Sticky Deposits, not Depositors [*]

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Abstract

This paper examines deposit stickiness using account-level data from over 10 million retail accounts across 152 U.S. credit unions. We find significant skewness in deposit distributions, with 10% of depositors controlling 70% of total deposits. Low-balance depositors are sensitive to exogenous interest rate changes, but high-balance depositors are not. High-balance depositors are also relatively insensitive to discontinuous rate jumps at specific balance thresholds and are more likely to experience large, sudden withdrawals. Taken together, our evidence suggests that aggregate deposit stickiness is driven by relatively few high-balance accounts that are used as medium-run liquidity stores rather than for long-term savings.

KEYWORDS: deposit stickiness, bank pricing, interest rate pass-through

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Our data provider nCino OpCo, Inc. had the right to review this manuscript for the inadvertent release of confidential information. I have nothing else to disclose.

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1 Introduction

Deposit-taking institutions typically invest and lend at long rates while borrowing at short rates, primarily in the form of deposits. The resulting maturity mismatch is usually mitigated by the relative stability of deposits (Bryant, 1980; Diamond and Dybvig, 1983; Gorton and Pennacchi, 1990; Kashyap, Rajan, and Stein, 2002). Deposit stickiness, arising in part from deposit insurance (Hanson, Shleifer, Stein, and Vishny, 2015), depositor inattention (Adams, Hunt, Palmer, and Zaliauskas, 2021), differentiated services (d'Avernas, Eisfeldt, Huang, Stanton, and Wallace, 2023), and concentrated local deposit markets (Drechsler, Savov, and Schnabl, 2017), allows banks to manage liquidity risks.

While these factors help explain variation in deposit stickiness *across* institutions, we identify novel drivers of depositor rate insensitivity by examining deposit elasticities *within* institutions. Using account-level data from over 10.6 million retail depositor accounts across 152 U.S. credit unions, we document significant skewness in the within-depository distribution of deposit balances and significant heterogeneity in deposit elasticities. We find that low-balance depositors *are* sensitive to changes in interest rates, while high-balance depositors are not. Given the additional evidence presented below, this surprising result cannot be explained by the usual rationales for deposit stickiness established by the current literature. As we discuss, these findings provide important considerations for banking competition policy, understanding bank branching decisions, and the pass-through of monetary policy through deposit rates.

We begin by documenting the substantial skewness in within-depository deposit account balances.[1] Most depositors hold small-dollar amounts in their accounts while a large fraction of deposit dollars are held in the hands of a few individual depositors. In our sample, the average financial institution owes 70% of its total deposits to accounts with balances above $25,000, yet only around 10% of accounts fall into this category. Further, roughly 4% of depositors account for over 50% of the average institution's total deposits.

[1]Call report data also shows skewness in deposit balances. Only 1% of bank accounts hold balances in excess of the $250,000 FDIC insurance limit, but these accounts comprise 57% of total deposits (Michel, 2023).

We then leverage the granularity of our data to evaluate the sensitivity of deposit flows to changes in market interest rates at the account level. Using the spread between deposit rates and the federal funds rate as a measure of the opportunity cost of holding demand deposits (Drechsler, Savov, and Schnabl, 2017), we estimate the elasticity of deposit dollars with respect to deposit rates. We instrument for deposit spreads using surprises to the federal funds rate (Bauer and Swanson, 2023), finding that a 1 percentage point (p.p.) increase in spreads is associated with an 8.9% outflow of deposit dollars for the average account.

However, elasticity regressions at the account-level mask considerable heterogeneity in the response to interest rate shocks across depositors. The skewness of deposit balances implies that the overall, dollar-weighted sensitivity of deposits to interest rates ultimately depends on the behavior of the small fraction of depositors with the largest account balances. Our account-level data allow us to uncover a result that is otherwise obfuscated in the aggregate data. Accounts with balances between $25,000 and $1,000,000 are insensitive to deposit spreads, with small and statistically insignificant elasticities. An exogenous increase of 1 p.p. in deposit-rate spreads leads to an insignificant reduction in account balances of about 0.5% for accounts with balances in this range. The result is surprising given that the opportunity cost of increased spreads is higher for accounts with larger balances. In contrast, we estimate large and statistically significant elasticities with respect to deposit spreads for accounts holding less than $25,000, finding balances in such accounts decrease 9.2% for every 1 p.p. change in spreads. This disparity between high- and low-balance depositors shows that the average *depositor* is not "sleepy," even if the average *deposit dollar* is.

Why are high-balance depositors less likely to respond to changes in the deposit spread? We rule out two standard explanations. First, we note that our findings hold if we drop all accounts with uninsured balances, ruling out preferences over bank health as an explanation. Second, banking concentration cannot account for differences in demand elasticities given our sample of relatively small depositories and that our results are robust to depository fixed effects, which, among other things, hold institution market power fixed.

We instead evaluate two potential alternative explanations for our results. First, depositors with high-balance accounts likely enjoy higher-quality services from their depository institution. Such services could include concierge attention, wealth management, estate planning, preferential loan terms, and reduced fees. These perks could discourage high-balance depositors from moving their funds even when returns are higher elsewhere. This variation-in-services channel is examined *across* institutions by d'Avernas et al. (2023). Even conditional on bank or account fixed effects, differences in service quality within the same institution, across account balances, could still drive the observed difference in elasticities.

A second candidate explanation for lower sensitivities is that depositors with larger balances view these accounts as liquidity holding pools, to be drawn down when making large transactions. That is, high-balance deposit accounts may not be focused on earning high interest income or gaining access to differentiated banking services but function more like a lumpy consumption or investment staging facility. Under this explanation, the demand for liquidity is not correlated with deposit spreads because a significant portion of the timing of large transactions is idiosyncratic. As a result, deposit flows may appear to be "sleepy" when evaluated relative to changes in interest rate spreads. The liquidity pool intuition is consistent with households being willing to accept lower deposit rates in exchange for the liquidity offered by depository institutions as in Fleckenstein and Longstaff (2024). Our results suggest that this trade-off may be especially applicable to high-balance accounts.

