The Dynamics of Retail Deposit Balances[*]

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Abstract

We investigate the dynamics of household deposits using account-level data from 12 million accounts across 154 U.S. credit unions. Significant skewness in the retail deposit distribution—with 10% of depositors controlling 70% of total deposits—means large-balance accounts drive aggregate retail deposit flows. On average, high-balance accounts become large after significant one-time inflows and are more likely to experience large, idiosyncratic drawdowns. Unlike low-balance households, high-balance retail depositors are not sensitive to interest rate shocks. Additional evidence suggests that overall retail deposit stickiness is driven by high-balance accounts that are used as medium-run liquidity stores rather than for interest income.

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1 Introduction

In this paper, we use novel account-level data from millions of retail accounts at dozens of financial institutions to document several novel facts about the dynamics of household deposit balances. First, we show that prior work finding deposit distributions to exhibit significant skewness holds for retail deposits.[1] In our data, 10% of depositors (depositors with balances over $25,000 in 2023) control 70% of deposits. This skewness implies that the behavior of high-balance retail depositors will have strong predictive power for aggregate retail flows. Furthermore, attempts to learn about retail deposit dynamics from aggregate deposit flows will reveal the dynamics of the average *deposit* dollar but not necessarily the average individual *depositor*.

Second, we show that high-balance accounts generally become large after a single, sizable deposit.[2] Moreover, large accounts are more likely to be held by depositors that are joint account holders, white, older, and that have higher credit scores. Third, we find that while low-balance account balances are fairly stable over time, high-balance account balances decline over time. High-balance accounts also have a significantly higher substantial withdrawal hazard, being more likely to experience large drawdowns of the majority of their account balance.

Fourth, we find that these withdrawals out of high-balance retail accounts are largely idiosyncratic. Whether using raw interest rate changes or instrumenting with monetary policy shocks, we find high-balance account balances to be insensitive to contemporaneous interest-rate changes. Low-balance accounts, by contrast, are (somewhat) more sensitive; we estimate a semi-elasticity of deposit sizes with respect to a 100 basis point (bp) Federal Funds Rate increase of -0.09. We further confirm this differential interest-rate sensitivity using bunching around bank-specific interest-rate notches that increase deposit rates discontinuously at balance thresholds.[3] Low-balance retail accounts are more likely to bunch around a given size interest-rate notch than

[1] Call Report data similarly show substantial skewness in overall deposit balances. Only 1% of bank accounts hold balances exceeding the $250,000 FDIC insurance limit, yet these accounts comprise 57% of total deposits (Michel, 2023).

[2] We define large accounts as accounts with balances above $25,000, although our results are robust to alternative definitions.

[3] We use the term "bank" loosely throughout to refer to any depository institution.

high-balance retail accounts. Because there are many more small-balance accounts, this implies that the average *depositor* exhibits some elasticity to interest rates while the average retail deposit *dollar*, which is what matters for aggregate retail deposit stickiness, is wholly inelastic.

Finally, we explore several candidate explanations for the phenomenon of sticky retail deposits. Many traditional explanations for aggregate deposit stickiness operate across banks, e.g., market power (Drechsler, Savov, and Schnabl, 2017), search costs (Yankov, 2024), or bundled services (d'Avernas, Eisfeldt, Huang, Stanton, and Wallace, 2023). However, because large retail accounts are sticky even when conditioning on account fixed effects, any explanation that operate across banks or banking markets is insufficient. We are left with two remaining plausible explanations for the stickiness-size relationship. The first possibility is that high-balance households receive a bundle of services that low-balance depositors at the same institution do not enjoy. An alternative explanation is that high-balance retail depositors are sticky in large part because they value deposits for their liquidity as money per se more than as an interest-income generating asset. While both stickiness rationalizations may be true, additional evidence combined with the facts established above are uniquely consistent with households using high-balance deposits as a temporary liquidity holding bin.

A differentiated-services hypothesis implies that high-balance depositors derive greater utility from their current depository's services, keeping them from pursuing higher-yielding deposits elsewhere. We evaluate this possibility against the evidence from our bunching-at-interest-rate-notches analysis. If service thresholds coincide with thresholds at which interest rate jumps occur, high-balance depositors should bunch more aggressively at these thresholds to obtain the valuable service benefits. However, our non-parametric bunching tests show that high-balance depositors do not bunch at these thresholds, inconsistent with differentiated services. Of course, it is possible that service thresholds do not line up with interest-rate thresholds. In this case, differentiated services do not affect the analysis using interest rate jumps since services are constant across the thresholds, and thus services cannot explain the lack of bunching by high-balance depositors. Further, we empirically identify all products that may have other thresholds at which services increase and exclude these products from our analysis.[4] Our results are unchanged in this subsample, further confirming that differentiated services do not explain the sticky behavior of high-balance depositors.

The liquidity holding bin hypothesis suggests that the dynamics of high- and low-balance accounts should differ over time. Low-balance accounts should remain relatively stable, with balances that only gradually evolve after account opening. In contrast, high-balance accounts that act as liquidity holding pools should experience significant declines over time, as account holders draw down their balances idiosyncratically to meet lumpy liquidity needs. High-balance accounts being used as a staging ground for discrete needs for funds is consistent with the empirical fact that high-balance accounts are much more likely to completely draw down their account over a short period of time. While our data do not show how withdrawn funds are ultimately used, these large outflows are consistent with financing a major expenditure like a car purchase, educational expense, a downpayment on a home, or a significant investment. Moreover, high-balance accounts typically appear following large, one-time inflows rather than steadily accumulating over long periods, also consistent with temporary liquidity storage rather than systematic saving behavior.

Taken together, our findings suggest that the rate insensitivity of high-balance depositors reflects how these accounts are used rather than differences in within-institution services. Large depositors appear to use their accounts as temporary liquidity holding bins, wherein large dollar amounts are deposited and from which money is subsequently deployed in large amounts. Outflows from these retail accounts are not correlated with changes in market rates, making them idiosyncratically sticky and a substantial source of value for depository institutions (Egan, Lewellen, and Sunderam, 2022).

Contribution to the Literature

The granularity and breadth of our microdata allow us to provide new empirical facts on retail

[4]Because we cannot observe service thresholds in the data, to perform this exercise we look for products with observed extreme bunching behavior that is not associated with interest rate jumps and conservatively assume that this bunching is due to preferred services.

deposits that are novel to the banking literature. Notable prior work using deposit microdata includes Iyer and Puri (2012) and Iyer, Puri, and Ryan (2016), who use account-level data from a single Indian bank to understand depositors' information about bank failure risk. More recently, Adams, Hunt, Palmer, and Zaliauskas (2021) use account-level data from multiple banks to study switching behavior, de Roux and Limodio (2022) use account-level data from a Colombian bank to study bunching responses to deposit insurance, and Basten and Juelsrud (2023) use account-level data from Norway to study bank cross-selling. Our contribution is to provide the first large-scale, cross-institution evidence of several novel empirical facts about the dynamics of retail deposits. We document significant skewness in retail deposits within hundreds of unique institutions that is masked in aggregate data. Additionally, we provide novel evidence describing the accumulation and liquidation of accounts. Finally, we identify depositors whose balances exhibit near-zero elasticity with respect to deposit spreads and who are insensitive to interest-rate notches.

These empirical facts contribute to the development of a liquidity services hypothesis that provides a novel retail-oriented view on the subject of sticky deposits. Aggregate deposit stickiness has been linked to concentrated local deposit markets (Drechsler, Savov, and Schnabl, 2017), deposit insurance (Hanson, Shleifer, Stein, and Vishny, 2015), depositor inattention (Adams et al., 2021), search costs (Yankov, 2024), and cross-bank differences in services (d'Avernas et al., 2023). Our liquidity services explanation for the stickiness of large retail deposits can comfortably coexist with the aforementioned hypotheses explaining aggregate deposit stickiness via market-level frictions. The relevance of our proposed retail deposit mechanism to aggregate deposit dynamics depends on the composition of overall aggregate deposits. Data constraints prevent a precise decomposition of aggregate deposits, but household deposits likely represent close to 50% of aggregate deposits (Buksa, Pakhawala, Cope, and Ambigapathi, 2024). It is also possible that the same factors that drive large retail depositors to be insensitive to rate changes also drive corporate depositors to hold large amounts of liquidity in deposit accounts. However, given that large corporate depositors professionally manage working capital and treasury accounts, it is unlikely that large corporate accounts (which comprise a significant portion aggregate deposits) are sticky for the same reasons as the household accounts we study.

Our analysis contributes to a long-standing literature on cash and other safe assets as stores of value and media of exchange. Households value the liquidity and transactional services that cash provides (Sidrauski, 1967; Feenstra, 1986; Lucas and Stokey, 1987; Lucas, 2000; Lagos and Wright, 2005). See also Krishnamurthy and Vissing-Jorgensen (2012) and Nagel (2016) for evidence of the liquidity benefits of money and near-money assets. In a similar fashion, we show that some households are willing to accept lower yields on deposit accounts in exchange for their liquidity services.

We further contribute to recent work on how households manage liquidity. One emerging theme is that households hold liquidity even when it might not be financially optimal. Olafsson and Pagel (2018) document household liquidity cushions that are larger than theory would predict and not easily explained by financial constraints. Gathergood and Olafsson (2024) show that households cohold debt and cash savings (though at more modest rates than shown in Vihriälä, 2025). Our empirical evidence builds on these themes. We document saving and spending patterns suggesting that households manage liquidity reserves in anticipation of large transactions.

In contemporaneous work, Usenko (2025) studies the universe of deposits held at U.S. banks and shows that deposits over \$250,000 are responsive to monetary policy shocks. Given that deposits above \$250,000 are likely dominated by commercial accounts, it is not surprising that large, professionally managed commercial deposits are more responsive to monetary policy changes than moderately large household deposits.[5] See also Cirelli and Olafsson (2025), who use transaction-level data from a large Icelandic bank and find that while most households do not respond to interest rate spreads, wealthy households are substantially more responsive. One key difference in our settings is the lack of financial advisors or wealth management services tied directly to U.S. credit unions, whereas these services are more pronounced at the largest Icelandic banks.

