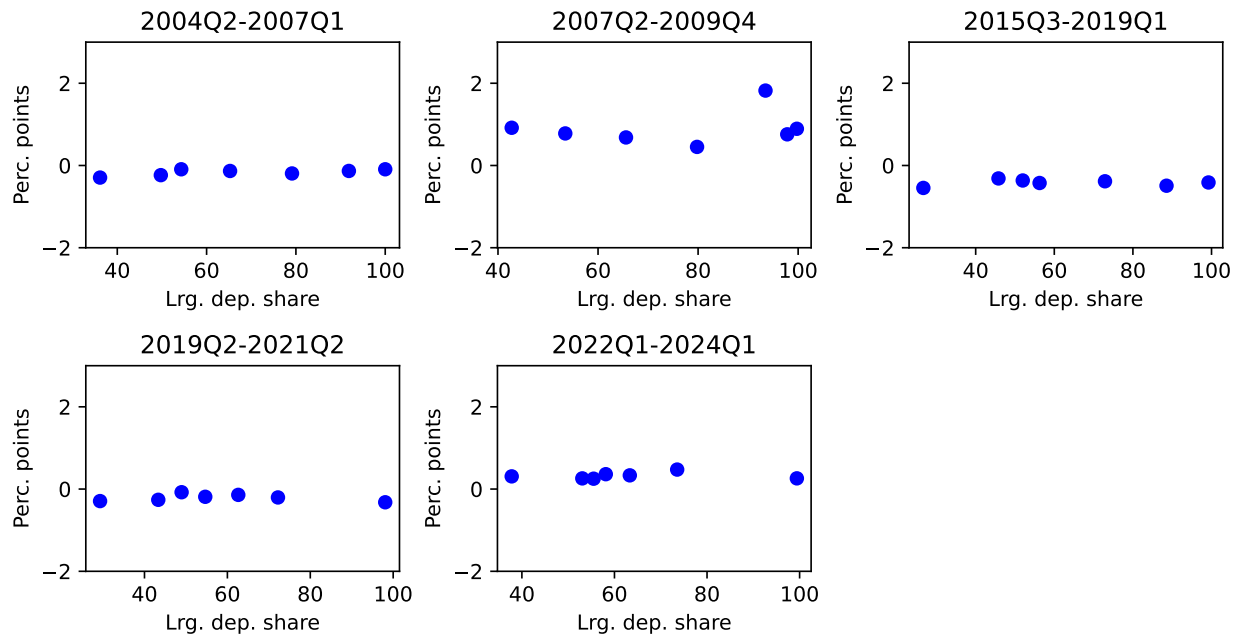


Figure A29. Bank bond spreads by large deposits share, 2004-2024: Levels at the start and end of monetary policy cycles

This figure is similar to [Figure A28](#), but it plots levels of bank bond spreads at the start and end of monetary policy cycles.

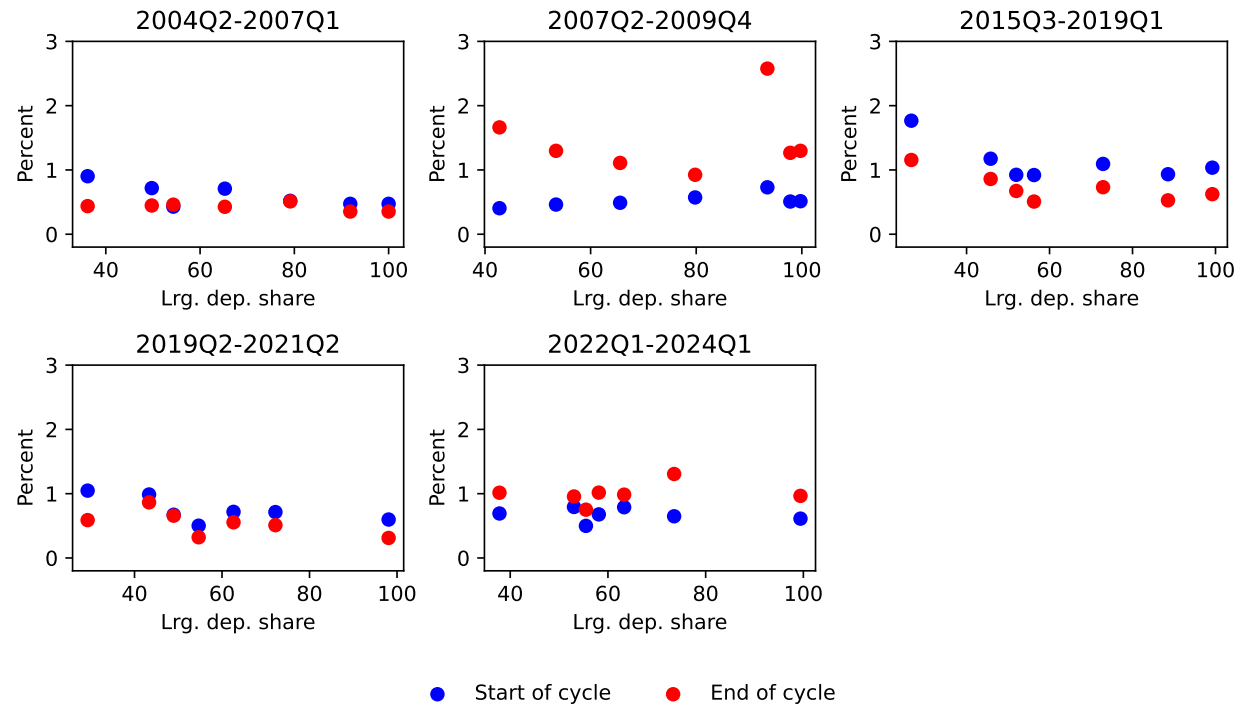
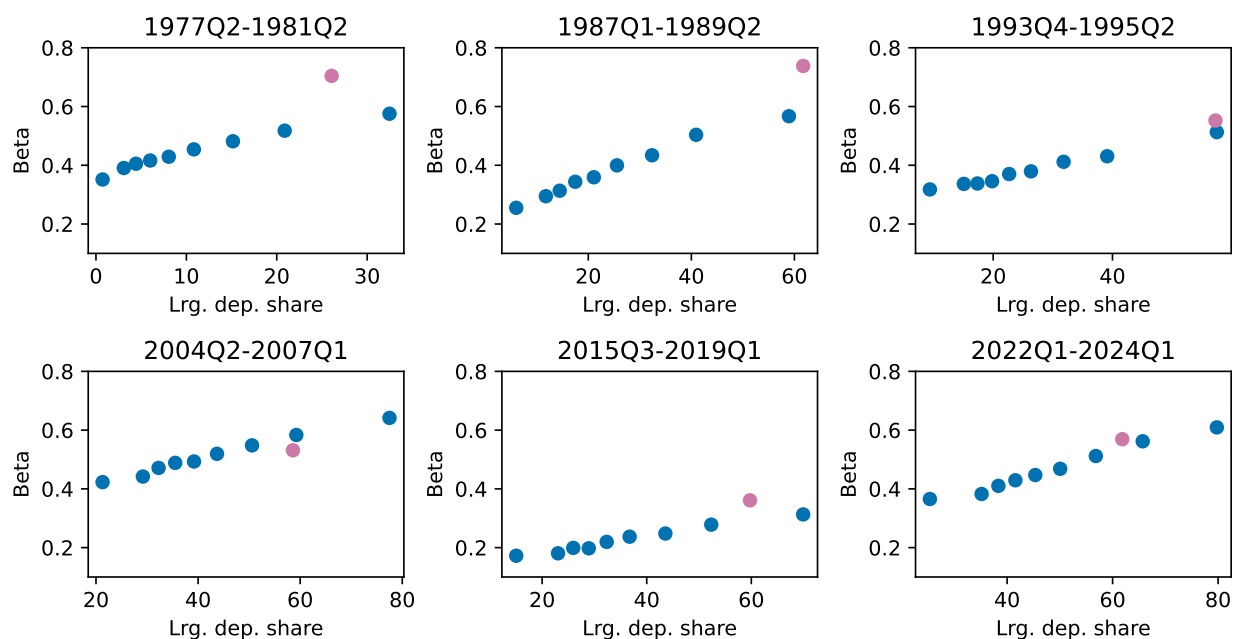