We present three main pieces of evidence to separate the liquidity pool explanation from a differentiated-services explanation. First, a nonparametric analysis of deposit behavior shows that high-balance deposit accounts more frequently experience large declines (e.g., a decrease of more than at least 75% of the account balance). While our data do not distinguish how withdrawn funds are spent or invested, this sudden withdrawal behavior is consistent with high-balance deposit accounts serving as the source of liquidity for large transactions like a car purchase, lumpy educational expense, or a down payment on a home.

Second, we exploit the prevalence of deposit products with discontinuous rate jumps at specific balance thresholds to directly test for high-balance depositor preferences for services. For example, one product in our sample offers a 1 p.p. higher interest rate to depositors that have \$5,000 in an account compared to those with \$4,999. We construct an excess bunching measure as the difference in the bunching around a dollar-amount threshold, e.g. \$5,000, for products with a rate discontinuity compared to bunching at the same threshold for products without a rate discontinuity. An underlying assumption of a differentiated-services explanation is that the derived utility from services is higher for depositors with larger accounts, which keeps them sticky. If this were true, we would expect to find weakly higher excess bunching at higher thresholds, as high-balance depositors seek to qualify for better services. Instead, we find the opposite: excess bunching occurs at lower thresholds but disappears at higher ones. Not only does this evidence contradict the differentiated-services hypothesis, but it also reinforces our main findings that high-balance accounts are insensitive to interest rates.

Finally, there are stark differences between the typical path of balances for low- and high-balance accounts through time. Low-balance accounts remain roughly constant, with balances similar to those observed at account opening. In contrast, high-balance accounts on average demonstrate a significant decline in their balances over time, consistent with account holders drawing down their balances idiosyncratically when liquidity needs arise.

Contribution to Literature This paper makes three primary contributions. First, using microdata with an unusual level of granularity and breadth, we document new empirical facts on within-institution deposit skewness and within-institution heterogeneity in depositor stickiness.[2] Second, we propose a new liquidity management explanation for this heterogeneity. Third, our results provide novel insights into policy questions related to bank competition, branching decisions, and monetary policy pass-through that are not readily apparent absent account-level data.

Understanding how and why banks pass through interest rate changes to depositors is criti-

[2]Notable prior work using deposit data 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 et al. (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.

cal for researchers and policymakers. Banks' ability to only partially pass through rate increases to depositors creates a deposit franchise, which is an important source of bank value (Egan, Lewellen, and Sunderam, 2022).[3] Prior research has explored the determinants of deposit rate pass-through, emphasizing local bank concentration (Drechsler, Savov, and Schnabl, 2017), search frictions (Duffie and Krishnamurthy, 2016), and differences in account services (d'Avernas et al., 2023).[4] While these factors are important, our paper introduces a new and distinct channel: deposit balance skewness and heterogeneity in depositor elasticities driven by expected liquidity needs.

Our findings complement recent work by Lu, Song, and Zeng (2025), who show that frictions in money transfers lead depositors to hold larger balances as a buffer against liquidity shocks. The behavior of large-dollar depositors also relates to the literature on uninsured depositors and bank stability (e.g., Jiang, Matvos, Piskorski, and Seru, 2024). Because the relatively small set of high-balance depositors—who hold the vast majority of funds in the banking system—exhibit low elasticity to interest rate changes, banks are able to keep deposit rates lower than they would if all depositors were as rate-sensitive as small-balance depositors.

This new channel has implications for banking competition, monetary policy pass-through, and financial regulation. First, traditional competition measures such as the Herfindahl-Hirschman Index (HHI) may overstate the degree of competitive pressure in markets dominated by high-balance depositors. Even in nominally competitive markets with many banks, institutions might exercise de facto market power if their primary depositors are rate-insensitive. This builds on recent work showing that deposit rate competition varies across banks (Drechsler, Savov, and Schnabl, 2017, 2021) by demonstrating that pass-through heterogeneity can emerge from deposit composition as well as market structure.

Second, deposit skewness weakens monetary policy transmission. Our findings extend research on monetary policy pass-through (Driscoll and Judson, 2013; Drechsler, Savov, and Schn-

[3] Bolton, Li, Wang, and Yang (2020) show that the deposit franchise also creates risks for banks facing large deposit inflows due to uncertainty about deposit duration.

[4] See also work by Begenau and Stafford (2021) finding a limited ability by large banks to set deposit rates that vary with local market power.

abl, 2017; Duquerroy, Matray, and Saidi, 2020) by showing that differences in pass-through can also be driven by the preferences of high-balance depositors. Because these depositors are sticky, banks adjust deposit rates sluggishly in response to policy rate changes, dampening aggregate savings and consumption responses. These resulting low deposit rates reduce savings and returns for low-balance depositors, reducing the benefit of higher policy rates relative to an equilibrium where banks cater to their higher elasticities. Given that low-balance depositors are most responsive to interest rate changes and have the highest marginal propensity to consume, this suggests that the effectiveness of monetary policy is blunted by the concentration of deposits among high-balance accounts. On the other hand, low equilibrium deposit rates and the stability of high-balance deposits enhance the value of deposit franchises, creating high surplus for banks and more robust credit markets.

Finally, our results inform policy discussions on banking regulation and financial access. Because high-balance deposits generate stable, low-cost funding, banks have strong incentives to expand into high-income areas, exacerbating geographic disparities in financial services. This contributes to credit desert formation and may limit financial access for many depositors. Our findings suggest that policymakers evaluating bank mergers could consider not only traditional competition measures but also the composition of depositors served by merging institutions. Further, policies that encourage the development of deposit products tailored to small-balance households may improve financial inclusion and strengthen monetary policy transmission.