A complementary set of contemporaneous papers highlights the role of depositor inattention in shaping retail deposit behavior. Egan, Hortaçsu, Kaplan, Sunderam, and Yao (2025) show that

[5]We also note that our findings are unchanged if we drop all household accounts with balances greater than \$250,000, which make up less than 1% of total accounts and about 14% of total deposits in our sample.

most depositors rarely shop for rates, allowing banks to sustain low interest rates on inactive or "sleepy" accounts, while Lu and Wu (2025) provide transaction-level evidence that more inattentive households adjust deposit balances less in response to monetary policy and that banks serving such depositors exhibit weaker pass-through and deposit flows. We show that these inattentive depositors are concentrated in high-balance accounts. Our findings are also related to Lu, Song, and Zeng (2025), who show that frictions in money transfers lead households to hold larger deposit balances, consistent with the transaction-cost economics that underlie our liquidity holding bin interpretation.

Conceptual Motivation

The liquidity services hypothesis we advance to explain heterogeneous deposit behavior borrows insights from the economics of household consumption and savings modeled in Kaplan and Violante (2014). In their model, tapping into illiquid wealth involves high transaction costs. As a result, even wealthy households can live "hand-to-mouth," exhibiting large marginal propensities to consume from transitory income shocks despite holding substantial illiquid wealth. In our context, liquidity holding bins are plausibly driven by the transaction costs—including effort and attention—associated with continuously moving liquid wealth to the highest yielding instruments. Rather than exerting the effort to move wealth to higher yielding accounts, large depositors keep money in liquidity bins in anticipation of making one-time, outsized consumption or investment decisions that involve high transaction and attention costs. Thus, while Kaplan and Violante (2014) feature high costs to liquidate illiquid investments, liquidity holding bins are governed by the high costs of placing money into illiquid investments or large but infrequent consumption decisions. This mechanism is also similar to the hypothesis in Andersen, Campbell, Nielsen, and Ramadorai (2020), where consumers are slow to refinance mortgages despite clear monetary benefits because major financial decisions involve high fixed costs. In a similar way, moving large deposits of cash may only occur when the return on switching exceeds the fixed costs of reoptimization.

While large transaction or cognitive costs à la Kaplan and Violante (2014) or Andersen et al.

(2020) can rationalize sticky deposits for high-balance households, they likely do not fully explain why depositors fail to move money into higher yielding products *within* the same institution. Such behavior likely reflects inattention, rational or otherwise, consistent with the depositor inattention documented in Adams et al. (2021) and mortgagor inattention documented in Byrne, Devine, King, McCarthy, and Palmer (2023).

Importantly, not all existing household finance models deliver the prediction that high-balance accounts will be less sensitive to interest rates. For example, if high-balance households are on average more financially sophisticated (Lusardi and Mitchell, 2014), one might expect high-balance depositors to be *more* sensitive to rate changes, given that financial sophistication affects consumer saving and mortgage decisions (Jørring, 2024; Fuster, Gianinazzi, Hackethal, Schnorpfeil, and Weber, 2025). However, financial sophistication is not the only trait that differs across households. Because prior literature documents wide variation in rationality, financial sophistication, and behavioral biases, identifying the reason retail deposit stickiness varies with account balances is ultimately an empirical question we address using novel, disaggregated deposit data.

2 Demand Deposit Account Data

We use a large sample of more than 12 million demand deposit (i.e., checking and savings) accounts to examine retail deposit behavior in the United States between 2011 and 2023. The account data are sourced from 154 financial institutions, almost entirely credit unions, and are provided to us by a technology firm specializing in administrative data warehousing and analytics services for retail-oriented lenders. More than 133 million people in the U.S. are credit union members, and credit unions hold about 10% of total U.S. retail deposits (NAFCU, 2022). As shown in Appendix Table A1, the scope of the data has expanded over time as the technology firm broadened its client base. In 2011, the data were sourced from fewer than 10 financial institutions. By the end of our sample in 2023, the data included 92 financial institutions. During this period, the size of the financial institutions in our data also increased. The average number of accounts per institution rose from approximately 20,000 to nearly 50,000, while the average total retail demand deposit balance per institution grew from $111 million to $600 million.

For each financial institution in our data, we have monthly data on every deposit account held at that institution, totaling about 12.1 million accounts.[6] Financial institutions in our sample offer a large variety of different types of checking and savings accounts—the average number of deposit products has increased over time from 10 products in 2014 to 43 different products in 2023 at a given institution. These accounts frequently have different balance requirements, fees, and interest rates. For each account-month, we observe the associated balance and interest rate, whether the account is jointly owned, address (aggregated to the census tract level), age, gender, and, for a subset of depositors, credit scores.

To evaluate the representativeness of our credit union sample, we present three plots in Figure 1. Panel (a) plots the distribution of asset size for all banks and credit unions on a log scale, using call report data from the Federal Reserve and the National Credit Union Association (NCUA), respectively. While credit unions are small relative to the largest U.S. commercial banks, the overlap in asset size is reasonably large. In Panel (b) we plot the size distribution of credit unions in our sample against the full distribution of credit unions from Panel (a), revealing that our sample is comprised entirely of above-median sized credit unions. Panel (c) plots our sample's size distribution against the full distribution of bank size from Panel (a). The considerable overlap indicates that our sample, in terms of asset size, is representative of a large swath of banks (by count) in the U.S.

While the credit unions in our sample are similar in size to the distribution of commercial banks, credit unions differ from banks more substantially in the composition of deposits between retail and business accounts. Aggregate NCUA data indicate that fewer than 5% of deposits at credit unions are business accounts. In contrast, calculations from FDIC disclosures reveal that business accounts at banks make up about 50.4% of total non-CD deposits.[7] Based on account

[6]We exclude all accounts with balances below $50 or in excess of $1,000,000.

[7]Banks above $1 billion in assets are required to break out deposit products "intended primarily for individuals for personal, household, or family use" on the Call Reports. We calculate this estimate using Call Report data from September 30, 2024 for the full set of banks with more than $1 billion in assets.

features and types, we exclude all business/commercial accounts from our sample. We exclude business accounts because they constitute only a small portion of total deposits at credit unions and the dynamics that determine business deposits may vary substantially from those of households. Removing business accounts allows us to focus on forces that affect household deposit behavior.[8]

The accounts in our data are held by individuals residing in 35,160 different zip codes (i.e., more than 80% of all zip codes) in all 50 states. The data provider also calculates an imputed measure of race. For the 16% of accounts that are jointly owned, we attribute the demographic characteristics of the account to the account holder with the highest credit score. Table 1 shows the distribution of depositor characteristics in our institution-account-month panel. Approximately half of the depositors are male, with an average age of 51.5 years and an interquartile range from 37 to 67 years. This closely aligns with the age distribution of the U.S. population aged 18 and older, based on 2020–2023 U.S. Census estimates. However, the racial diversity in our sample is somewhat lower than that of the overall U.S. population. White depositors constitute 79% of our sample, compared to 74% in the 2022 ACS Census 5-year estimate. Additionally, our depositors have modestly higher credit scores, with an average score of 737, compared to the national average of 715.[9] Despite these differences, our overall sample appears to be broadly representative of the U.S. adult population.

2.1 Documenting Deposit Skewness

Most accounts in our data are relatively small (see Table 1). The average balance in a demand deposit account is $11,115, while the median balance is only $1,185. These accounts pay very low interest rates; the average rate from 2011 to 2023 is about 10 basis points, which had only increased to 16 basis points by 2023. Despite earning low interest rates, the average account grows

[8]Since business accounts in our data are small, including them in our analysis has very little effect on our estimates.

[9]As reported by Experian, see https://www.experian.com/blogs/ask-experian/what-is-the-average-credit-score-in-the-u-s/.

by about 1% per month, suggesting that depositors steadily save.[10] However, Appendix Table A2 reveals that there is a noticeable jump in account balances post-COVID. The average account balance increased from $7,644 pre-2020 to $13,955 post-2020—an increase of more than 80%. This increase in balances does not appear to be driven by changes in depositor demographics, which have remained relatively stable over time, but instead likely reflects changes in saving behavior as a result of the COVID-19 pandemic.[11]

A striking feature of financial institutions' total demand deposit exposure is its pronounced skewness. In 2023, 4% of accounts held 50% of all demand deposits, and 26% of accounts held 90% of deposits. Table 2 shows that this skewness has remained relatively stable over time; the percentage of accounts holding 50% of total demand deposits has fluctuated between 3% and 4%. Only 10% of retail accounts in our data have balances above $25,000 in 2023, yet these accounts hold 70% of total deposits. Although less than 1% of retail demand deposit accounts in our sample exceed the deposit insurance limit of $250,000, these accounts hold 14% of total balances. Over the last three years, there has been an increase in both the fraction of accounts with high balances and the proportion of deposits held in these accounts, making these accounts even more important to financial institutions. Table 3 presents summary statistics by account size. Not surprisingly, larger accounts are more likely to be jointly owned, with 20% of accounts above $250,000 jointly owned compared to only 14% of accounts with balances below $200. Additionally, higher balance accounts tend to be owned by older, less racially diverse depositors with higher credit scores. In Section 4.2 we explore how the elasticity of deposits to interest rates varies based on account size.

2.2 Patterns of Accumulation and Liquidation in Retail Deposits

The pronounced skewness in retail deposits raises questions about deposit dynamics. How do large retail accounts arise? One possibility is that substantial balances accumulate gradually as the result of disciplined saving. Alternatively, balances may increase abruptly when liquidity

[10] This growth is primarily driven by deposits into accounts with balances under $1,000.

[11] A similar spike occurred at commercial banks; see https://www.federalreserve.gov/econres/notes/feds-notes/understanding-bank-deposit-growth-during-the-covid-19-pandemic-20220603.html.

is realized, such as following an inheritance, a salary bonus, the liquidation of an investment, or the reallocation of funds across accounts. To evaluate deposit dynamics, we designate low-balance accounts as those with balances that never exceed $25,000 during our sample period, and high-balance accounts are those that at any point exceed this threshold.[12] We then analyze both the origins of high-balance accounts and the evolution of their balances through time. Figure 2 illustrates the buildup of high-balance accounts. For all accounts that ever exceed $25,000, we normalize account balances at the first month they cross $25,000 and plot balances over the preceding 48 months. Balances remain low until a sharp, recent inflow push them to exceed a normalized amount that exceeds at least $25,000. The plot indicates that roughly 80% of the large balance amount is deposited in one month. Unfortunately our data are silent on the source(s) of these funds.