Figure A30. “Too-big-to-fail” banks, large deposits share, and deposit expense betas

Panel A plots binscatters similar to Figure 1, but splits out the 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

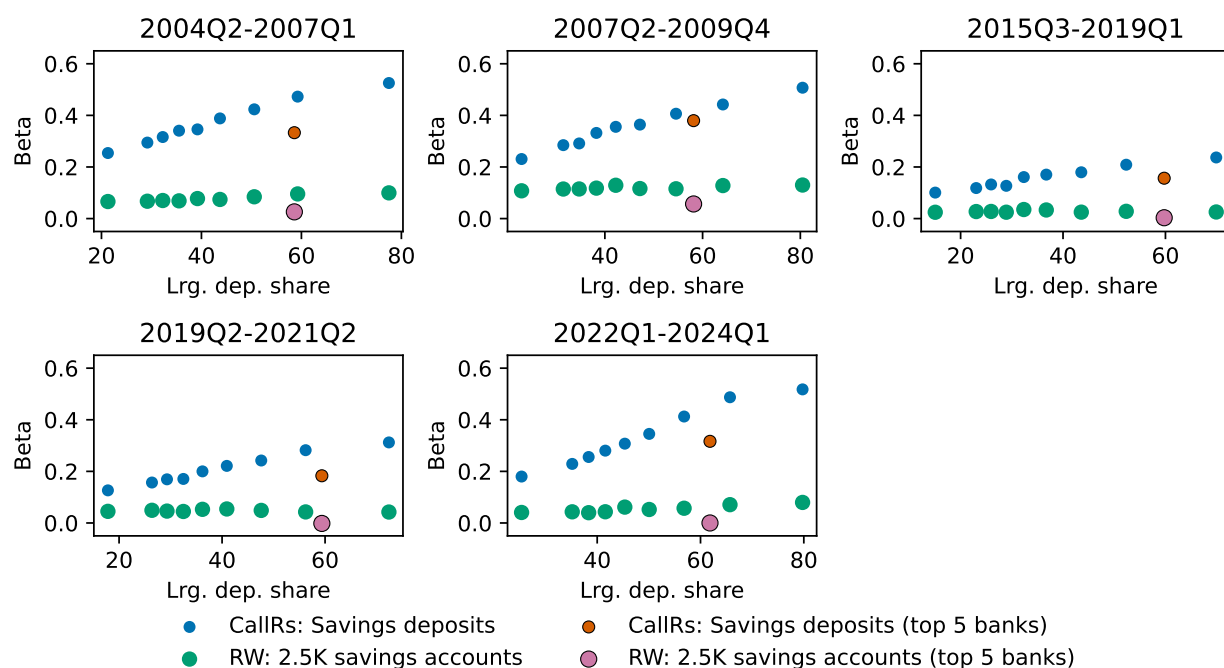


Figure A31. Large deposits flow out following monetary tightening even at the “too-big-to-fail” banks

This figure is similar to [Figure 6](#) but is estimated on deposit series (total, large, small) for the largest 5 banks in the U.S. as of 2020Q1 only. These banks are: Bank of America, JPMorgan Chase, Wells Fargo, Citibank, and US Bank. The quarter-on-quarter real deposit growth series of individual banks are first cleaned of any quarterly observations where they recorded a merger or where total asset growth is $< -90\%$ or $> 100\%$. The surviving observations are then aggregated using lagged deposits as weights. Any quarter with less than 2 bank observations (out of 5 possible) is marked as missing. Cumulative growth rates from $t - 1$ to $t + h$, $h = 0, 1, \dots, 8$ are then built from these aggregated quarterly growth rates. Other estimation details are as in [Figure 6](#). The monetary shock is [Romer and Romer \(2004\)](#) narrative shock.

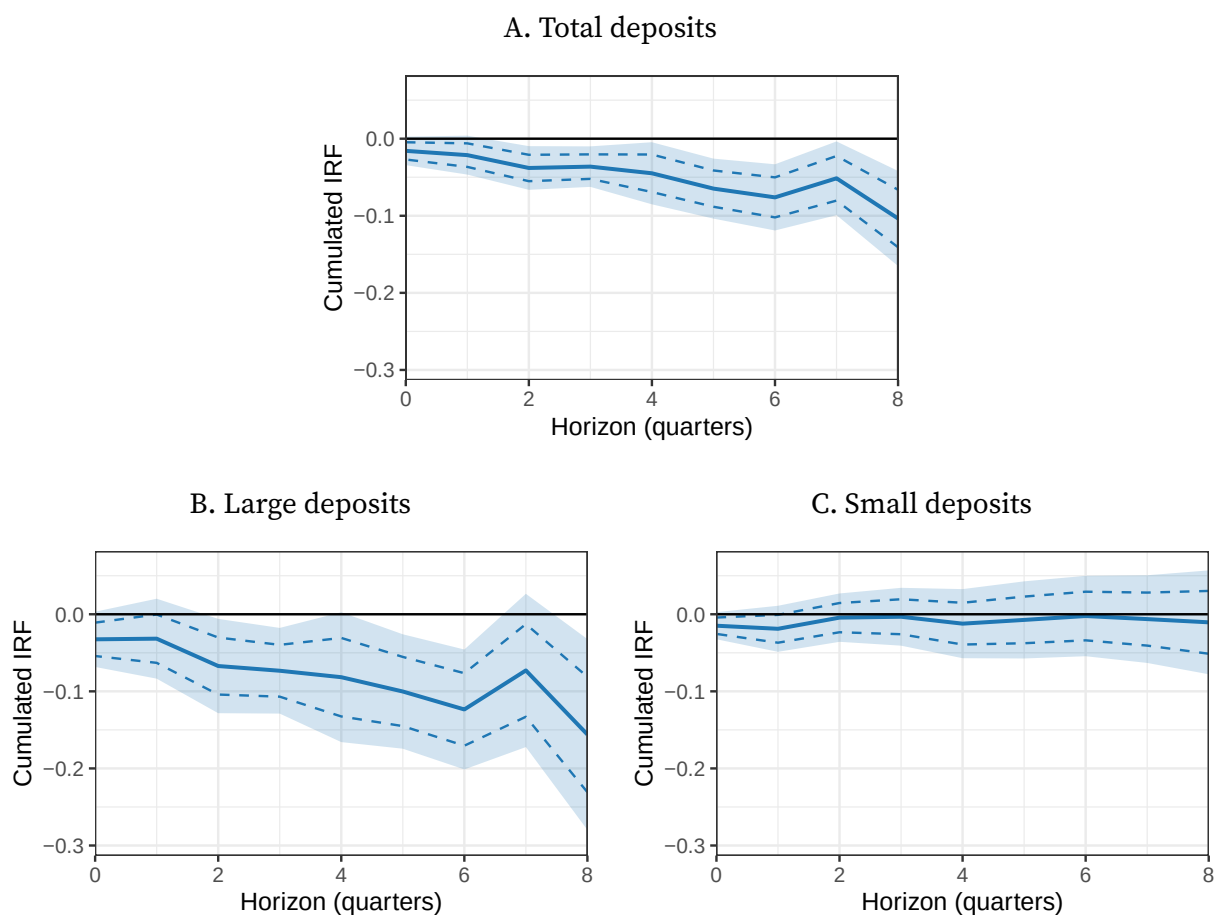


Figure A32. Deposit rates response to monetary policy shocks by large deposit share and market concentration

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.