2 Demand Deposit Account Data

We use a large sample of 10.6 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 152 financial institutions and are provided to us by a technology firm specializing in administrative data warehousing and analytics services for retail-oriented lenders. The majority of the financial institutions represented in the data are credit unions, with average total assets of about $835 million.

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 a single financial institution. 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 more than 10.6 million accounts.[5] Financial institutions in our sample offer a large variety of different types of checking and savings accounts—the average number of account options has increased over time from 10 options in 2014 to 43 options in 2023. 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, the name(s) associated with the account, address (aggregated to the census tract level), age, gender, and, for a subset of depositors, credit scores. Based on both names and account types, we exclude all business/commercial accounts from our sample. We exclude business accounts because many of these accounts are explicitly transactional accounts that will be insensitive to interest-rate movements. The fraction of business deposits at credit unions is also quite small, less than 5% on average. Even at commercial banks, retail deposits make up over half of total deposits.

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 sam-

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

ple 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. Finally, we note that 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).

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.[6] 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. 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 increased to 16 basis points in 2023. Despite earning low interest rates, the average account grows by about 1% per month, suggesting that depositors steadily save.[7] However, Appendix Table A2 reveals that there is a noticeable jump

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

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

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.

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%. Currently, only 10% of accounts have balances above $25,000, 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 depositors with higher credit scores and less racial diversity. In Section 4.2 we explore how the elasticity of deposits to interest rates varies based on account size.

3 Identifying the Elasticity of Deposits to Spreads

We estimate account-level elasticities using regressions of the following form:

$$\ln \text{Deposits}_{i,j,t} = \beta \, \text{Deposit Spread}_{i,j,t} + \alpha_q + \gamma_i + \varepsilon_{i,j,t} \tag{1}$$

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.[8] This spread, measured in percentage points, reflects the opportunity cost of leaving money in a deposit account. We include year-quarter fixed effects (α_q) 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 account (or individual) characteristics that influence deposit behavior.

The coefficient β in Equation 1 represents the semi-elasticity of deposit balances to deposit spreads. 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 and f_{t-1} is the rate the day before.[9] 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.

[8]Treasury yields are obtained from FRED series GS2.

[9]The rate is defined by the contract price, which is equal to 100 minus the implied average rate. We obtain Fed Funds futures prices from Bloomberg.

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.[10] 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:

$$\text{Deposit Spread}_{i,j,t} = \pi \, \text{FF Surprise}_t + \delta_q + \eta_i + v_{i,j,t}. \tag{3}$$

This instrument will satisfy the relevance condition for identification given that changes in the federal funds rate are rapidly reflected in market bond yields and consequently 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 the following second stage regression:

$$\ln \text{Deposits}_{i,j,t} = \beta \, \text{Deposit Spread}_{i,j,t} + \alpha_q + \gamma_i + \varepsilon_{i,j,t}. \tag{4}$$

For β in Equation 4 to identify the sensitivity of deposits to spreads, 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 two-stage least squares (2SLS) approach allevi-

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

ates concerns that our estimates of the elasticity of deposits to interest rates are confounded by simultaneous changes in economic fundamentals.

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). Our paper investigates the economic source(s) of this deposit stickiness. We begin by using the 2SLS methodology described above to estimate the elasticity of deposit balances to interest rates. Motivated by the skewness in deposits documented in Section 2.1, we then investigate how the sensitivity of deposit balances to interest rates varies with the size of the account.

4.1 First Stage Estimates

Table 4 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 expected.

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). This stickiness, indicative of market power in deposit markets, 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 why deposit balances are slow to adjust to changes in spreads is important for both policy decisions and the overall stability of the financial industry.

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 Equation 4. 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 (1) indicates that a 1 p.p. exogenous increase in deposit spreads leads to an 8.9% decrease in deposit balances. It is important to note that this semi-elasticity of −8.9 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.

To directly test for such 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).[11] In contrast, high-balance accounts, with balances above $25,000, hold about 70% of total demand deposits. We re-estimate Equation 4 for these subsamples and report the results in Columns (2) and (3) of Table 5. We find that the negative elasticity between deposit balances and spreads is driven entirely by accounts

[11] Our results are qualitatively insensitive to the definition of this partition between high- and low-balance accounts, including defining it at $50,000 or $100,000.

with low balances. For these accounts, the semi-elasticity is -9.2. In contrast, the estimated elasticity for high-balance accounts is small and statistically insignificant (-0.005).

These results suggest 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 quite 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 Evidence on High-Balance Accounts as Liquidity Pools

Why are deposits in high-balance accounts sticky, 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 the switching benefits (Adams et al., 2021). While these factors likely contribute to overall deposit stickiness, they do not explain the heterogeneity in depositor behavior that we document in our setting.

Our analysis leverages within-account balance changes to estimate deposit elasticity.[12] Accordingly, factors that do not vary within accounts, such as bank market power or search costs, cannot account for our findings. Further, we observe substantial variation in deposit stickiness within a range of insured balances, which contradicts deposit insurance-based explanations. Finally, Adams et al. (2021) conclude that inattention and pessimistic beliefs are not specific to a particular type of depositor.

Could our empirical results be explained by high-balance depositors experiencing higher utility from services than low-balance depositors?[13] For this to explain our results, it would have to be the case that these services are institution-specific (d'Avernas et al., 2023; Zhang, Muir, and

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

[13] Such utility could come from services and service quality increasing with account balances or from high-balance depositors valuing the same services more.

Kundu, 2024); otherwise, a high-balance depositor would be indifferent between institutions and would still be sensitive to interest rates. Moreover, it would also have to be the case that the utility derived from these institution-specific services increases with balance levels to explain the difference in elasticities documented above. Specifically, the key requirement for a services explanation of our elasticity heterogeneity is that high-balance depositors manifest lower interest rate elasticities because they derive higher utility from services than low-balance depositors.[14] Section 5.1 below presents evidence inconsistent with this requirement, making it unlikely that services are the main explanation for the heterogeneity we document.