We next analyze the likelihood of experiencing a material drawdown over the course of a single month. Table 4 summarizes drawdown frequencies. Among low-balance accounts, 28% experience a 75% drawdown at some point during our sample. In comparison, 33% of high-balance accounts experience a drawdown of this magnitude, and the 5 p.p. difference is statistically significant. This divergence becomes even more pronounced for more extreme drawdowns. Only 5% of low-balance accounts ever experience a 95% drawdown, whereas high-balance accounts are more than three times as likely (16%) to experience such a severe balance reduction.

Figure 3 evaluates drawdown behavior through a different lens. The solid circles plot average normalized account balances for low-balance accounts. Each account in the below $25,000 sample is normalized by the balance of the first observation for that account. Average normalized amounts are then plotted over the next 48 months. The hollow triangles follow the same procedure for high-balance accounts. These balances are normalized relative to the balance when the account first becomes a high-balance account, i.e., when the balance first goes above $25,000. The low-balance plot indicates that, on average, low-balance accounts remain relatively constant over a long time horizon, consistent with ongoing inflow-outflow cycles around a steady level.

[12]This categorization differs slightly from that used later in Section 4.2, where accounts are categorized by whether the balance held in each given month exceeds $25,000, rather than if the account ever exceeds $25,000.

By contrast, average normalized balances for high-balance accounts decline through time, bottoming out at close to 50% of their initial balance on average. As shown in Table 4, high-balance depositors are more likely to withdraw nearly all of their funds idiosyncratically, which would result in the average gradually declining as seen in Figure 3. The decline shown in the figure is also likely due to some high-balance depositors withdrawing a significant portion (but less than 75% or 95%) of their funds.

3 Identifying the Elasticity of Deposits to Spreads

The abrupt nature and magnitude of flows in and out of retail deposits raise the possibility that retail deposit dynamics are idiosyncratic as opposed to driven by systematic movements in markets. Rates rarely move in such magnitude and velocity to be the catalyst for the timing of outsized deposit reallocations observed in the data. Thus, while retail deposits are not necessarily sticky in absolute terms, by virtue of the fact that considerable withdrawals frequently occur, large deposits are likely sticky with respect to market rates. The idiosyncratic withdrawal of deposits is the source of their strategic value to depository institutions.

To more thoroughly explore the nature of deposit dynamics, particularly with respect to movements in rates, we formally estimate account-level elasticities using regressions of the following form:

$$\ln \text{Deposits}_{ijt} = \beta \, \text{Deposit Spread}_{ijt} + \alpha_{q(t)} + \gamma_i + \varepsilon_{ijt} \tag{1}$$

for account i at financial institution j in month t. We define the *Deposit Spread* as the difference between the monthly yield on the 2-year constant maturity U.S. Treasury and the monthly interest rate earned on deposits in account i at financial institution j.[13] This spread, measured in percentage points, reflects the opportunity cost of leaving money in a deposit account. We include year-quarter fixed effects ($\alpha_{q(t)}$) to account for general economic trends that might affect both spreads and deposit balances, and we include account fixed effects (γ_i) to absorb any fixed

[13]Monthly Treasury yields are obtained from FRED series GS2.

account, individual, or institution characteristics that influence deposit behavior. Conditioning on account-level fixed effects focuses our estimation within a given household, exploiting variation in how balances change with respect to deposit spreads for a given account. We find similar results when using bank fixed effects instead.

The coefficient β in Equation (1) represents the semi-elasticity of deposit balances to deposit spreads. We first estimate this relationship in a simple OLS regression for the full sample of deposits and report results in Column 1 of Table 5. The estimate indicates that a 1 p.p. increase in deposit spreads is associated with a 3.6% reduction in deposits. Interpreting this elasticity as causal, however, is complicated by the fact that changes in interest rates are not random. In particular, interest rates fluctuate in response to changes in broader economic conditions. Consequently, any observed shifts in deposit behavior may be driven by reactions to these underlying economic shocks rather than changes in interest rates themselves.

We address this challenge by using surprise changes in the federal funds rate as an instrument for changes in deposit spreads. A large literature uses 30-day Fed Funds futures contracts to measure surprise changes in interest rates (see, e.g., Kuttner, 2001; Gürkaynak, Sack, and Swanson, 2005; Gertler and Karadi, 2015; Gorodnichenko and Weber, 2016; Nakamura and Steinsson, 2018; Bauer and Swanson, 2023; Indarte, 2023). These contracts are traded on the Chicago Mercantile Exchange and are cash settled based on the average of the effective federal funds rate over the contract period. Following Indarte (2023), we calculate the surprise component of rate changes announced by the Federal Open Market Committee (FOMC) as

$$\text{FF Surprise}_t = \frac{M}{M-d}(f_t - f_{t-1}), \tag{2}$$

where f_t is the Fed Funds futures rate at the end of the day t on which the announcement occurs, f_{t-1} is the rate the day before, M is the number of days in the contract month, d is the day of the month on which the announcement occurs, and the $M/(M-d)$ term adjusts for the fact that Fed Funds futures settle based on the average federal funds rate over the month.[14]

[14] The futures rate is defined by the contract price, which is equal to 100 minus the implied average rate. We

Because our analysis is conducted at the monthly-level, we transform *FF Surprise* into a monthly variable. Most months in our sample either have zero or one FOMC announcement.[15] For months with no announcements, *FF Surprise* is equal to zero. For months with a single announcement, *FF Surprise* is computed as in Equation (2). In the rare cases where the FOMC committee announces multiple interest rate changes in a single month (e.g., during the COVID-19 pandemic), we sum all of the individual surprises occurring within that month.

Using surprises in the federal funds rate as an instrument, we estimate the following first stage regression

$$\text{Deposit Spread}_{ijt} = \pi \text{ FF Surprise}_t + \delta_{q(t)} + \eta_i + v_{ijt}. \tag{3}$$

This instrument satisfies the relevance condition for identification given that changes in the federal funds rate are rapidly reflected in market bond yields and subsequently in deposit spreads. Given the inclusion of fixed effects, we identify the impact based on within-quarter variation in federal funds rate surprises. We then use the predicted deposit spread from Equation (3) to estimate Equation (1) by 2SLS.

For β in Equation (1) to identify the sensitivity of deposits to spreads after instrumenting, the key assumption is that surprise movements in Fed Funds future prices during the 24-hour window around FOMC announcements are uncorrelated with any changes in the underlying state of the economy that directly influence deposit behavior. Conceptually, the intuition behind this exclusion restriction is that futures prices reflect investors' understanding of the current economic environment in the hours before the FOMC announcement and that the announcement itself primarily conveys new information about shifts in monetary policy rather than other economic developments. The fact that FOMC announcements are scheduled to avoid overlapping with releases of major economic indicators supports this assumption. Using this 2SLS approach alleviates concerns that our estimates of the elasticity of deposits to interest rates are confounded by simultaneous changes in economic fundamentals.

obtain Fed Funds futures prices from Bloomberg.

[15] There are 8 regularly scheduled FOMC meetings per year.

In addition to 2SLS, we use discontinuous interest rate changes within accounts to non-parametrically identify differences in rate sensitivity across high- and low-balance accounts. These estimates are discussed in Section 5 and provide corroborating evidence to the OLS and 2SLS estimates we present in Section 4.

4 Heterogeneity in Deposit Elasticities by Balance Size

A long literature in banking has shown that deposit flows adjust slowly to interest rate changes (Flannery, 1982; Flannery and James, 1984; Hutchison and Pennacchi, 1996; Drechsler, Savov, and Schnabl, 2017; Adams et al., 2021). Motivated by the skewness in deposits documented in Section 2.1 and the dynamics of deposit flows in Section 2.2, we investigate how the sensitivity of deposit balances to interest rates varies with the size of the account. We use the 2SLS methodology described above to estimate the elasticity of deposit balances to interest rates.

4.1 First-Stage Estimates

Table 6 presents results from estimating the first-stage regression of deposit spreads on surprise movements in the federal funds rate as specified in Equation (3). We find that surprise changes in interest rates positively predict deposit spreads, regardless of the set of fixed effects that we include. Focusing on the most stringent specification, which includes both quarter and account fixed effects, we find that a 100 basis point unanticipated increase in the federal funds rate leads to a 2.23 basis point rise in deposit spreads (see Column 4). This is somewhat smaller than the 10 to 14 basis point increase reported by Drechsler, Savov, and Schnabl (2017) for commercial banks located in high-concentration counties. However, since our sample primarily consists of credit unions, which are smaller, less sophisticated, and operate as not-for-profit organizations, a larger pass-through rate (i.e., smaller increase in spreads) is less surprising.

The widening of deposit spreads in response to rising interest rates suggests that deposit rates are sticky, a phenomenon supported by substantial evidence (Hannan and Berger, 1991; Neumark and Sharpe, 1992; Driscoll and Judson, 2013; Usenko, 2025). This stickiness plays an important role in monetary policy pass-through (Drechsler, Savov, and Schnabl, 2017; Wang, Whited, Wu, and Xiao, 2022), and drives a substantial portion of bank value (Egan, Lewellen, and Sunderam, 2022). Thus, understanding how retail deposit balances adjust to changes in spreads is important for policy decisions, the overall stability of the financial industry, and our understanding of how households manage liquidity.

4.2 Second-Stage Estimates of Deposit Elasticities

Using surprise movements in the federal funds rate as an instrument for deposit spreads, we estimate the relationship between spreads and deposit balances as specified in Equations (1) and (3). By including account fixed effects, the elasticity is identified from balance changes within an individual's specific checking or savings account. The time fixed effects further restrict the comparison to balance changes within the same year-quarter and control for broader economic conditions and trends. Table 5 reports the results. The estimate in Column (4) indicates that a 1 p.p. exogenous increase in deposit spreads leads to a 9.0% decrease in deposit balances. It is important to note that this semi-elasticity of -9.0 is measured at the account level on an equally-weighted basis, and is therefore not directly comparable to the semi-elasticity of -5.3 reported by Drechsler, Savov, and Schnabl (2017), who measure the elasticity of deposits at the bank branch level using commercial bank data. The difference in estimates could be partially due to different samples. However, at the account level, our data is dominated by accounts holding small-dollar balances, while branch-level data gives more weight to depositors with higher balances in their accounts. The 2SLS estimate of -9.0% also exceeds the full-sample OLS estimate of -3.6% reported in Column (1), indicating a potential bias towards zero in the endogenous elasticity estimates.