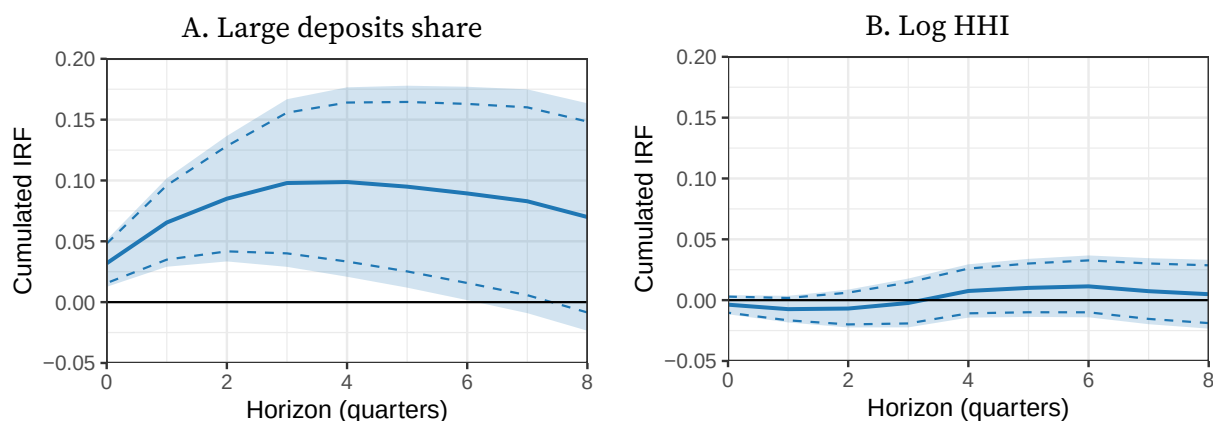


Figure A33. Share of large deposits is more important than local deposit market concentration in explaining deposit pricing across banks: Savings deposits

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

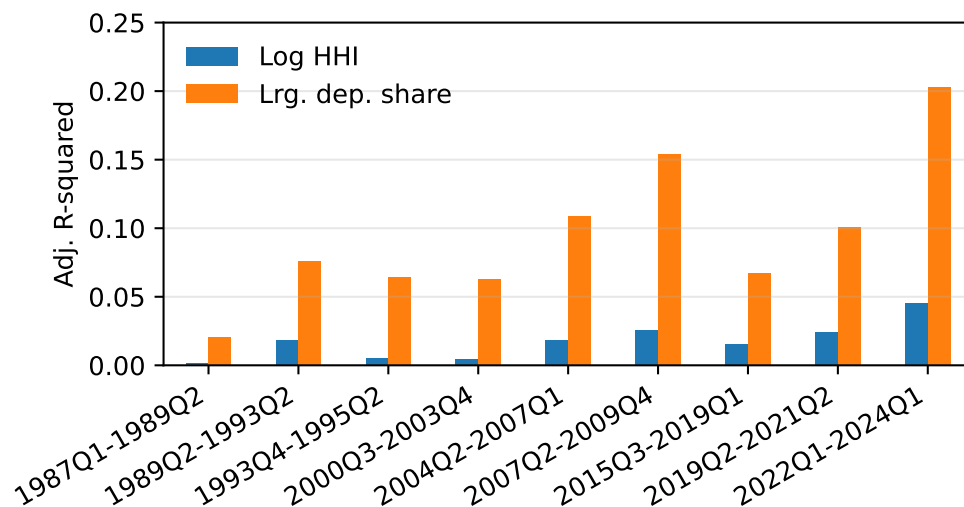


Figure A34. HHI has weak explanatory power for *retail* deposit pricing: Analysis by deposit product

This figure is similar to [Figure 7](#) Panel B, but for select retail deposit products separately.

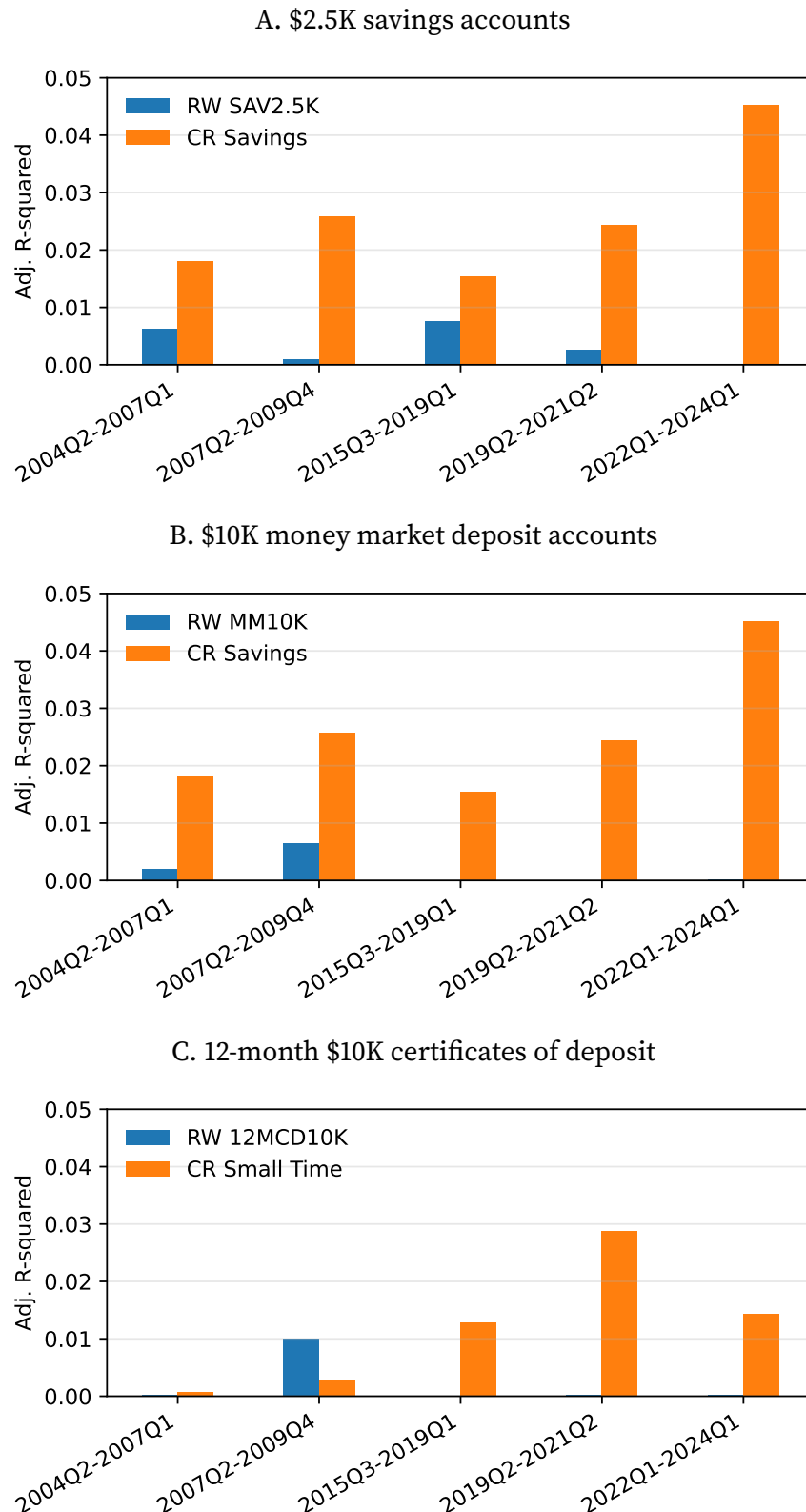
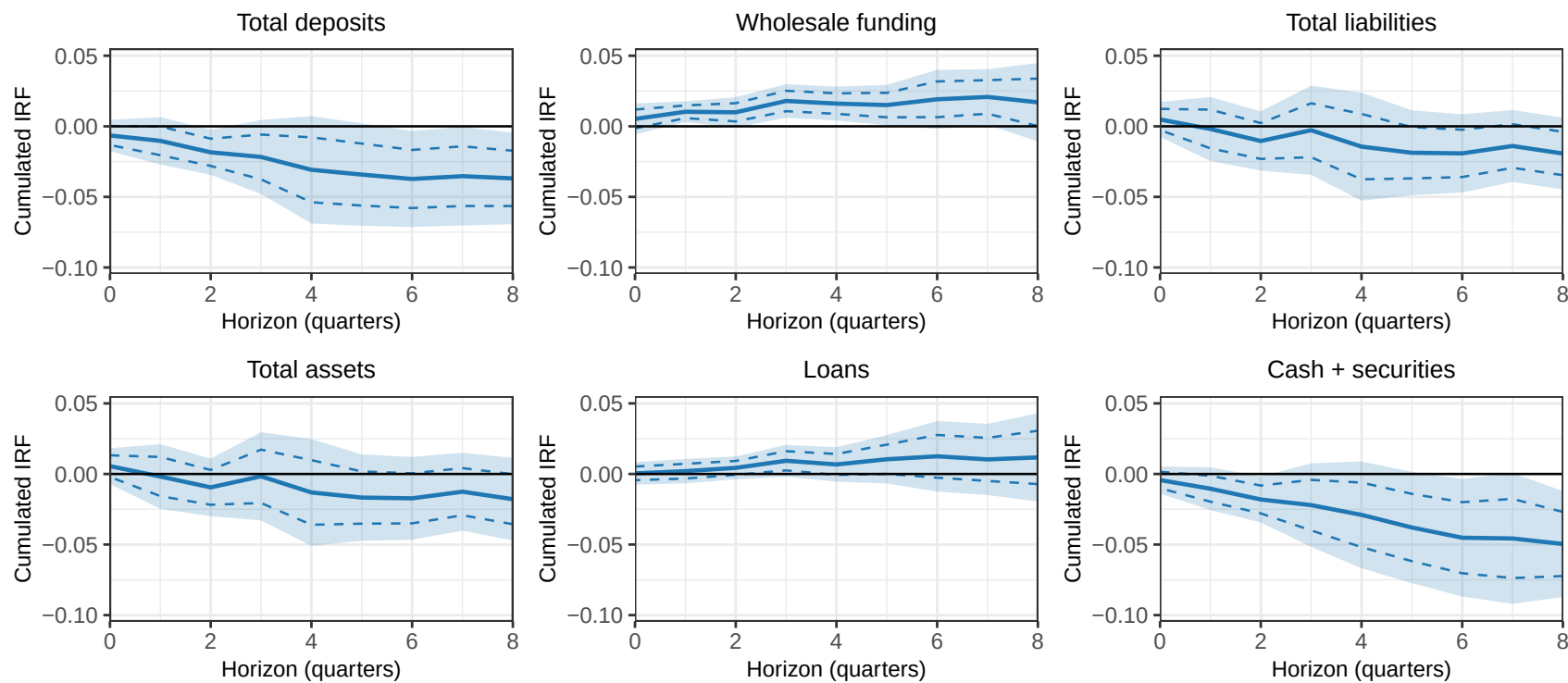