Instead, we introduce a new mechanism to explain differences in interest-rate sensitivities: high-balance accounts primarily function as liquidity pools rather than long-term savings vehicles. A liquidity pool holds funds temporarily for imminent expenses or reallocation to other investments. Such balances are often earmarked for a specific use, such as tuition payments or a home purchase. Because these funds have a designated and short-run non-investment purpose, deposits in a liquidity pool are less responsive to interest rate changes. We expect these balances to remain stable until the account is suddenly drawn down for the planned expenditure. In Section 5.2, we provide evidence that high-balance accounts are more frequently used in this way than low-balance accounts. This liquidity pool mechanism is also consistent with a more fundamental explanation for the increased deposit stickiness of high-balance accounts: high-balance depositors experience lower marginal utility from an additional dollar.

5.1 Bunching Around Interest Rate Discontinuities

To distinguish whether demand for services or demand for liquidity explains deposit stickiness among high-balance depositors, we exploit a unique institutional feature of demand deposit accounts: interest rate discontinuities. Many financial institutions set deposit thresholds at which

[14] If this assumption is not true (i.e., if high-balance depositors derive the same or lower utility than low-balance depositors), services would not explain the difference in elasticities identified in Section 4.2. For example, if low-balance depositors derived higher utility from services than high-balance depositors, low-balance depositors would not be more elastic with respect to rate changes.

interest rates increase sharply. Such discontinuities occur in 5% of products in our sample.[15] For example, one financial institution in our dataset has a savings product that offers a 25 basis point higher interest rate for accounts with balances of at least $10,000 compared to accounts with $9,999. A depositor holding $9,950 in one account and $550 in another at the same institution could seamlessly move $50 into the larger account to earn the higher interest rate.

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, the liquidity pool and services mechanisms predict different patterns of bunching across account sizes. If high-balance accounts are sticky primarily because they are used as liquidity pools, their holders are less likely to monitor interest rate thresholds closely. In this case, we would observe less bunching at higher thresholds. In contrast, if high-balance accounts are sticky due to the utility derived from the services they offer, there is no reason to expect less bunching at higher thresholds. In fact, the services hypothesis, which relies on the assumption that utility from services increases as balances increase across thresholds, would predict *more* bunching at higher balances.

To test these predictions, we first identify the extent of bunching driven by interest rate changes. Because previous studies document the use of round-number heuristics in financial settings (e.g., Argyle, Nadauld, and Palmer, 2020; Cortés, Singh, Solomon, and Strahan, 2023; Sakaguchi, Gathergood, and Stewart, 2024), it seems likely that depositors target balances around salient round numbers (e.g., $1,000 or $5,000) regardless of the interest rate schedule. To isolate bunching caused by interest rate discontinuities, we compare the magnitude of bunching in products at thresholds where discontinuities occur to the counterfactual bunching at the same thresholds in products without interest rate discontinuities. This approach allows us to estimate 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

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

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 2. Solid bars represent accounts for products with an interest rate break at the threshold, while dashed bars represent accounts for products without such breaks. Figure 2 reveals striking 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, indicating a strong preference for round-number balances.

However, this tendency is even more pronounced for accounts at institutions with interest rate breaks (solid bars). These accounts exhibit greater bunching above the threshold, particularly for lower dollar amounts such as $1,000 or $5,000. The difference between the solid and dashed bars to the right of the threshold in Figure 2 represents "excess bunching" caused by interest rate breaks. A different way of visualizing this excess bunching is shown in Figure 3. Each panel shows a scatter plot of the number of account-months in $2 increments within the $100 window surrounding a threshold. Orange triangles indicate accounts with an interest rate break, while green dots indicate accounts without one. There are clear jumps in the number of accounts just above the threshold, and these jumps are generally larger for the orange triangles, consistent with interest rate breaks leading to excess bunching.

To formally test the statistical significance of the excess bunching depicted in Figures 2 and 3, we construct a bunching estimator similar to Collier, Ellis, and Keys (2021). For each threshold ($1,000, $5,000, $10,000, $25,000, and $50,000), we first limit the sample to a window of accounts with a balance ±$100 of the threshold (e.g., [$900-$1,100] for the $1,000 threshold). Then for each month, we calculate the fraction of accounts in the window that are above the threshold. We do this both for products that have an interest rate break at the threshold and for those that do not. This procedure effectively integrates under the curves in Figure 3 separately to the left and right of a given threshold. Unlike many settings where the baseline rate of bunching must be estimated, we directly observe it through accounts in products without interest rate breaks. For each month-threshold, we calculate the fraction of the accounts in the window that is above and below the threshold, and we calculate this separately for all products with and without a rate break at the threshold. This results in a total of four observations for each month-threshold pair: the fraction of accounts above and below the threshold across all products with an interest rate break, and similar fractions across all products without a rate break.

We calculate the excess bunching by estimating the following regression separately for each threshold:

$$\text{Fraction of Window}_{bjt} = \beta \text{Above Threshold}_{bjt} \times \text{Has Break}_{jt} + \gamma \text{Above Threshold}_{bjt} + \delta_{t,Has\ Break_{jt}} + \varepsilon_{bjt}, \tag{5}$$

where t indexes months in our data, j indexes each balance threshold, and b indexes balance bins. The dummy variable $Above\ Threshold_{bjt}$ is an indicator variable for bin b above balance threshold j, and $Has\ Break_{jt}$ is an indicator for the products that have an interest rate break at balance threshold j. Finally, we include fixed effects $\delta_{t,Has\ Break_{jt}}$ for month t separately for products with and without a rate discontinuity at threshold j. These fixed effects absorb macroeconomic trends that might vary by month and to which products with and without breaks might have different exposures. We cluster standard errors at the month level. The coefficient γ represents the amount of bunching for products without an interest rate break (i.e., the fraction of the accounts in the window that have balances to the right of the threshold), which captures naturally occurring bunching due to preferences to maintain a balance level above a salient round-number threshold. The coefficient β represents the bunching due to the interest rate break in excess of naturally occurring bunching.