To directly test for heterogeneity in deposit stickiness, we partition our sample into low- and high-balance accounts. We define low-balance accounts as those with balances below $25,000, comprising about 90% of all demand deposit accounts (see Table 2).[16] In contrast, high-balance

[16]Our results are qualitatively insensitive to the definition of this partition between high- and low-balance ac-

accounts, with balances above $25,000, comprise only 10% of all accounts but hold about 70% of total demand deposits. We re-estimate Equations (1) and (3) by 2SLS for these subsamples and report the results in Columns (5) and (6) of Table 5. We find that the negative elasticity between deposit balances and spreads is driven entirely by accounts with low balances. For these accounts, the semi-elasticity is nearly the same as the full sample, −9.0. In contrast, the estimated elasticity for high-balance accounts is small and statistically insignificant (-0.005). We report OLS estimates of the sample split in Columns (2) and (3). Consistent with the 2SLS results, the elasticity response is concentrated entirely in the low-balance sample. Estimates in Column (7) of Table 5 confirm that the differences between high-balance and low-balance accounts is statistically significant.

These results show that the average deposit *account* is much less sticky than the average deposit *dollar*. For the majority of accounts in our sample, deposit balances are somewhat sensitive to changes in spreads. However, since most deposit dollars are held in large accounts, the average deposit dollar is very sticky and does not move when interest rates fluctuate.

5 Nonparametric Evidence of Heterogeneity in Stickiness

Many financial institutions set balance thresholds at which interest rates paid on the entire account balance increase sharply. Such discontinuities occur in 5% of products in our sample.[17] For example, one institution in our dataset offers a savings product that pays 25 basis points more once balances reach $10,000. A depositor holding $9,999 in one account and at least $1 in another at the same institution could move $1 into the larger account to earn the higher interest rate on the entire $10,000 balance. Figure 4 illustrates interest-rate discontinuities in a City of Boston Credit Union advertisement from December 2024.[18]

These interest-rate discontinuities provide sharp incentives for depositors to adjust their balances to exceed the interest rate cutoff, leading to bunching just above the threshold. However,

counts, including defining it at $50,000 or $100,000.

[17]We only include thresholds where interest rates increase and drop the rare cases where they decrease.

[18]Balances totaling at least $20,000 are offered 30 bp yields as compared to the 15 bp yield for accounts with $1,000. Rates jump to 50 bp at $50,000 and 100 bp at $100,000.

because round-number heuristics are common in household finance (e.g., Argyle, Nadauld, and Palmer, 2020; Cortés, Singh, Solomon, and Strahan, 2023; Sakaguchi, Gathergood, and Stewart, 2024), depositors might target balances at salient levels (e.g., $1,000 or $5,000) even absent a rate jump. To isolate rate-induced bunching, we compare bunching at thresholds with discontinuities to counterfactual bunching at the same thresholds in products without interest-rate discontinuities. The difference identifies excess bunching attributable solely to changes in offered interest rates.

We begin by counting the number of account-months with balances within $100 of common thresholds ($1,000, $5,000, $10,000, $25,000, and $50,000) for products with and without interest-rate discontinuities at these thresholds. For each threshold, we calculate the fraction of accounts in these windows that fall above vs. below the threshold and plot the results in Figure 5. Solid bars represent products with an interest rate break at the threshold, while dashed bars represent products without such breaks. Figure 5 reveals clear evidence of deposit bunching at round numbers, even for products without interest-rate discontinuities. For these products (dashed bars), there are approximately four times more accounts just above the threshold than just below it, consistent with round-number targeting.

However, this bunching is even more pronounced for accounts at institutions with interest rate breaks (solid bars), especially at lower thresholds such as $1,000 or $5,000. The difference between the solid and dashed bars to the right of the threshold in Figure 5 represents "excess bunching" caused by interest rate breaks. A different way of visualizing this excess bunching is shown in Figure 6. Each panel shows a scatter plot of the number of account-months in $2 increments within the $100 window surrounding a threshold. Orange triangles (with breaks) exhibit visibly larger jumps just above thresholds than green dots (without breaks), consistent with rate-induced excess bunching.

To formally test the statistical significance of the excess bunching depicted in Figures 5 and 6, we construct a bunching estimator similar to Collier, Ellis, and Keys (2021). For each threshold $j \in$ {$1,000, $5,000, $10,000, $25,000, $50,000}, we restrict the data to account-months with balances within ±$100 of j and, for each month t, compute the share of accounts above the threshold separately for products with and without a break.[19] This yields, for each month-threshold pair, two observations: the fraction of accounts above the threshold for products with a break, and the same for products without a break. We then estimate

$$\text{Fraction Above Threshold}_{jt} = \beta\,\text{Has Break}_{jt} + \delta_t + \varepsilon_{jt}, \tag{4}$$

where $\textit{Has Break}_{jt}$ indicates products with a rate break at j during month t. The month fixed effects δ_t absorb time-varying factors, such as macroeconomic trends, that may affect bunching behavior. We cluster standard errors at the month level. The coefficient β captures excess bunching due to the interest rate discontinuities.

We estimate Equation (4) separately for each threshold and report the results in Table 7. At lower thresholds, excess bunching is economically large and statistically significant. At the $1,000 threshold, Column (1) shows that there are 11% more accounts just above the threshold when an interest rate break is present. Similarly, excess bunching is 8.5% at $5,000, 5% at $10,000, and 4.4% at $25,000 (see Columns 2 through 4).

These findings align with the elasticity estimates in Table 5 and suggest that depositors with lower balances pay attention to interest rates and adjust their account balances accordingly. In contrast, higher thresholds do not exhibit excess bunching, despite evidence in Appendix Figure A1 that the return on bunching would be greater at higher balance thresholds. Column (5) of Table 7 reveals that for the $50,000 threshold, excess bunching is statistically insignificant and small (and even slightly negative). Moreover, excess bunching monotonically decreases as thresholds increase. Consequently, the bunching estimates confirm the conclusions from our earlier elasticity estimates—high-balance depositors are insensitive to interest rate changes.

[19] Unlike many settings where the baseline rate of bunching must be estimated, we directly observe it through accounts in products without interest rate breaks.

6 Explanations for Deposit Stickiness

Why are deposits in high-balance accounts essentially wholly insensitive to deposit spreads, while those in low-balance accounts are not? The literature suggests several explanations for aggregate deposit stickiness: bank market power (Drechsler, Savov, and Schnabl, 2021), deposit insurance (Hanson et al., 2015), high search costs (Duffie and Krishnamurthy, 2016; Yankov, 2024), inattention to interest rates (Kahn, Pennacchi, and Sopranzetti, 1999), and pessimistic beliefs about both the benefits and hassle of switching banks (Adams et al., 2021). While these factors have been shown to contribute to aggregate deposit stickiness, they do not, by themselves, account for the depositor-level heterogeneity we document in retail accounts.

Our analysis leverages within-account balance changes to estimate deposit elasticities.[20] The results in Table 5 show not only that high-balance depositors are on average insensitive to deposit spreads but furthermore that the average depositor is insensitive when her balance is high and more sensitive when its low. Accordingly, factors that do not vary within accounts, such as bank market power or search costs, cannot explain our findings. Further, we observe substantial variation in deposit stickiness within a range of insured balances, which is inconsistent with deposit insurance-based explanations. Finally, Adams et al. (2021) conclude that pessimistic beliefs about switching are not specific to a particular type of depositor, which makes these explanations unlikely to explain heterogeneity across balance size.

Could our empirical results be explained by high-balance depositors having higher utility from services than low-balance depositors? For example, high-balance depositors could receive concierge attention, estate planning, preferential loan terms, or reduced fees, any of which might discourage reallocation even when higher rates are available elsewhere. For services to explain our within-institution heterogeneity, two conditions must hold: (i) the relevant services (d'Avernas et al., 2023; Zhang, Muir, and Kundu, 2024) must be institution-specific; otherwise, a high-balance depositor would be indifferent between institutions and would presumably still

[20] Our baseline includes depositor account-level fixed effects; the results are robust to using bank-level fixed effects instead.

be sensitive to interest rates, and (ii) the utility derived from such services must increase with balance levels. Such utility could come from services and service quality increasing with account balances or simply from high-balance depositors valuing the same services more. If high-balance and low-balance depositors derive similar utility from services, the services mechanism would not generate rate insensitivity for high-balance and not low-balance depositors.

We evaluate two pieces of evidence that suggest that our results are not driven by a within-institution services explanation. First, we consider the possibility that credit unions not only increase interest rates at certain thresholds but that they also increase services at those same thresholds. If this is the case, the services hypothesis would not predict the decline in excess bunching at higher thresholds that we observe (see Section 5).

While it is plausible that institutions increase service-quality at the same balance thresholds where interest rates jump, it is also possible that service quality shifts at other thresholds (e.g., free wire transfers or reduced fees at $25,000 while rate tiers shift at $30,000). To analyze this possibility, we take steps to exclude accounts that potentially benefit from bank services at alternative thresholds and test if this affects our main results.

Because we do not directly observe service thresholds, we implement an indirect approach to identify products that may feature discontinuous increases in service quality. We assume that any such thresholds are most likely to occur at large, salient round numbers. For each potential threshold between $30,000 and $50,000, in $5,000 increments, we calculate the degree of bunching for each institution–product pair.[21] We then classify products in the top quartile of bunching at a given threshold as potential "high-service" products, assuming the high bunching is due to an unobservable change in services.

To illustrate, suppose we observe substantial bunching at $35,000 in Credit Union X's checking accounts, relative to bunching at the same threshold in other products both within Credit Union X and for products at other institutions. In this case, we infer that this excess bunching could be due to a discontinuous increase in service quality at $35,000 for that particular type of checking

[21] In a robustness exercise, we extend this range to $20,000–$50,000 in $1,000 increments and find similar results.

account. While this procedure may misclassify some products as "high-service," it should capture most accounts that genuinely offer balance-dependent services.

To assess whether differentiated services drive our results, we exclude all deposit accounts associated with these "high-service" products and then re-estimate our elasticity regressions in Equation (1) by 2SLS. By dropping these "high-service" accounts from the sample, we should drop out high-balance depositors who are insensitive to rate changes due to the higher services they obtain for holding high balances. In our example, this would be dropping all deposit observations of Credit Union X's checking accounts. Figure 7 shows that removing these accounts has essentially no effect on our estimated elasticities—our estimates remain identical for low-balance accounts and economically and statistically indistinguishable from zero for high-balance accounts. Taken together, this evidence indicates that differentiated bank services are unlikely to be the primary source of interest-rate insensitivity among high-balance accounts.