Figure A35. High-frequency monetary shocks and the balance sheet of the banking system

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

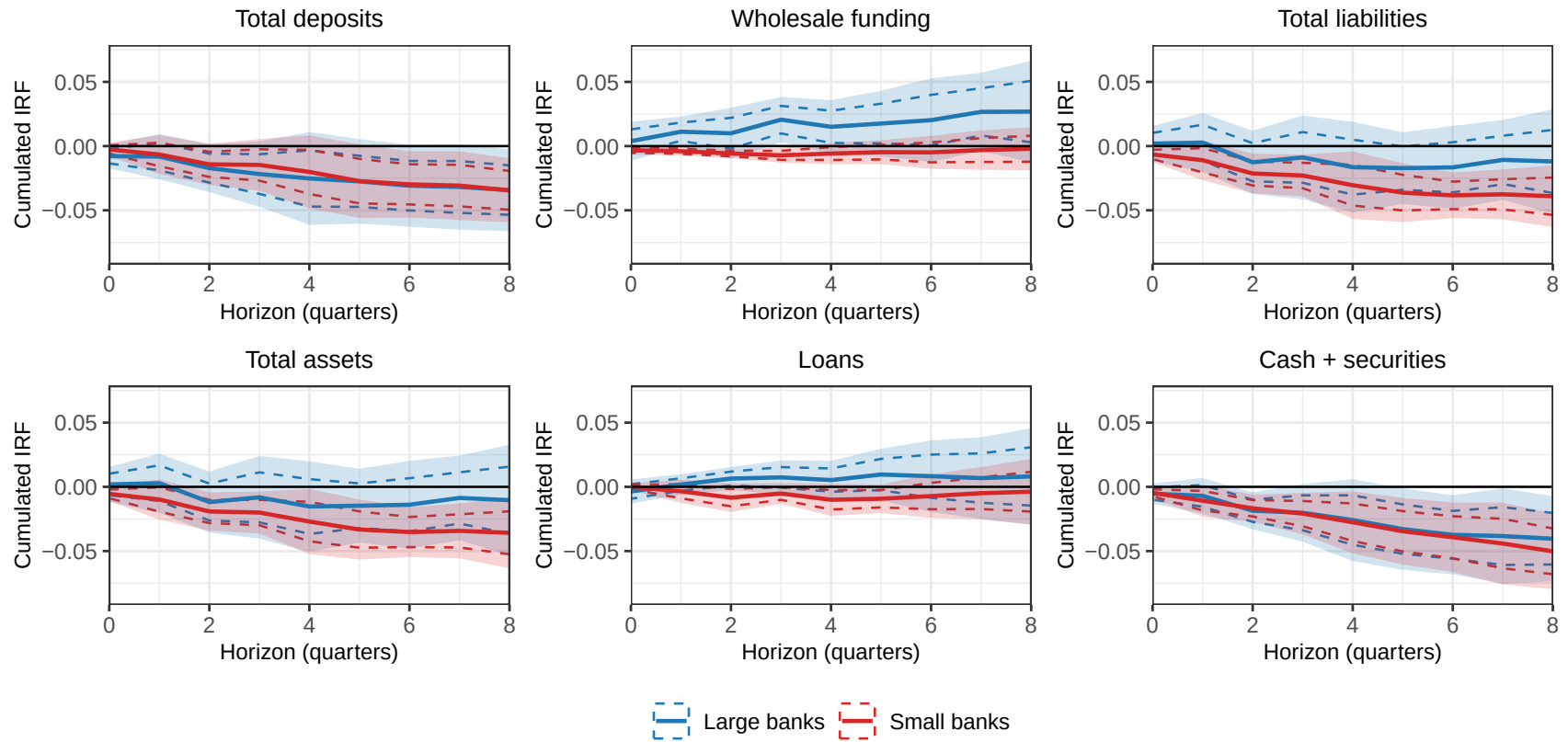


Figure A36. Interest expense, interest income, and net interest margin: Response to monetary policy by large deposits share

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 the change in either the interest expense rate, interest income rate, or NIM for bank i over the horizon h , and ΔFFR_t is the 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 the 25th to 75th percentile in its distribution within each quarter. The sample is all U.S. commercial banks over the period 1985Q1-2024Q1.