We estimate Equation 5 separately for interest rate thresholds of \$1,000, \$5,000, \$10,000, \$25,000, and \$50,000. Table 6 reports the results. For lower thresholds, the estimates reveal significant excess bunching. At the \$1,000 threshold, Column (1) shows that there are 23% more accounts just above the threshold when an interest rate break is present. Similarly, excess bunching is 18% at \$5,000 and 10% at \$10,000 (see Columns (2) and (3)). 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. Columns (4) and (5) of Table 6 reveal that for the $25,000 and $50,000 threshold, the excess bunching estimates are statistically insignificant and small (and even slightly negative for $50,000). Moreover, excess bunching monotonically decreases as thresholds increase, consistent with the liquidity pools hypothesis but inconsistent with the institution-specific, varying-by-balance services explanation introduced earlier. We also note that this behavior cannot be attributed to market power or search costs, since in this bunching analysis, depositors could earn higher interest rates by moving funds within the same financial institution. Even after controlling for these channels, depositors with high-balance accounts still exhibit a lower elasticity to interest rate incentives.

5.2 Large Accounts Experience Sudden Drawdowns

If high-balance accounts serve as liquidity pools, one would expect that these accounts would be more likely to experience sudden drawdowns as depositors find uses for the funds, such as purchasing a costly durable or paying for college tuition. To test if this is the case, we categorize accounts into two groups: low-balance accounts, defined as those with balances that never exceed $25,000 during our sample period, and high-balance accounts, which at some point exceed this threshold.[16] We then analyze the likelihood of experiencing a material drawdown, defined as a balance reduction of at least 75% over a single month.

Table 7 summarizes the prevalence of various drawdown events across the two groups. 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. Low-balance accounts experience a 95% drawdown with only a 5% probability, whereas high-balance accounts are more than three times as likely (16%) to experience

[16] This categorization differs slightly from that used 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.

such a severe balance reduction.

Figure 4 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. The low-balance plot indicates that, on average, low-balance accounts remain relatively constant over a long time horizon. This pattern is consistent with the notion that lower dollar accounts experience a pattern of inflows and outflows over time that result in consistent balances.

In contrast, average normalized balances for high-balance accounts decline through time, bottoming out at close to 50% of their initial balance on average. This pattern is consistent with high-balance depositors placing funds in these accounts as liquidity pools, which they subsequently draw down over time as needs arise. As shown in Table 7, 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 4. 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. Importantly, analysis in Table 5 shows that these drawdowns are uncorrelated with interest rate changes, thereby reinforcing the hypothesis that the declines observed in high-balance accounts represent idiosyncratic liquidity needs rather than systematic reactions to interest rate movements.

Depositors who prioritize an account as a liquidity pool are likely to be less sensitive to changes in interest rates, as the purpose of the account is not primarily to earn income on unused funds. This behavior explains why high-balance accounts exhibit greater stickiness than low-balance accounts. Taken together, the evidence from Sections 5.1 and 5.2 suggests that high-balance deposit accounts are more inelastic because they function as temporary liquidity reserves.

6 Conclusion

A bank's deposit franchise, primarily driven by the stickiness of deposits, accounts for a substantial portion of a bank's value (Egan, Lewellen, and Sunderam, 2022). Although various explanations have been examined for the insensitivity of deposits to interest rate changes, we do not have the full economic picture of how individuals make deposit decisions. Using data from over 10 million accounts across more than 150 financial institutions, we provide new insights into the causes of deposit stickiness. We find that approximately 90% of deposit accounts are quite responsive to deposit spreads. However, the owners of the remaining 10% of accounts are inattentive to interest rate changes. Given the highly skewed distribution of deposits, with 70% of deposit assets held in these high-balance accounts, this small number of inattentive accounts drives aggregate deposit stickiness.

Our results suggest that the economic sources of deposit stickiness are unique to high-balance accounts. We argue that the stickiness observed among high-balance accounts is likely due to how these accounts are used. These accounts frequently serve as liquidity pools, where owners temporarily park funds in preparation for large expenses or investments. Because these funds are not primarily intended for long-term savings and the expected duration is short, owners of these accounts have little incentive to pay attention to interest rates.

The fact that high-balance deposit accounts drive deposit stickiness has important implications for bank stability and monetary policy. Our results suggest that the deposits channel of monetary policy (Drechsler, Savov, and Schnabl, 2017) operates primarily through low-balance accounts, enabling these account holders to more easily benefit from higher interest rates when monetary policy is tightened. Since owners of low-balance accounts are generally less wealthy than those with high-balance accounts, this aspect of the deposits channel may help reduce inequality. Moreover, our findings suggest that banks with a higher concentration of deposits from low-balance accounts are 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 should influence 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 might consider incentivizing the creation of accounts that cater to low-balance depositors so that these households have better access to financial services that play a crucial role in building wealth among this group.

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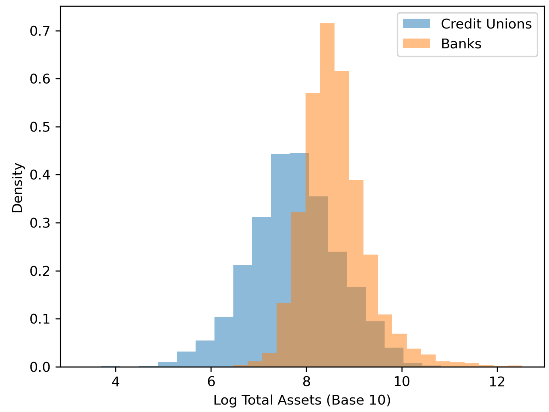
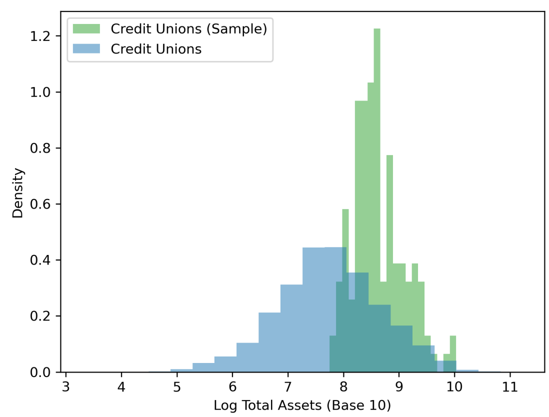
Figure 1. Assets for Credit Unions and Banks in the USA