Liquidity Holding Bins

We propose a new mechanism to explain differences in interest-rate sensitivities: high-balance accounts primarily function as liquidity holding bins rather than long-term savings vehicles. Funds are temporarily parked for imminent expenditures or redeployment into other assets (e.g., tuition, downpayments, or investments). Because these balances have a designated, short-run idiosyncratic purpose, they are less responsive to interest-rate changes.

The patterns documented in Section 2.2 are consistent with a liquidity hypothesis given the distinct predictions a liquidity explanation would have for balance dynamics. Unlike long-term savings accounts, liquidity bins are unlikely to accumulate gradually over time. Instead, liquidity-driven balances should spike when liquidity is realized (e.g., following an inheritance, salary bonus, liquidation of an investment, or transfer of funds). The balance will then exhibit a sudden and near-complete drawdown when the funds are redeployed to another use. In contrast, balances in low-balance accounts, which are not used as liquidity holding bins, evolve more smoothly over time.

Figures 2 and 3, together with Table 4, indicate that high-balance retail deposits exhibit patterns consistent with the predictions of a liquidity hypothesis. On average, large deposits are not built up slowly over time. Rather, large depositors place a windfall of cash in deposit accounts in anticipation of redeploying a large fraction of the money in the subsequent months. The funds are then drawn down abruptly when liquidity needs arise. These dynamics suggest that high-balance accounts are insensitive to interest rate movements because they function as temporary holding bins for idiosyncratic liquidity needs. This explanation is consistent with a long-standing literature uncovering the value of cash as a liquidity provision (Sidrauski, 1967; Feenstra, 1986; Lucas and Stokey, 1987; Lucas, 2000; Lagos and Wright, 2005). The results are also compatible with Krishnamurthy and Vissing-Jorgensen (2012) and Nagel (2016) who estimate premiums investors are willing to pay for the liquidity benefits of money and near-money assets. In a similar fashion, households appear willing to accept lower yields on deposit accounts in exchange for their liquidity services.

7 Conclusion

This paper documents new facts about the dynamics of retail deposit balances using novel, disaggregated data on millions of depositors across many institutions. The pronounced skewness in retail deposits we uncover implies that the dynamics governing the average dollar of retail deposits is a function of a small subset of households. Further analysis reveals that these relatively few large accounts move with idiosyncratic lumpiness in and out of having large balances. We formally estimate the semi-elasticity of retail deposits in OLS and 2SLS regressions, finding that larger accounts are on average completely insensitive to movements in rates. We confirm these patterns in non-parametric bunching estimates. The largest deposits are insensitive to products offering higher rates even *within* the same institution.

Subsequent analysis investigates two possible explanations for retail deposit stickiness; a within-institution preference for services and an alternative liquidity services explanation. Several empirical facts appear more consistent with retail deposit stickiness being driven by households' preferences for the liquidity services deposits provide.

The fact that high-balance deposit accounts drive retail deposit stickiness could have implications for bank stability and monetary policy, since household deposits make up around half of aggregate deposits. Our results suggest that the deposits channel of monetary policy (Drechsler, Savov, and Schnabl, 2017) likely operates most strongly through low-balance retail accounts, which may have higher marginal propensities to consume and enabling these account holders to more easily benefit from higher interest rates when monetary policy is tightened. Moreover, our findings suggest that banks with a higher concentration of deposits from low-balance accounts would be more likely to experience outflows when interest rates go up, which could further incentivize banks to tilt their branch locations towards wealthier areas. Understanding this behavior is important for developing strategies that enhance the resiliency of banks to interest-rate shocks.

Lastly, the deposit behavior we document could aid policymakers who are concerned with regulating both the banking market and setting monetary policy. For example, when evaluating the benefits of a banking merger, antitrust law might consider not only the concentration of a local banking market but also the types of consumers each bank serves. Similarly, policymakers considering incentivizing the creation of accounts that cater to low-balance depositors could take into account that these households do exhibit some responsiveness to interest rates and a willingness to seek higher interest income.

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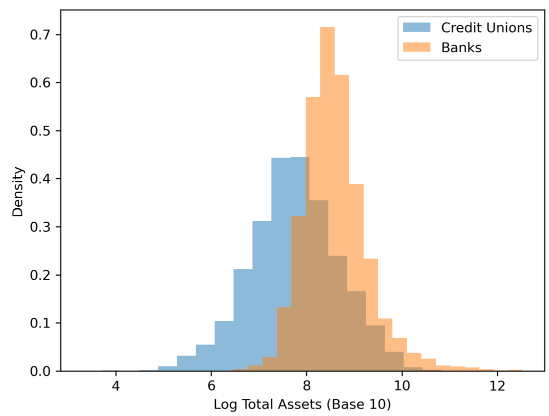
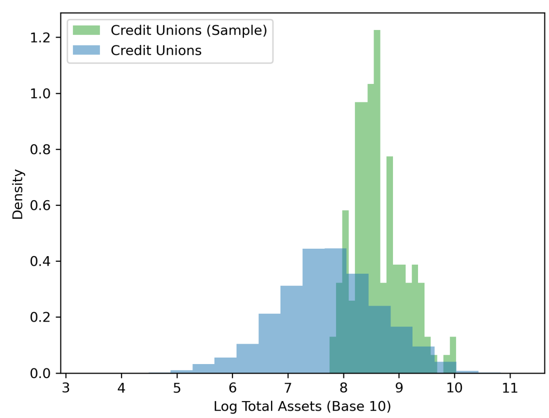
Figure 1. Assets for Credit Unions and Banks in the USA