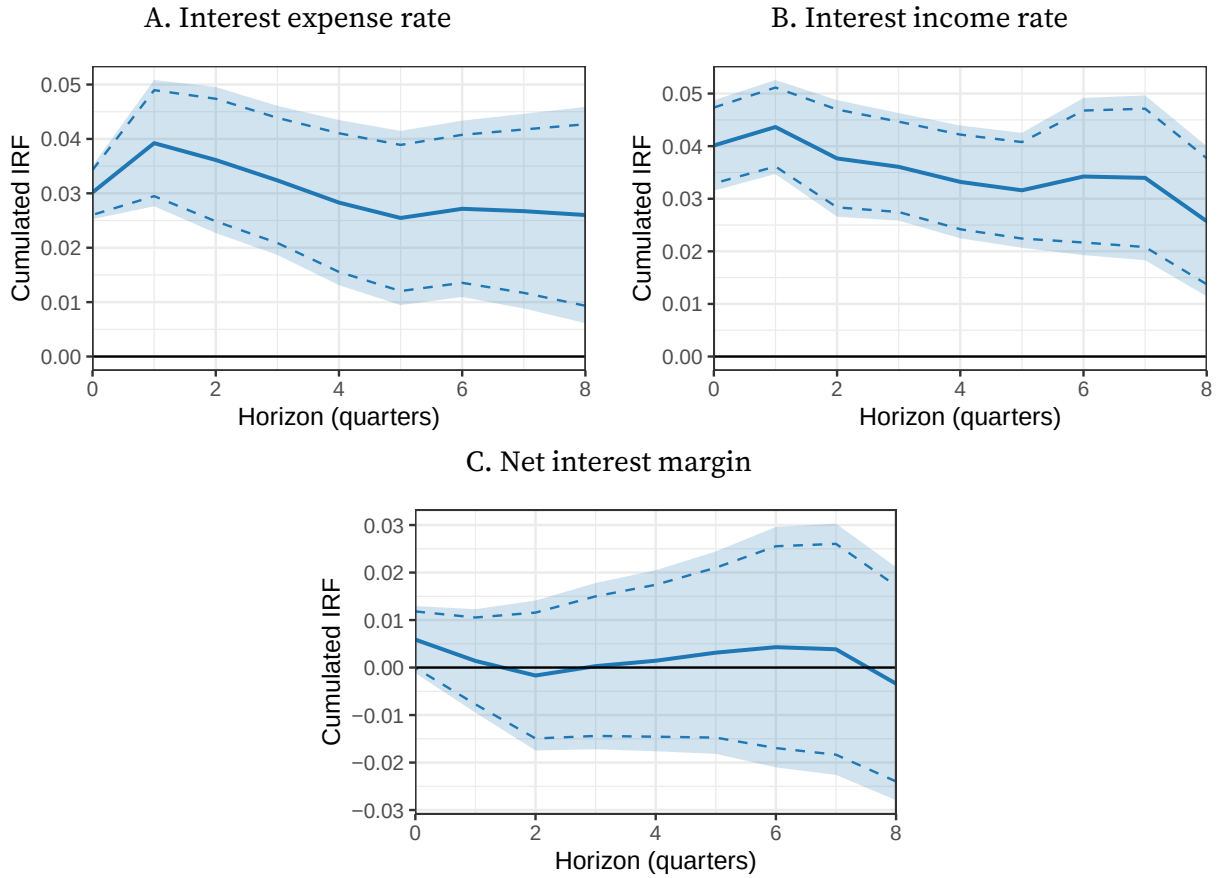


Figure A37. NIM by large deposits share: Romer & Romer (2004) shocks

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

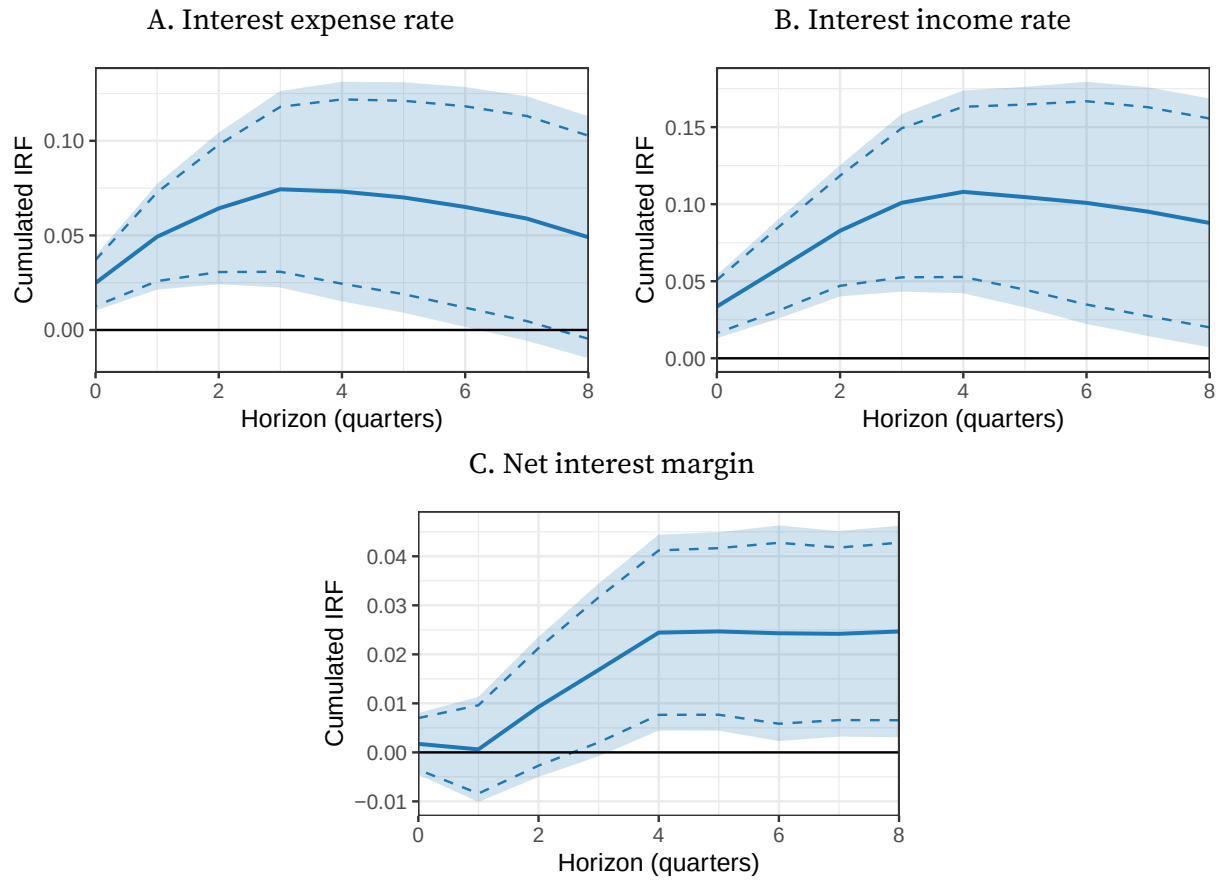


Figure A38. Banks with more large deposits hold shorter-maturity assets

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.

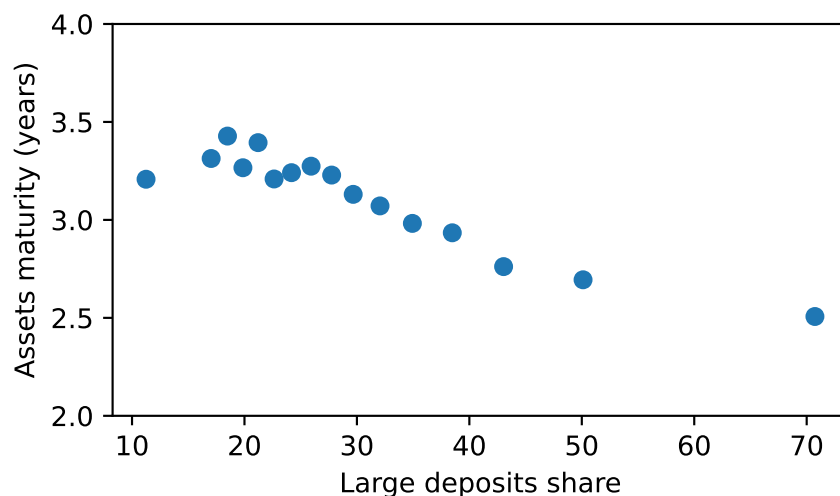


Figure A39. Banks with more large deposits hold more C&I loans

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.