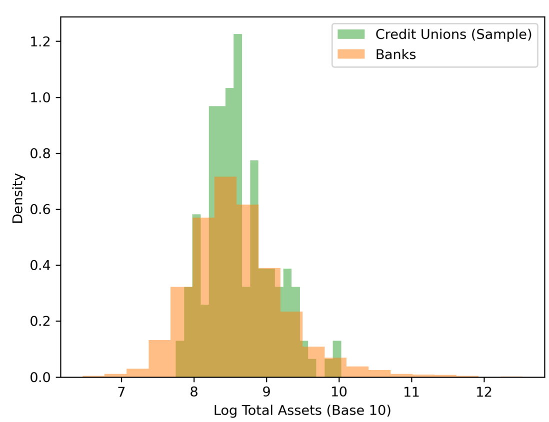
(a) NCUA Credit Unions vs Banks



(b) NCUA Credit Unions vs Data Sample

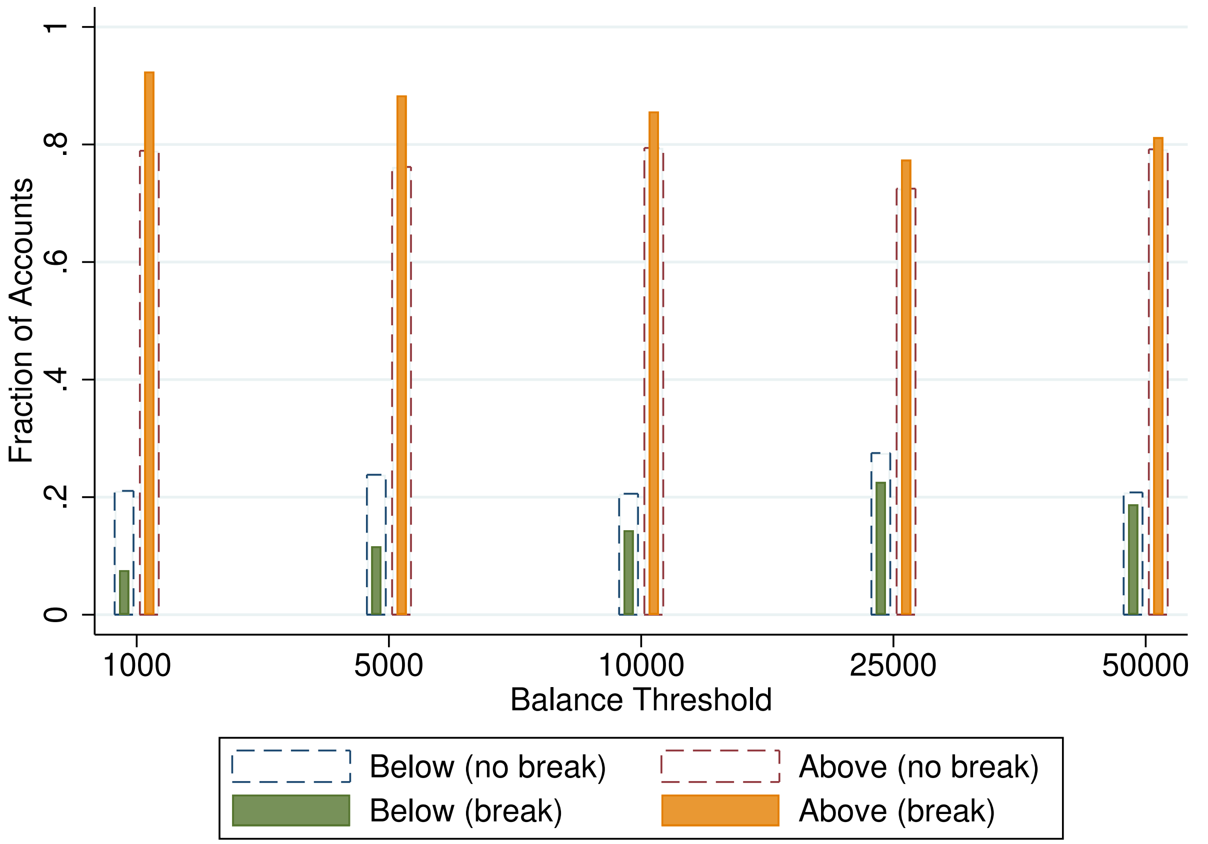


(c) Data Sample vs Banks



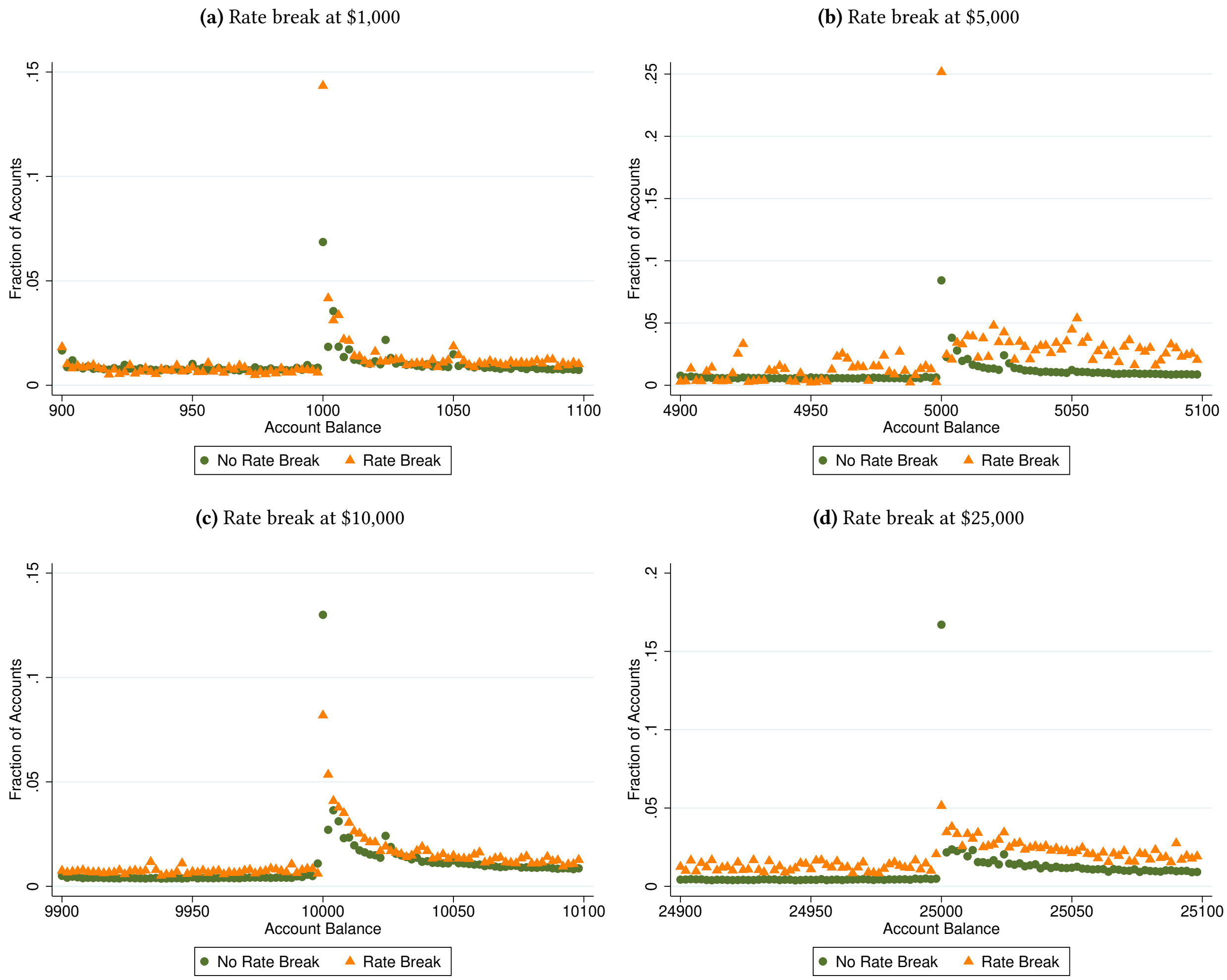
Notes: This figure shows the histogram of assets for all credit unions (blue) and commercial banks (orange) in panel (a), for all credit unions (blue) and our data sample (green) in panel (b), and for our data sample (green) and all banks (orange) in