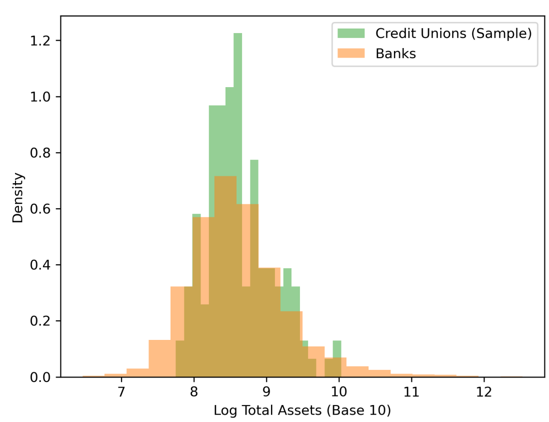
(a) NCUA Credit Unions vs Banks



(b) NCUA Credit Unions vs Data Sample

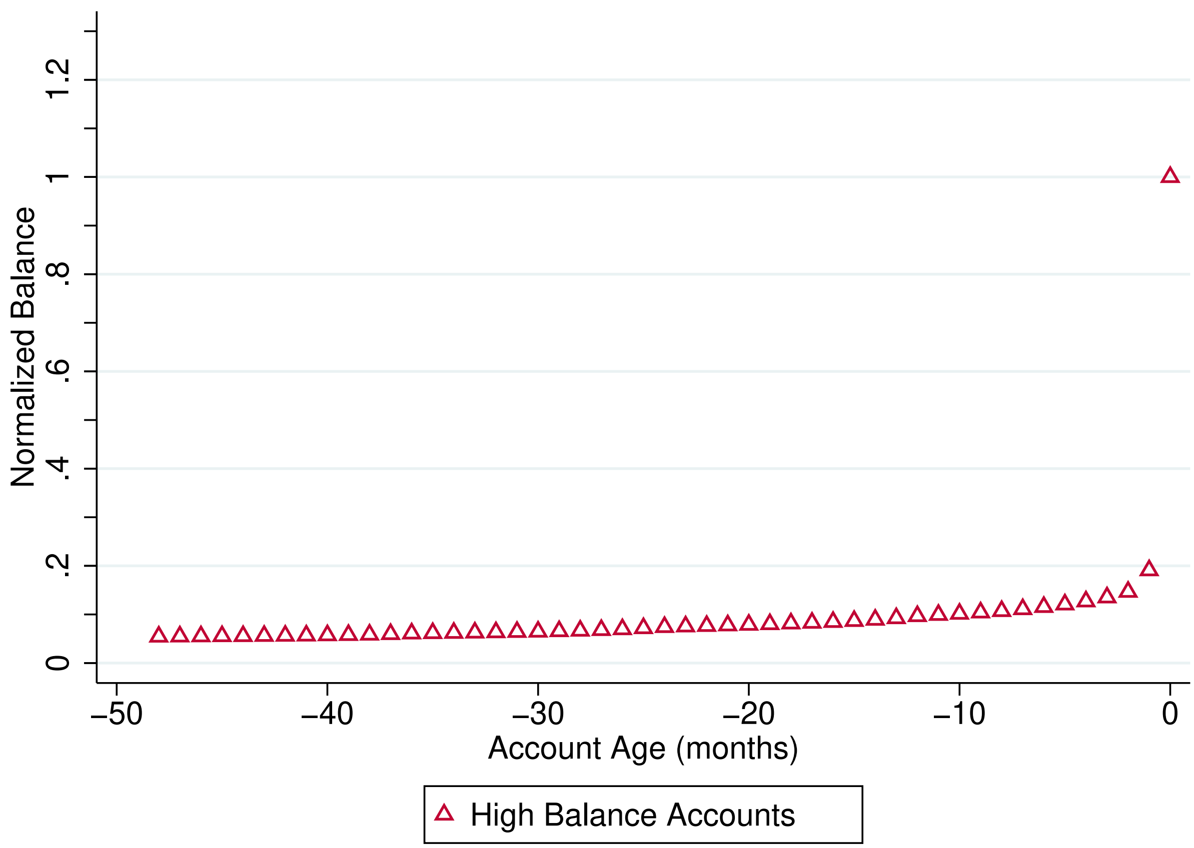


(c) Data Sample vs Banks



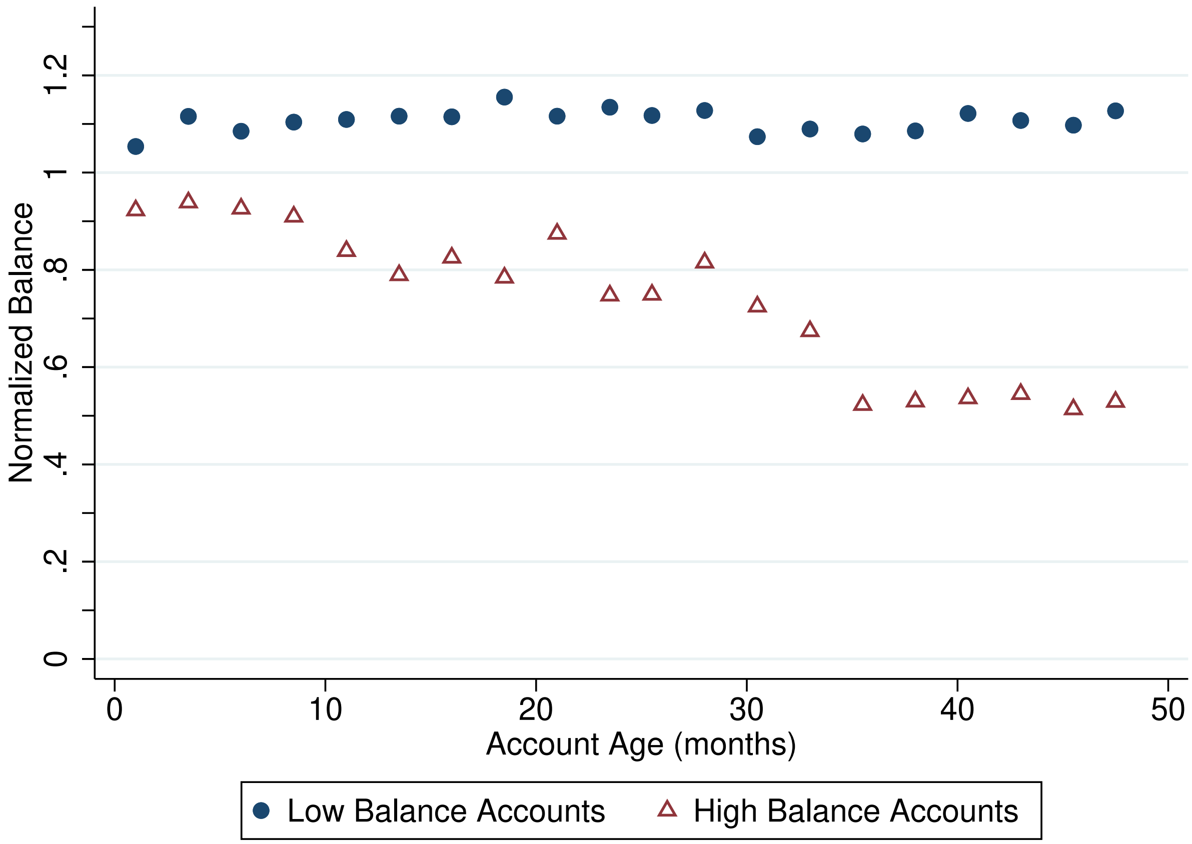
Notes: This figure shows the histogram of assets for all credit unions (blue) and commercial banks (orange) in panel (a), for all credit unions (blue) and our data sample (green) in panel (b), and for our data sample (green) and all banks (orange) in panel (c). The underlying data is sourced from the FFIEC and NCUA Call Reports as of September 2023.

Figure 2. Genesis of a High-Balance Account



Notes: This figure shows the average formation of a high-balance account. For every high-balance account, we look at the normalized balance relative to the first month that the account was deemed "high-balance," i.e., balance $\geq$ \$25,000 occurs at account age equal to zero.

Figure 3. Normalized Average Account Balance



Notes: This figure shows the average normalized account balance by account age. Each account balance is normalized by the balance of the first observation for that account, and the average normalized account balance is plotted against account age for accounts whose balance remains below \$25,000 (low balance) and for those who at some point in our sample have a balance above \$25,000 (high-balance). Account age is measured in months from the first observation of the account—either from the opening of the account (for low-balance accounts) or the first observation that the account balance is above \$25,000 (for high-balance accounts).

Figure 4. Example of Rate Discontinuity

CITY OF BOSTON CREDIT UNION®

Rates as of December 13, 2024

Savings Rates | Vehicle Loans | Home Loans | Consumer Loans

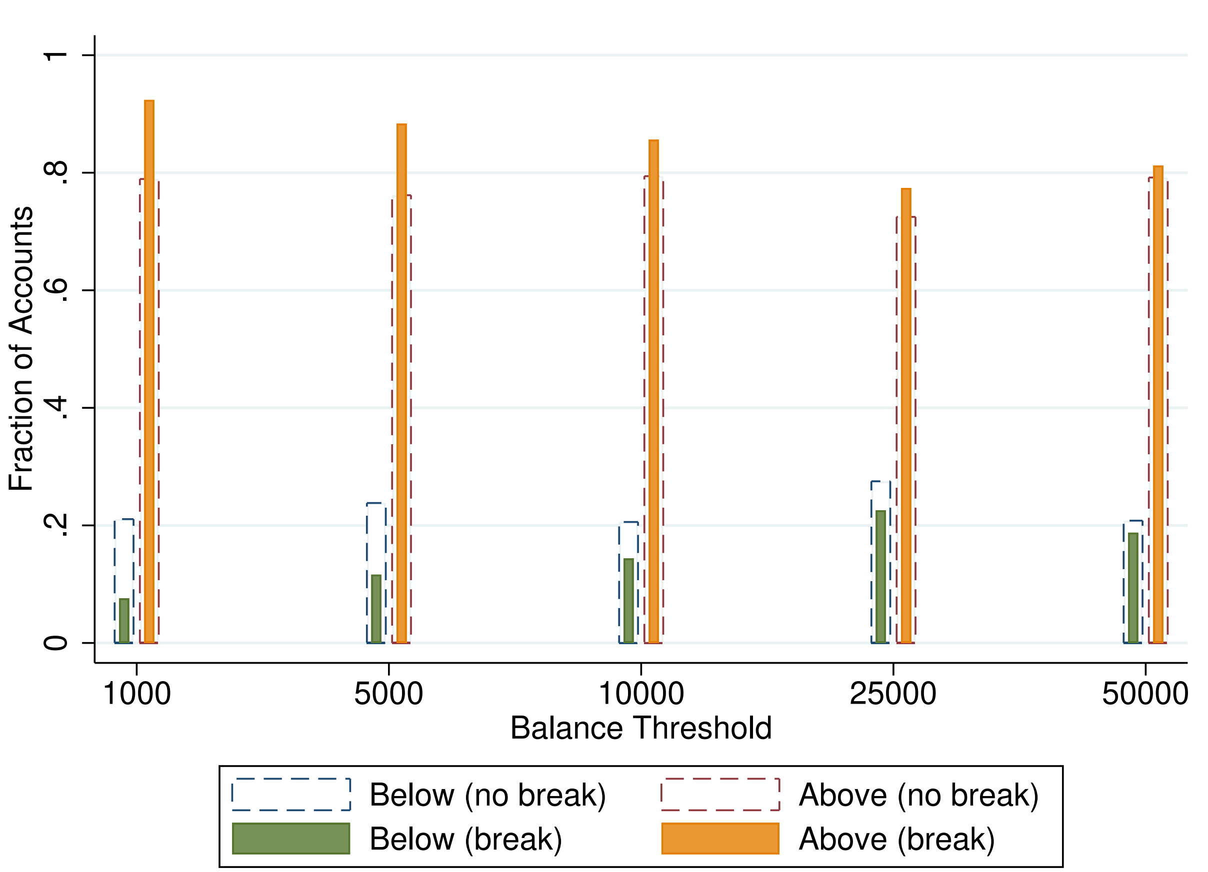
Savings Rates

Dividend Rates

Account Name	Min. Balance to Earn Dividends	Dividend Rate	APY[1]
Money Market Tier I[2]	$1,000.00	0.15%	0.15%
Money Market Tier II[2]	$20,000.00	0.30%	0.30%
Money Market Tier III[2]	$50,000.00	0.50%	0.50%
Money Market Tier IV[2]	$100,000.00	1.00%	1.00%

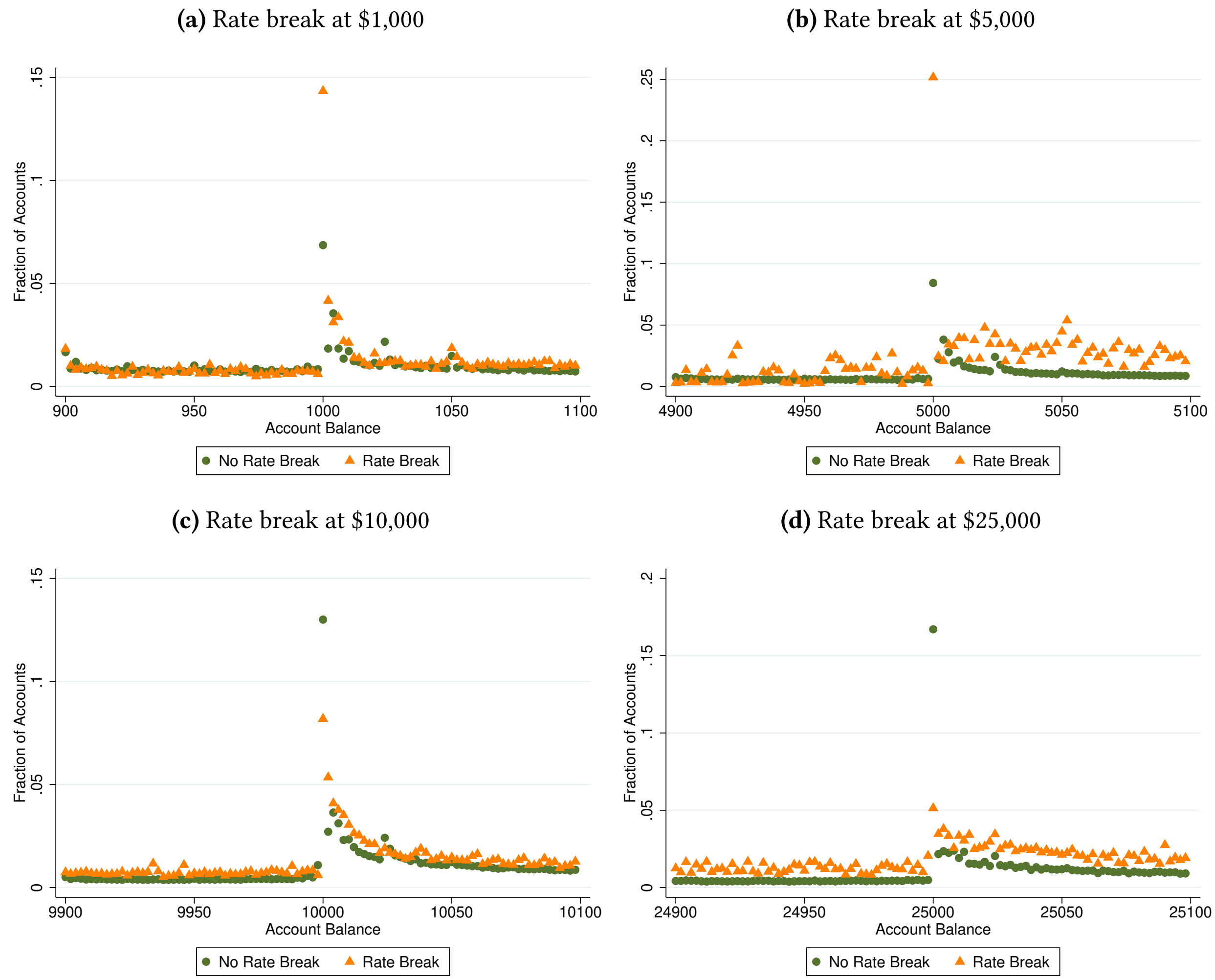
Notes: This figure shows the interest-rate schedule as a function of account balance for the "Money Market" account at the City of Boston Credit Union. This schedule is publicly available at cityofbostoncu.com/rates.