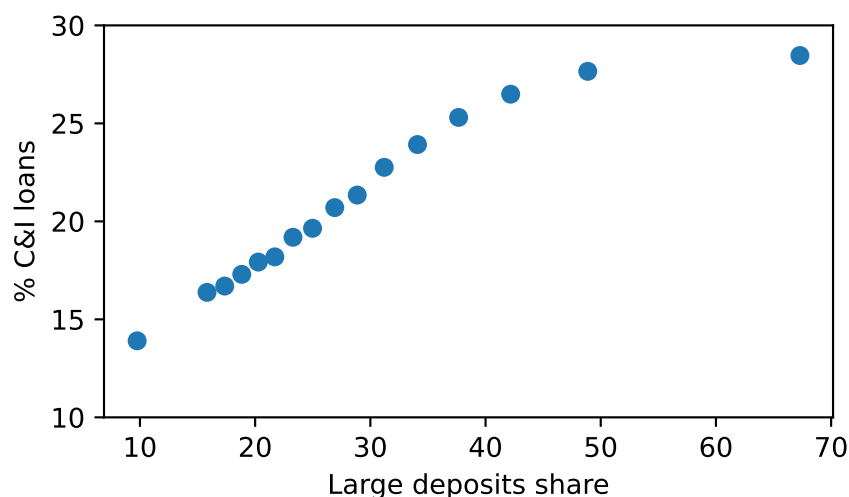


Table A1. Average deposit holdings by income distribution

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 deposit (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	13,771	120,666	13,876	143,462
1992	4,161	48,540	12,094	123,663	11,126	42,880
1995	4,599	64,572	8,910	145,293	8,889	123,837
1998	5,387	58,217	12,136	169,766	9,951	66,312
2001	6,043	68,952	14,275	205,391	9,371	54,442
2004	7,260	68,677	19,027	287,074	10,153	88,262
2007	5,721	104,948	16,536	354,176	11,139	180,219
2010	6,874	94,170	21,854	449,718	10,413	175,951
2013	8,166	217,225	19,445	434,647	5,444	96,666
2016	9,713	183,565	22,255	825,204	5,308	81,623
2019	10,437	197,603	23,093	532,876	7,358	180,042
2022	14,502	252,095	27,398	695,904	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 A4](#), 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 $_{i,t-1} \times$ RR shock $_t$	0.032*** (0.010)	0.085*** (0.026)	0.099** (0.040)	0.089** (0.045)	0.070 (0.048)
log(HHI $_{i,t-1}$) $\times$ RR shock $_t$	-0.004 (0.004)	-0.007 (0.008)	0.008 (0.011)	0.011 (0.013)	0.005 (0.014)
log(Bank age $_{i,t-1}$) $\times$ RR shock $_t$	-0.009* (0.005)	-0.024** (0.012)	-0.025 (0.016)	-0.028 (0.019)	-0.026 (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 $_{i,t-1} \times$ HF shock $_t$	0.033** (0.015)	0.122** (0.047)	0.157** (0.066)	0.137* (0.082)	0.133 (0.091)
log(HHI $_{i,t-1}$) $\times$ HF shock $_t$	0.003 (0.009)	-0.012 (0.017)	-0.015 (0.024)	-0.009 (0.029)	-0.012 (0.032)
log(Bank age $_{i,t-1}$) $\times$ HF shock $_t$	-0.007 (0.008)	-0.023 (0.023)	-0.045 (0.028)	-0.038 (0.034)	-0.016 (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. Betas on small and large deposits do not reliably increase with large deposits share

This table reports the results of the following regressions, estimated separately for each monetary policy cycle c :

$$\text{Sav. dep. beta}_{i,c} = \gamma_{0,c} + \sum_{q=2}^5 \gamma_{q,c} \mathbf{1}\{\text{Lrg. dep. share}_{i,c} \in Q_{q,c}\} + \varepsilon_{i,c},$$

where $Q_{q,c}$ are quintiles of the share of large deposits as of the beginning of cycle c . The dependent variable Sav. dep. beta $_{i,c}$ is one of: savings deposit expense beta from Call Reports (Total), rate beta on small (\$2,500 minimum balance) savings deposits from Ratewatch (Small), or the beta on large deposits inferred using Equation 1 (Large). The imputation of the large beta is restricted to banks with a large deposits share of at least 10%, since dividing by small shares severely magnifies measurement error; small and large betas are winsorized within cycle at the 5th and 95th percentiles. Within each cycle all columns are estimated on the same sample; cycles that predate Ratewatch coverage report only the total beta. The sample is all U.S. commercial banks. Panel A reports tightening cycles, Panel B easing cycles. Heteroskedasticity-robust standard errors are in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

A. Tightening cycles

	1987Q1– 1989Q2	1993Q4– 1995Q2	2004Q2–2007Q1			2015Q3–2019Q1			2022Q1–2024Q1		
	Total	Total	Total	Small	Large	Total	Small	Large	Total	Small	Large
Constant (Q1)	0.142*** (0.007)	0.108*** (0.004)	0.249*** (0.006)	0.065*** (0.002)	0.874*** (0.022)	0.101*** (0.005)	0.024*** (0.001)	0.423*** (0.017)	0.163*** (0.006)	0.034*** (0.002)	0.494*** (0.018)
Lrg. dep. share Q2	0.005 (0.009)	0.012* (0.006)	0.046*** (0.009)	−0.000 (0.004)	−0.015 (0.030)	0.017** (0.007)	0.000 (0.002)	−0.021 (0.023)	0.053*** (0.009)	0.003 (0.003)	0.040* (0.024)
Lrg. dep. share Q3	0.018* (0.009)	0.023*** (0.006)	0.080*** (0.009)	−0.000 (0.004)	−0.033 (0.029)	0.033*** (0.007)	0.001 (0.002)	−0.022 (0.023)	0.107*** (0.009)	0.005* (0.003)	0.107*** (0.023)
Lrg. dep. share Q4	0.045*** (0.009)	0.059*** (0.006)	0.116*** (0.009)	0.008** (0.004)	−0.090*** (0.027)	0.068*** (0.007)	0.008*** (0.002)	−0.011 (0.022)	0.163*** (0.010)	0.012*** (0.003)	0.128*** (0.023)
Lrg. dep. share Q5	0.113*** (0.010)	0.134*** (0.007)	0.209*** (0.010)	0.016*** (0.004)	−0.104*** (0.026)	0.091*** (0.007)	0.001 (0.002)	−0.064*** (0.020)	0.286*** (0.010)	0.019*** (0.003)	0.184*** (0.021)
R^2	0.017	0.052	0.098	0.006	0.005	0.054	0.005	0.003	0.211	0.014	0.024
N	11,700	10,258	5,174	5,174	5,174	4,106	4,106	4,106	3,757	3,757	3,757

B. Easing cycles

	1989Q2– 1993Q2	2000Q3– 2003Q4	2007Q2–2009Q4			2019Q2–2021Q2		
	Total	Total	Total	Small	Large	Total	Small	Large
Constant (Q1)	0.468*** (0.003)	0.430*** (0.004)	0.228*** (0.005)	0.107*** (0.002)	0.620*** (0.016)	0.114*** (0.005)	0.043*** (0.002)	0.393*** (0.015)
Lrg. dep. share Q2	0.031*** (0.005)	0.032*** (0.005)	0.042*** (0.007)	0.002 (0.004)	0.011 (0.022)	0.040*** (0.007)	0.001 (0.002)	0.056*** (0.021)
Lrg. dep. share Q3	0.037*** (0.004)	0.056*** (0.005)	0.082*** (0.008)	0.005 (0.004)	0.024 (0.021)	0.056*** (0.007)	0.001 (0.002)	0.041** (0.021)
Lrg. dep. share Q4	0.062*** (0.005)	0.077*** (0.005)	0.133*** (0.008)	0.009** (0.004)	0.047** (0.021)	0.098*** (0.007)	0.006** (0.002)	0.068*** (0.020)
Lrg. dep. share Q5	0.120*** (0.005)	0.115*** (0.006)	0.204*** (0.008)	0.009** (0.004)	0.026 (0.019)	0.152*** (0.008)	−0.000 (0.002)	0.063*** (0.019)
R^2	0.066	0.061	0.138	0.002	0.001	0.102	0.002	0.004
N	10,563	7,259	5,031	5,031	5,031	3,978	3,978	3,978

Table A8. 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*** (0.007)	0.156*** (0.005)	0.030*** (0.005)	0.022*** (0.006)	-0.046*** (0.010)
Lrg. dep. share _{i,c}	0.436*** (0.017)	0.444*** (0.012)	0.311*** (0.014)	0.428*** (0.016)	0.724*** (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*** (0.006)	0.087*** (0.005)	0.023*** (0.006)	0.014* (0.007)	-0.022** (0.011)
Lrg. dep. share _{i,c}	0.281*** (0.017)	0.245*** (0.013)	0.249*** (0.018)	0.333*** (0.021)	0.497*** (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 A9. 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 A10. Large-minus-small differences in aggregate deposit flow responses

This table reports pooled local-projection estimates corresponding to the impulse responses in [Figure 6](#) and [Figure A23](#). For each deposit category, the small- and large-deposit series are stacked and the following regressions are estimated:

$$\Delta_{t-1,t+h} \log Y_{s,t} = \beta_S^h \text{RR shock}_t + \beta_{L-S}^h \text{RR shock}_t \times \mathbb{1}[\text{Large}]_t + \Gamma^h X_{s,t} + \varepsilon_{s,t+h}^h,$$

where $s \in \{S, L\}$ indexes small and large deposits and RR shock_t is the [Romer and Romer \(2004\)](#) monetary policy shock, normalized to correspond to a 100bps increase in the federal funds rate. $\mathbb{1}[\text{Large}]_t$ equals one for large-deposit observations. The coefficient β_S^h is the cumulative response of small deposits, while β_{L-S}^h is the difference between the cumulative responses of large and small deposits. The vector $X_{s,t}$ includes two lags of deposit growth, two lags each of the monetary policy shock, real GDP growth, and inflation, ZLB indicator and quarter dummies, together with the corresponding interactions with $\mathbb{1}[\text{Large}]_t$. Standard errors are Driscoll-Kraay with bandwidth 8 quarters. The point estimates in this table reproduce the separately estimated responses plotted in [Figure 6](#) and [Figure A23](#), while allowing a direct test of the difference between large and small deposits. The differences are stronger when monetary policy is measured using high-frequency shocks or ΔFFR (not reported). *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