panel (c). The underlying data is sourced from the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

Figure 2. 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. The difference between the solid bar above the threshold (orange) and the dashed bar above the threshold (red) captures the amount of bunching due to breaks in interest rates (i.e., "excess bunching").

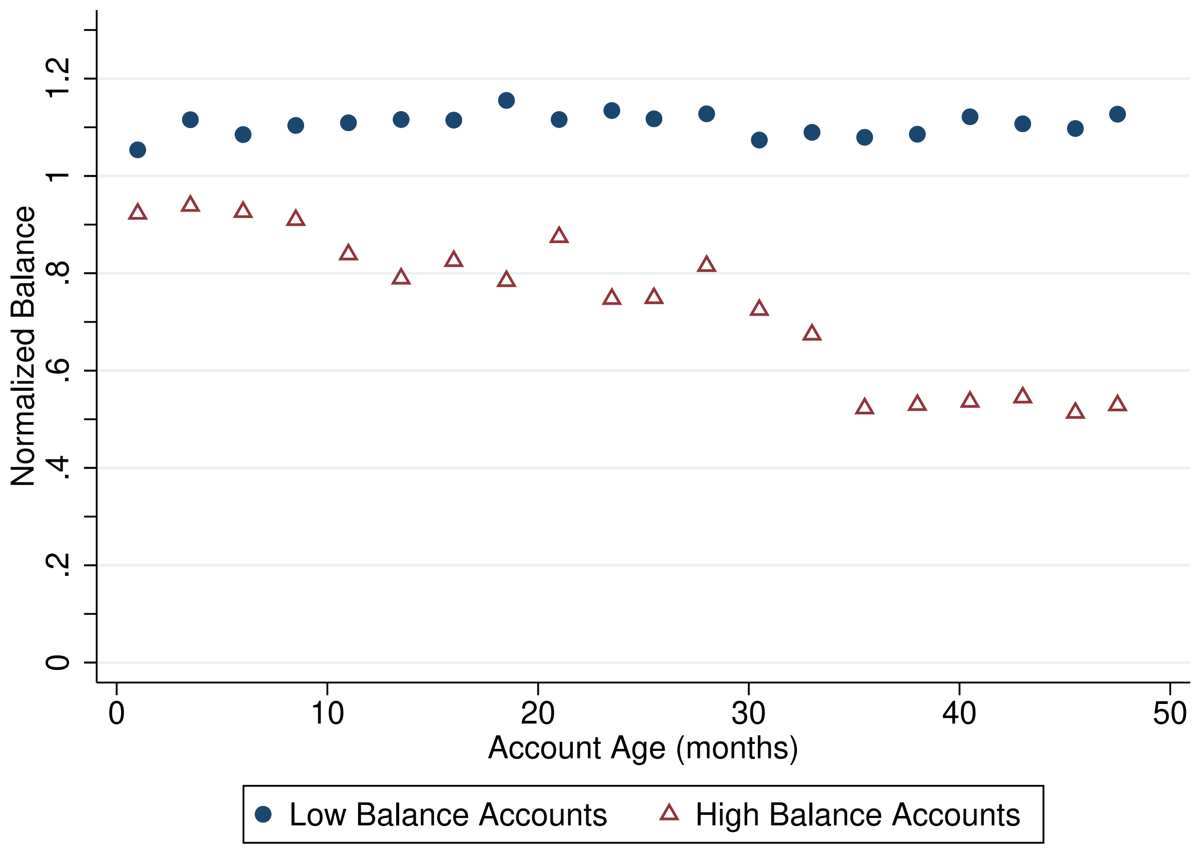
Figure 3. Account Bunching Around Balance Thresholds