Figure 5. Excess Bunching



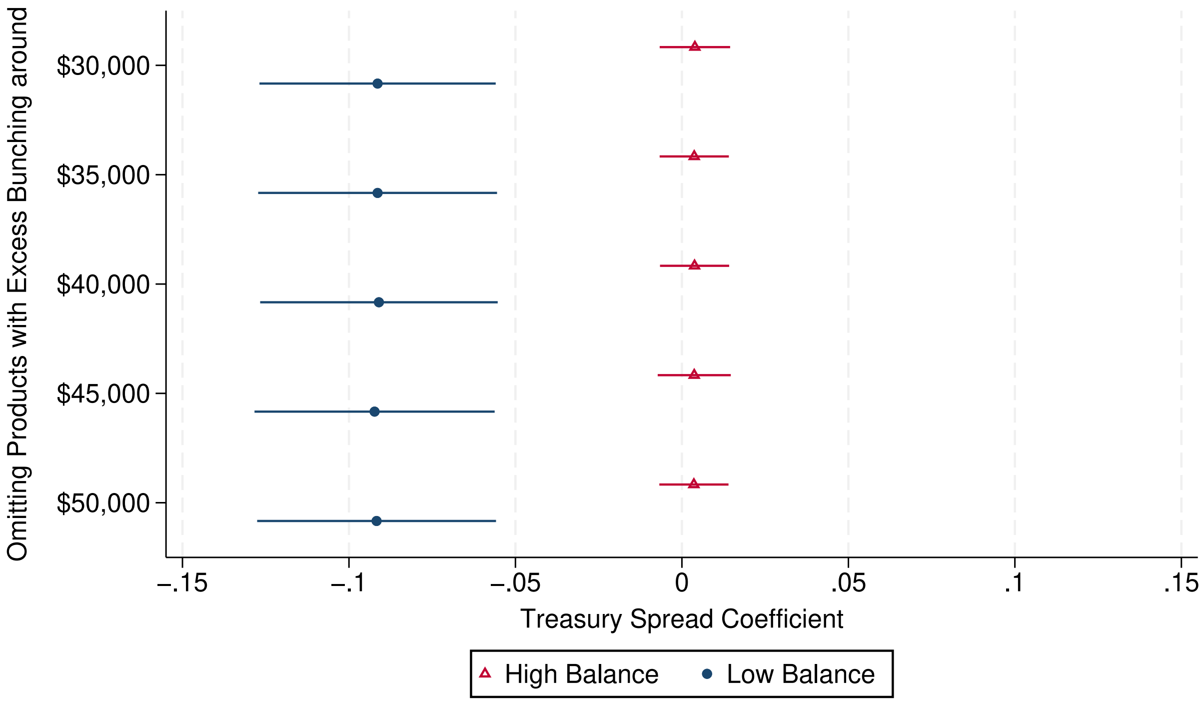
Notes: This figure shows the fraction of account-months in a ± $100 window around various balance thresholds. The solid bars include the subset of accounts that have a discontinuous interest rate break at the indicated threshold, while the dashed bars include all accounts that have no break at that threshold.

Figure 6. Account Bunching Around Balance Thresholds



Notes: This figure plots the distribution of account-months in $2 increments within the $100 window above and below each indicated balance threshold. Orange triangles represent the subset of products that offer a discontinuous interest rate break at the balance threshold, while green dots include all products without such a break. Panel (a) shows the distribution around a balance threshold of $1,000, (b) shows the distribution around a threshold of $5,000, (c) shows the distribution around a threshold of $10,000, and (d) shows the distribution around a threshold of $25,000,

Figure 7. Elasticity Estimates After Removing Products with Extreme Bunching



Notes: This figure shows the 2SLS coefficient of Equation 1, similar to columns (5) and (6) of Table 5, after excluding all observations for products with the top quartile of bunching around the thresholds on the y-axis.

Table 1. Characteristics of Demand Deposit Accounts

	N	Mean	SD	p25	p50	p75
Balance ($)	144,826,174	11,114.6	46,151.7	301.6	1,185.0	5,064.7
Interest Rate	144,826,174	0.0010	0.0027	0.0000	0.0001	0.0010
Deposit Spread (%)	143,085,878	1.72	1.47	0.23	1.42	2.62
Male	89,102,812	0.51	0.50	0.00	1.00	1.00
White	108,339,334	0.79	0.40	1.00	1.00	1.00
Joint	144,826,174	0.16	0.37	0.00	0.00	0.00
Credit Score	79,844,409	736.9	83.8	689.0	757.0	802.0
Age (years)	127,565,830	51.5	19.5	37.0	53.0	67.0

Notes: This table reports summary statistics for demand deposit accounts. *Balance* is the month-end dollar amount in the account; *Interest Rate* is the accompanying interest rate. *Deposit Spread* is the difference in percentage points between the prevailing 2-year Treasury rate and the account Interest Rate. *Male* is a dummy equal to one if the account holder is male. *White* is a dummy equal to one if the account holder is white (imputed race). *Joint* is a dummy equal to one if the account is maintained as a joint account. *Credit Score* is the current credit score of the account holder. *Age* is the age (in years) of the account holder. Observations are at the institution-account-month level.

Table 2. Demand Deposit Skewness by Sample Year

	Fraction of Accounts Representing X% of Total Deposits			Fraction of Accounts with Balances above		Fraction of Deposits held in Accounts with Balances above	
Year	50%	75%	90%	$25,000	$250,000	$25,000	$250,000
2011	0.04	0.14	0.29	0.06	0.00	0.58	0.057
2012	0.04	0.14	0.29	0.07	0.00	0.60	0.064
2013	0.04	0.14	0.29	0.08	0.00	0.63	0.070
2014	0.04	0.13	0.29	0.06	0.00	0.55	0.059
2015	0.04	0.11	0.26	0.06	0.00	0.61	0.090
2016	0.03	0.11	0.25	0.06	0.00	0.63	0.098
2017	0.03	0.11	0.25	0.07	0.00	0.65	0.114
2018	0.03	0.11	0.25	0.08	0.01	0.65	0.116
2019	0.03	0.11	0.25	0.07	0.00	0.64	0.105
2020	0.04	0.13	0.29	0.06	0.00	0.58	0.094
2021	0.04	0.13	0.28	0.09	0.01	0.65	0.118
2022	0.04	0.11	0.25	0.10	0.01	0.72	0.160
2023	0.04	0.11	0.26	0.10	0.01	0.70	0.144

Notes: This table shows the evolution of demand deposit skewness over time. For each institution-month, we calculate the fraction of demand deposit accounts that cumulatively hold 50%, 75%, and 90% of the institution's total demand deposits. We also calculate the fraction of demand deposit accounts with balances above $25,000 and $250,000, as well as the fraction of the institution's total demand deposits held in accounts with balances above those levels. Observations are at the *institution-month* level and averaged within a given year.

Table 3. Characteristics of Demand Deposit Accounts by Account Size

Balance Bin	Balance ($)	Interest Rate	Deposit Spread (%)	Male	White	Joint	Credit Score	Age	Fraction of Observations
$50 - $200	106.8	0.00082	1.708	0.51	0.77	0.14	713.9	47.0	0.19
$200 - $500	331.9	0.00083	1.719	0.49	0.77	0.15	716.7	47.5	0.15
$500 - $1,000	711.3	0.00082	1.710	0.49	0.78	0.16	720.8	48.6	0.13
$1,000 - $5,000	2,356.1	0.00088	1.704	0.50	0.80	0.17	741.3	51.9	0.28
$5,000 - $10,000	7,011.4	0.00104	1.700	0.52	0.81	0.18	762.5	55.6	0.09
$10,000 - $25,000	15,594.1	0.00125	1.727	0.52	0.82	0.19	771.6	58.3	0.08
$25,000 - $50,000	34,901.9	0.00148	1.781	0.53	0.83	0.20	777.4	61.4	0.04
$50,000 - $1,000,000	156,370.3	0.00181	1.851	0.54	0.84	0.20	775.4	63.6	0.05

Notes: This table reports summary statistics for all demand deposits, split based on the underlying account balance. *Balance* is the month-end dollar amount in the account; *Interest Rate* is the accompanying interest rate. *Deposit Spread* is the difference in percentage points between the prevailing 2-year Treasury rate and the account Interest Rate. *Male* is a dummy equal to one if the account holder is male. *White* is a dummy equal to one if the account holder is white (imputed race). *Joint* is a dummy equal to one if the account is maintained as a joint account. *Credit Score* is the current credit score of the account holder. *Age* is the age (in years) of the account holder. Observations are at the institution-account-month level and averaged within a given balance bin.