A. Total deposits

	Horizon, quarters				
	$h = 0$	$h = 2$	$h = 4$	$h = 6$	$h = 8$
RR shock _t	-0.003 (0.007)	0.011 (0.013)	0.024 (0.018)	0.030 (0.027)	0.024 (0.033)
RR shock _t × $\mathbb{1}[\text{Large}]_t$	-0.010 (0.018)	-0.038 (0.027)	-0.059 (0.040)	-0.088** (0.043)	-0.102 (0.070)
Controls	✓	✓	✓	✓	✓
N	166	166	166	166	166
Adjusted R ²	0.546	0.557	0.564	0.566	0.553

B. Non-time deposits

	Horizon, quarters				
	$h = 0$	$h = 2$	$h = 4$	$h = 6$	$h = 8$
RR shock _t	-0.029*** (0.011)	-0.053*** (0.017)	-0.063** (0.028)	-0.074** (0.030)	-0.090** (0.036)
RR shock _t × $\mathbb{1}[\text{Large}]_t$	-0.014 (0.032)	-0.058 (0.037)	-0.092* (0.050)	-0.112*** (0.037)	-0.147*** (0.045)
Controls	✓	✓	✓	✓	✓
N	162	162	162	162	162
Adjusted R ²	0.574	0.608	0.526	0.445	0.390

C. Time deposits

	Horizon, quarters				
	$h = 0$	$h = 2$	$h = 4$	$h = 6$	$h = 8$
RR shock _{t}	0.033*** (0.007)	0.089*** (0.013)	0.131*** (0.029)	0.133** (0.052)	0.158*** (0.058)
RR shock _{t} $\times$ $\mathbb{1}[\text{Large}]_t$	0.001 (0.025)	-0.023 (0.060)	-0.054 (0.091)	-0.089 (0.102)	-0.090 (0.130)
Controls	✓	✓	✓	✓	✓
N	178	178	178	178	178
Adjusted R^2	0.573	0.568	0.516	0.490	0.461

Table A11. Large-minus-small differences in aggregate deposit flow responses: High-frequency monetary policy shocks

This table is similar to Table A10, but uses Bauer and Swanson (2023) high-frequency monetary policy shocks.

A. Total deposits					
	Horizon, quarters				
	$h = 0$	$h = 2$	$h = 4$	$h = 6$	$h = 8$
HF shock $_t$	-0.018 (0.012)	-0.018 (0.021)	-0.009 (0.026)	0.022 (0.041)	0.045 (0.059)
HF shock $_t \times \mathbb{1}[\text{Large}]_t$	-0.034 (0.024)	-0.097*** (0.036)	-0.145** (0.062)	-0.241*** (0.069)	-0.308*** (0.082)
Controls	✓	✓	✓	✓	✓
N	204	204	204	204	204
Adjusted R^2	0.532	0.453	0.432	0.445	0.399
B. Non-time deposits					
	Horizon, quarters				
	$h = 0$	$h = 2$	$h = 4$	$h = 6$	$h = 8$
HF shock $_t$	-0.035*** (0.013)	-0.057** (0.024)	-0.068* (0.035)	-0.028 (0.064)	-0.002 (0.098)
HF shock $_t \times \mathbb{1}[\text{Large}]_t$	-0.037 (0.034)	-0.099*** (0.036)	-0.122* (0.062)	-0.220*** (0.070)	-0.260*** (0.081)
Controls	✓	✓	✓	✓	✓
N	200	200	200	200	200
Adjusted R^2	0.491	0.371	0.298	0.295	0.261
C. Time deposits					
	Horizon, quarters				
	$h = 0$	$h = 2$	$h = 4$	$h = 6$	$h = 8$
HF shock $_t$	0.010 (0.016)	0.081* (0.045)	0.141 (0.088)	0.096 (0.123)	0.050 (0.152)
HF shock $_t \times \mathbb{1}[\text{Large}]_t$	-0.008 (0.025)	-0.007 (0.071)	-0.127 (0.102)	-0.170 (0.108)	-0.285** (0.133)
Controls	✓	✓	✓	✓	✓
N	216	216	216	216	216
Adjusted R^2	0.548	0.582	0.428	0.414	0.363

Table A12. Large deposit flows in response to monetary policy by initial share of large deposits

This table reports cumulative responses of large and small deposit flows four quarters after a monetary policy shock, separately by quintiles of banks' lagged share of large deposits. Panel A reports log changes in deposits; Panel B reports changes in deposits relative to initial total assets. To construct each quintile series, I sort banks by their lagged large-deposit share in each quarter, aggregate deposit levels within each quintile, and then estimate the same time-series local projections as in [Equation 3](#) on the resulting aggregate flows. The table shows impulse responses to the quarter-on-quarter change in the effective federal funds rate (ΔFFR), [Romer and Romer \(2004\)](#) shocks, and [Bauer and Swanson \(2023\)](#) monetary shocks. The shocks are scaled to correspond to a 100bps change in the federal funds rate. Standard errors are Newey-West with bandwidth 8. *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

A. Elasticities

	Large deposits			Small deposits		
	ΔFFR	RR shock	HF shock	ΔFFR	RR shock	HF shock
Q1 (lowest)	-11.14*** (2.64)	-9.02*** (3.06)	-10.58** (5.24)	1.63 (1.26)	2.69 (1.85)	1.08 (1.98)
Q2	-9.62*** (2.10)	-8.72*** (2.63)	-7.73** (3.89)	2.31 (1.77)	1.74 (1.15)	-0.40 (2.03)
Q3	-10.37*** (2.75)	-5.65*** (1.89)	-8.05* (4.21)	-1.10 (1.26)	0.73 (1.78)	-2.60 (2.55)
Q4	-5.35** (2.12)	-4.45** (2.06)	-7.80** (3.19)	2.35** (1.13)	3.31** (1.49)	0.35 (1.89)
Q5 (highest)	-2.09 (2.69)	-0.67 (4.08)	-7.04 (4.42)	1.97 (1.30)	3.11* (1.67)	-0.91 (1.32)
<i>N</i>	113	85	110	113	85	110

B. Contributions

	Large deposits			Small deposits		
	ΔFFR	RR shock	HF shock	ΔFFR	RR shock	HF shock
Q1 (lowest)	-1.59*** (0.37)	-1.26*** (0.42)	-1.99** (0.89)	1.61 (0.98)	1.53 (1.26)	0.78 (1.34)
Q2	-1.97*** (0.45)	-1.68*** (0.49)	-2.28** (1.04)	1.30 (1.02)	0.97 (0.72)	-0.15 (1.14)
Q3	-2.81*** (0.90)	-0.91** (0.45)	-2.71* (1.54)	-0.68 (0.90)	0.61 (0.95)	-1.69 (1.73)
Q4	-1.54* (0.80)	-0.90 (0.66)	-2.50** (1.27)	1.10* (0.58)	1.51* (0.78)	-0.02 (0.94)
Q5 (highest)	-0.83 (1.05)	0.47 (1.24)	-2.71 (1.78)	0.45 (0.39)	0.75 (0.49)	-0.39 (0.34)
<i>N</i>	113	85	110	113	85	110

Table A13. Large deposit flows in response to monetary policy by total assets

This table is similar to [Table A12](#) but sorts banks into quintiles by total assets rather than by the share of large deposits.