Table 4. Likelihood of Drawdown of Low- vs. High-Balance Account

	Account Type		
	Low Balance	High Balance	Diff
Drawdown of 75%	0.28	0.33	0.05***
	(0.45)	(0.47)	
Drawdown of 80%	0.23	0.30	0.06***
	(0.43)	(0.46)	
Drawdown of 90%	0.12	0.22	0.09***
	(0.33)	(0.42)	
Drawdown of 95%	0.05	0.16	0.10***
	(0.23)	(0.37)	

Notes: This table reports, at the account level, the likelihood that an account experiences a sudden large drawdown. We define a drawdown event (i.e., *Drawdown of x%*) as an account-month where the account balance declines by more than x%. We show the probability of experiencing a drawdown event separately for accounts with low-balances (always between $50 and $25,000) and accounts with high-balances (between $25,000 and $1,000,000 at some point in our sample). Standard deviations are reported in parenthesis. The difference in drawdown probabilities for low-balance and high-balance accounts, along with the statistical significance of this difference, is shown in the last column. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5. Elasticity of Deposit Balances to Spreads

Estimator	OLS	OLS	OLS	2SLS	2SLS	2SLS	2SLS
Balance Sample	Full	Low	High	Full	Low	High	Full
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Deposit Spread	-0.036***	-0.0239***	-0.0025	-0.09***	-0.09***	-0.01	-0.09***
	(0.0129)	(0.0118)	(0.005)	(0.02)	(0.02)	(0.004)	(0.02)
High Balance Dummy							0.10***
× Deposit Spread							(0.02)
Observations	132,291,344	121,229,346	10,807,205	131,363,412	121,229,346	9,881,662	132,090,290
Year-Quarter FEs	YES	YES	YES	YES	YES	YES	YES
Account FEs	YES	YES	YES	YES	YES	YES	YES

Notes: This table reports estimates of the effect of the deposit spread on the natural log of demand deposit account monthly balances. We estimate the effects using the specification described in Equation (1) by OLS in columns (1) - (3). For columns (4) - (7), we estimate Equations (1) and (3) by 2SLS using surprise movements in the Fed Funds rate, defined in Equation (2), as an instrument for deposit spreads (see Table 6 for first stage results). Deposit spreads are defined as the difference, in percentage points, between the prevailing 2-year Treasury rate and the demand deposit account interest rate. Fixed effects are included as indicated. Reported standard errors in parentheses are clustered at the account and quarter level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6. First-Stage Effects of Fed Funds Futures Surprises on Deposit Spreads

	(1)	(2)	(3)	(4)
FF Surprise	5.51***	2.12***	2.25***	2.23***
	(1.29)	(0.17)	(0.15)	(0.17)
Observations	142,096,567	132,169,961	132,169,961	131,363,412
R-squared	0.04	0.94	0.95	0.97
Partial F-stat	18.35	177.32	255.91	202.96
Year-Quarter FEs	NO	YES	YES	YES
Institution FEs	NO	NO	YES	NO
Account FEs	NO	NO	NO	YES

Notes: This table reports estimates of the effect of surprise movements in the Fed Funds rate on demand deposit spreads. Deposit spreads are defined as the difference, in percentage points, between the prevailing 2-year Treasury rate and the demand deposit account interest rate. Surprise movements in the Fed Funds rate (FF Surprise) are calculated based on changes in the price of Fed Funds futures contracts around FOMC announcements as defined in Equation (2). Fixed effects are included as indicated. Reported standard errors in parentheses are clustered at the account and quarter level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

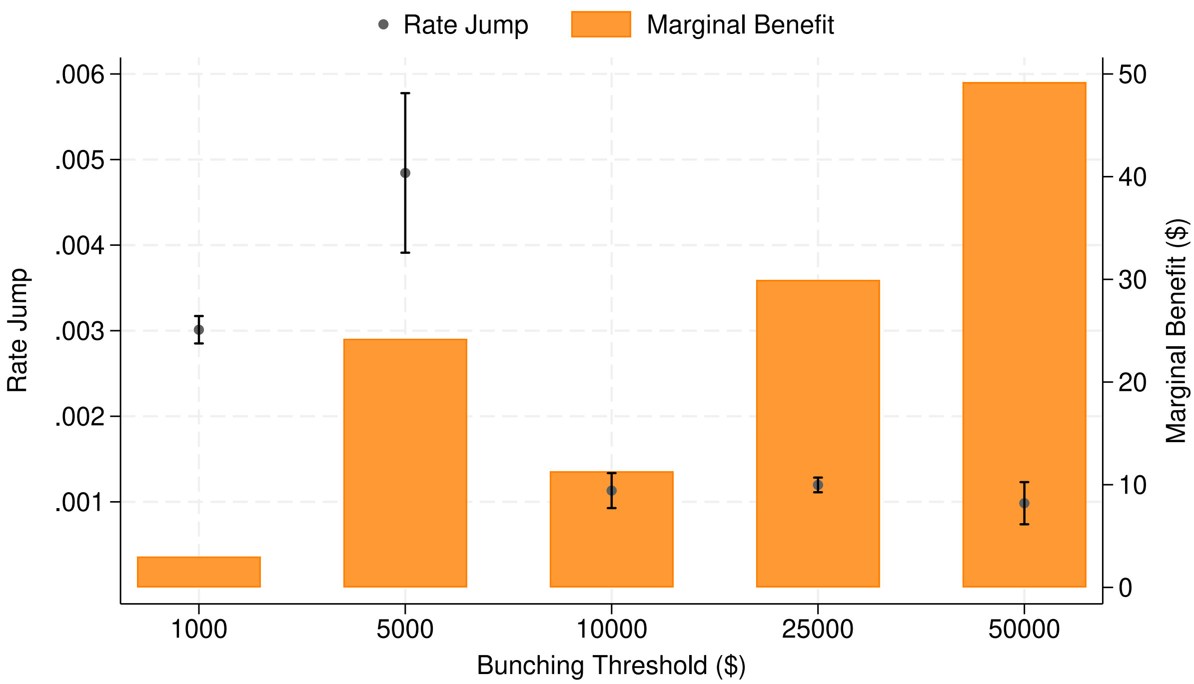
Table 7. Deposit Balance Bunching

Threshold	\$1,000	\$5,000	\$10,000	\$25,000	\$50,000
	(1)	(2)	(3)	(4)	(5)
Has Break	0.111***	0.085***	0.05***	0.044***	-0.0007
	(0.0079)	(0.024)	(0.0136)	(0.008)	(0.0089)
Observations	94	69	96	114	113
R-squared	0.85	0.65	0.50	0.67	0.58
Month FEs	YES	YES	YES	YES	YES

Notes: This table reports estimates of the effect of interest rate breaks on excess demand deposit account bunching. We estimate the amount of bunching using OLS regressions as specified in Equation (4), where we first collapse the data based on monthly account balances into the \$100 window around a specific threshold (i.e., balance $\in$ threshold $\pm$ \$100). The dependent variable is the fraction of accounts in this window that are above the threshold; we calculate this fraction over products with an interest rate break at the threshold and products with no such break (so that there are 2 observations each month). *Has Break* is an indicator variable equal to one for products that have a rate discontinuity at a given threshold. We estimate bunching for thresholds of \$1,000, \$5,000, \$10,000, \$25,000, and \$50,000, as indicated in the column header. We include *Month* fixed effects to account for potential time-varying factors that influence deposit account behavior. Reported standard errors in parentheses are clustered at the month level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Internet Appendix

Figure A1. Interest Rate Discontinuities and the Return on Bunching



Notes: This figure plots the average interest-rate discontinuity for deposit products in our sample with higher interest rates offered to balances over an indicated threshold. The right-hand axis plots a calculation of the implied return (in $) on bunching, defined as the increase in annual interest income from increasing a balance from just below to just above an indicated threshold.

Table A1. Sample Coverage Over Time

Year	Average # of Unique Institutions	Average # of Accounts per Institution	Average Total Balance per Institution	Average # of Unique Products per Institution
2011	$\leq$ 10	19,649	111,407,098	10.0
2012	$\leq$ 10	20,786	122,539,654	10.0
2013	$\leq$ 10	20,178	136,104,860	10.0
2014	$\leq$ 10	23,815	115,144,931	13.5
2015	$\leq$ 10	21,174	110,512,980	13.6
2016	21	51,048	276,702,789	22.1
2017	33	55,411	329,748,662	23.2
2018	41	59,201	404,832,077	26.6
2019	51	52,288	304,130,581	58.4
2020	69	53,355	304,671,002	52.2
2021	88	55,184	547,191,402	46.5
2022	97	56,994	648,352,121	45.2
2023	92	47,945	603,326,263	43.3

Notes: This table reports the average number of unique institutions in our sample, the average number of demand deposit accounts (i.e., checking and savings) per institution, the average total demand deposit balance per institution in dollars, and the average number of demand deposit products per institution each year from 2011 to 2023. The underlying observations are at the institution-month level and averaged within a given year.

Table A2. Average Sample Characteristics Over Time

Year	Balance ($)	Interest Rate	Deposit Spread (%)	Male	White	Joint	Credit Score	Age
2011	7,480.4	0.00032	0.395	.	.	0.01	.	.
2012	7,992.5	0.00031	0.238	.	.	0.01	.	.
2013	8,725.8	0.00031	0.292	.	.	0.01	.	.
2014	6,061.1	0.00038	0.479	0.49	0.92	0.13	758.1	54.9
2015	6,799.9	0.00082	0.674	0.51	0.83	0.12	753.3	54.8
2016	7,115.1	0.00078	0.789	0.51	0.75	0.23	743.2	55.3
2017	7,483.1	0.00147	1.321	0.51	0.80	0.18	742.6	53.6
2018	9,719.5	0.00158	2.388	0.51	0.81	0.14	739.4	52.9
2019	7,419.1	0.00120	1.737	0.51	0.80	0.17	740.5	51.9
2020	8,044.5	0.00048	0.267	0.50	0.80	0.16	734.1	49.9
2021	13,434.0	0.00041	0.269	0.50	0.80	0.16	732.5	50.5
2022	14,488.8	0.00102	3.043	0.50	0.78	0.17	734.6	51.3
2023	13,941.7	0.00157	4.277	0.50	0.78	0.16	733.3	51.1

Notes: This table reports summary statistics by year for all demand deposit accounts. *Balance* is the month-end dollar amount in the account; *Interest Rate* is the accompanying interest rate. *Deposit Spread* is the difference in percentage points between the prevailing 2-year Treasury rate and the account Interest Rate. *Male* is a dummy equal to one if the account holder is male. *White* is a dummy equal to one if the account holder is white (imputed race). *Joint* is a dummy equal to one if the account is maintained as a joint account. *Credit Score* is the current credit score of the account holder. *Age* is the age (in years) of the account holder. Observations are at the institution-account-month level and averaged within a given year.