A. Elasticities

	Large deposits			Small deposits		
	Δ FFR	RR shock	HF shock	Δ FFR	RR shock	HF shock
Q1 (lowest)	-7.27*** (1.55)	-5.62** (2.19)	-7.27*** (2.51)	-2.58*** (0.98)	-1.15 (1.43)	-3.14* (1.73)
Q2	-7.06*** (1.94)	-5.63*** (2.00)	-6.94** (3.23)	-1.40 (1.05)	0.21 (1.30)	-2.55 (1.67)
Q3	-6.93*** (1.70)	-6.14*** (1.93)	-6.25** (2.68)	-0.83 (1.05)	0.79 (1.09)	-2.18 (1.61)
Q4	-5.91*** (1.63)	-5.10** (1.98)	-5.67* (3.39)	0.09 (1.14)	1.33 (1.04)	-1.86 (1.50)
Q5 (highest)	-4.14* (2.43)	-3.25 (3.68)	-8.34** (3.86)	2.60** (1.09)	3.41** (1.55)	-0.21 (1.74)
<i>N</i>	113	85	110	113	85	110

B. Contributions

	Large deposits			Small deposits		
	Δ FFR	RR shock	HF shock	Δ FFR	RR shock	HF shock
Q1 (lowest)	-1.67*** (0.50)	-0.82* (0.50)	-1.70** (0.67)	-1.62** (0.65)	-0.93 (1.04)	-1.98* (1.18)
Q2	-1.88*** (0.62)	-0.95** (0.48)	-1.90* (1.01)	-0.84 (0.68)	-0.01 (0.89)	-1.49 (1.07)
Q3	-1.82*** (0.56)	-1.12** (0.50)	-1.85** (0.92)	-0.46 (0.64)	0.37 (0.70)	-1.26 (0.98)
Q4	-1.68*** (0.60)	-1.09** (0.55)	-1.90 (1.29)	0.08 (0.66)	0.73 (0.62)	-1.04 (0.88)
Q5 (highest)	-1.34 (0.91)	-0.32 (1.00)	-2.77* (1.51)	0.86** (0.41)	1.17** (0.54)	-0.14 (0.63)
<i>N</i>	113	85	110	113	85	110

Table A14. Large deposits flow relatively more into banks with higher large-deposit shares after monetary tightening, controlling for bank size

This table reports bank-level local projection estimates of the cumulative response of large and small deposits four quarters after a monetary policy tightening. The dependent variables are log changes in large deposits (Columns 1–3) and small deposits (Columns 4–6) from quarter $t - 1$ through quarter $t + 4$. The reported coefficients are on interactions of the monetary policy measure with banks' lagged large-deposit share and lagged log total assets. Columns 1 and 4 use the quarter-on-quarter change in the effective federal funds rate (ΔFFR). Columns 2 and 5 use [Romer and Romer \(2004\)](#) monetary shocks, and Columns 3 and 6 use [Bauer and Swanson \(2023\)](#) high-frequency monetary shocks; the shocks are scaled to correspond to a 100bps FFR hike. All specifications include quarter fixed effects and the full set of controls described in [Table 2](#), including interactions with lagged log local deposit market HHI, lagged log bank age, and lagged log assets. Large-deposit share, log HHI, and log assets are scaled by their within-quarter interquartile ranges. Standard errors are double clustered by bank and quarter. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Large deposits			Small deposits		
	ΔFFR	RR shock	HF shock	ΔFFR	RR shock	HF shock
Lrg. dep. share $_{i,t-1} \times \text{MP}_t$	0.016* (0.008)	0.014 (0.011)	0.019** (0.009)	-0.002 (0.002)	-0.002 (0.004)	-0.001 (0.003)
Time FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
N	615,456	519,525	615,456	618,654	522,586	618,654

Table A15. Bank-level local projections of deposit flows on alternative monetary policy measures

This table is similar to [Table 5](#), but it uses other monetary policy measures in place of [Romer and Romer \(2004\)](#) shocks. Panel A uses quarter-on-quarter changes in the effective federal funds rate ΔFFR_t , while Panel B uses [Bauer and Swanson \(2023\)](#) high-frequency monetary shocks. The high-frequency shock is scaled to correspond to a 100bps change in the federal funds rate.

A. Change in short rate

	Large deposits						Small deposits					
	$h = 0$		$h = 4$		$h = 8$		$h = 0$		$h = 4$		$h = 8$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ΔFFR_t	-0.018** (0.007)	-0.018** (0.007)	-0.071*** (0.019)	-0.072*** (0.019)	-0.069** (0.027)	-0.068** (0.027)	-0.006 (0.004)	-0.006 (0.004)	-0.009 (0.010)	-0.012 (0.009)	0.005 (0.012)	-0.001 (0.011)
Bank FE		✓		✓		✓		✓		✓		✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.139	0.144	0.072	0.159	0.060	0.216	0.081	0.100	0.105	0.227	0.104	0.306
N	616,746	616,511	616,746	616,511	616,746	616,511	619,849	619,611	619,849	619,611	619,849	619,611

B. High-frequency shocks

	Large deposits						Small deposits					
	$h = 0$		$h = 4$		$h = 8$		$h = 0$		$h = 4$		$h = 8$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
HF shock $_t$	-0.008 (0.008)	-0.007 (0.008)	-0.067** (0.028)	-0.066** (0.028)	-0.081** (0.036)	-0.079** (0.036)	-0.003 (0.004)	-0.004 (0.004)	-0.026* (0.013)	-0.028** (0.014)	-0.016 (0.011)	-0.021* (0.011)
Bank FE		✓		✓		✓		✓		✓		✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.138	0.144	0.070	0.158	0.059	0.215	0.082	0.101	0.102	0.225	0.098	0.302
N	616,746	616,511	616,746	616,511	616,746	616,511	619,849	619,611	619,849	619,611	619,849	619,611

Table A16. 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** (0.00642)	-0.00489 (0.01901)	0.01761 (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 A17. 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** (0.00532)	-0.00445 (0.01551)	0.01821 (0.02381)
Lrg. dep. share $\times \Delta\text{SR}$	0.00124 (0.00384)	-0.01788* (0.00938)	-0.02867* (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* (0.00618)	0.00323 (0.01945)	0.03241 (0.03012)
Lrg. dep. share $\times$ RR shock	-0.00536 (0.00567)	-0.02627* (0.01346)	-0.02410 (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 A18. Small business lending and large deposits flows: Positive vs negative flows

This table is similar to Table 6 but (a) splits the sample into top-1% by size (“large”) vs the rest (“small”), and (b) deflates large and small deposits year-on-year change scaled by lagged assets by CPI and then splits into positive (inflows) and negative (outflows) components.

	Small banks				Large banks			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta \text{Large deposits}_{i,t}^+ / \text{Assets}_{i,t-1}$	-0.059 (0.245)	0.251 (0.256)	-0.068 (0.268)	0.326 (0.273)	1.184*** (0.444)	1.647*** (0.516)	1.291** (0.602)	2.137*** (0.603)
$\Delta \text{Large deposits}_{i,t}^- / \text{Assets}_{i,t-1}$	0.809* (0.428)	0.975*** (0.368)	1.013** (0.446)	1.096*** (0.392)	0.022 (1.223)	-0.655 (1.211)	0.848 (1.475)	-0.061 (1.338)
$\Delta \text{Small deposits}_{i,t}^+ / \text{Assets}_{i,t-1}$	-0.143 (0.335)	0.307 (0.386)	0.104 (0.269)	0.721** (0.363)	-0.460 (0.908)	-0.616 (1.049)	0.835 (0.870)	1.004 (0.769)
$\Delta \text{Small deposits}_{i,t}^- / \text{Assets}_{i,t-1}$	1.459** (0.724)	1.420** (0.678)	1.300* (0.731)	1.097 (0.720)	3.913*** (1.319)	4.288*** (1.493)	2.681* (1.510)	2.109* (1.153)
Controls		✓		✓		✓		✓
ZLB			✓	✓			✓	✓
N	325,641	325,641	310,291	310,291	315,672	315,672	302,036	302,036
Within R^2	0.003	0.018	0.003	0.025	0.016	0.036	0.019	0.078

Table A19. 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 $\text{Assets maturity}_{it}$ is the average maturity (in years) of total assets at bank i at time t ; $\text{Lrg. dep. share}_{it}$ 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*** (0.001)	-0.014*** (0.001)	-0.014*** (0.001)	-0.015*** (0.001)	-0.027*** (0.001)	-0.030*** (0.002)	-0.027*** (0.002)	-0.030*** (0.003)	-0.035*** (0.003)	-0.029*** (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 A20. 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*** (0.010)	0.301*** (0.011)	0.321*** (0.016)	0.269*** (0.017)	0.171*** (0.012)	0.156*** (0.014)	0.223*** (0.011)	0.198*** (0.015)	0.156*** (0.016)	0.113*** (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