(a) Rate break at $1,000
(b) Rate break at $5,000
(c) Rate break at $10,000
(d) Rate break at $25,000

Notes: This figure plots the distribution of account-months in $2 increments within the $100 window above and below each indicated balance threshold. Red dots represent the subset of products that offer a discontinuous interest rate break at the balance threshold, while blue 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 4. 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 or the beginning of our sample).

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
$250,000 - $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: 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 surrounding 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 5: Elasticity of Deposit Balances to Spreads

Sample	Full	Low Balance	High Balance	Full
	(1)	(2)	(3)	(4)
Deposit Spread	-0.09***	-0.09***	-0.01	-0.09***
	(0.02)	(0.02)	(0.004)	(0.02)
High Balance Dummy (HBD)				0.10***
× Deposit Spread				(0.02)
Observations	131,363,412	121,229,347	9,881,662	132,090,290
Year-Quarter FEs	YES	YES	YES	YES
Account FEs	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 2SLS specification described in Equation 4. We use surprise movements in the Fed Funds rate, defined in Equation 2, as an instrument for deposit spreads (see Table 4 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: Deposit Balance Bunching

Threshold	\$1,000	\$5,000	\$10,000	\$25,000	\$50,000
	(1)	(2)	(3)	(4)	(5)
Above Threshold × Has Break	0.228***	0.179***	0.102***	0.066	-0.015
	(0.019)	(0.058)	(0.0032)	(0.020)	(0.021)
Observations	248	187	248	300	302
R-squared	0.99	0.95	0.98	0.99	0.99
Month × Has Break FEs	YES	YES	YES	YES	YES

Notes: This table reports estimates of the effect of interest rate breaks on the fraction of demand deposit accounts bunching. We estimate the amount of bunching using OLS regressions as specified in Equation 5, where we first collapse the data based on account balances into monthly \$2 bins in the \$100 window around a specific threshold (i.e., balance $\leq$ threshold $\pm$ \$100). The dependent variable is the fraction of accounts in this window contained in each bin; we separately bin accounts with an interest rate break at the threshold and accounts with no such break. *Above Threshold* is an indicator variable equal to one if the bin is above the threshold. *Has Break* is an indicator variable equal to one for products that have a rate discontinuity at a given threshold. The interaction of *Above Threshold* and *Has Break* estimates the fraction of demand deposit accounts that bunch just above the threshold because of the interest rate break. 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* × *Has Break* 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.

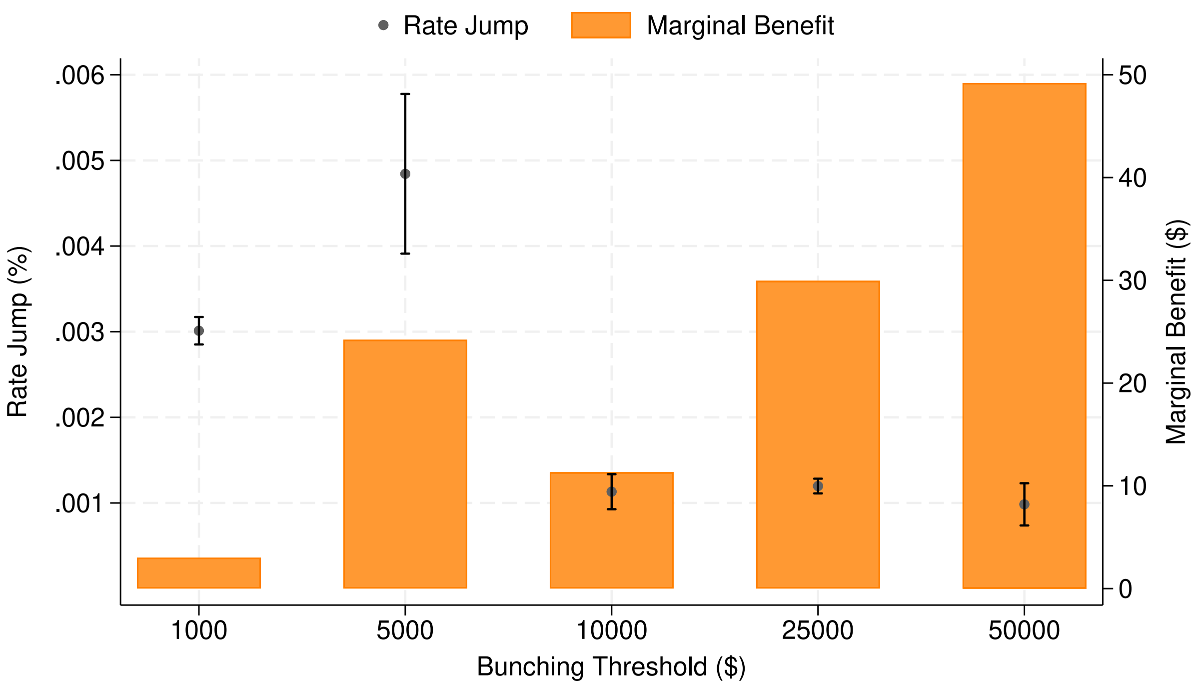
Table 7: Likelihood of Drawdown of Low- vs. High-Balance Account

	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 $5 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.

Internet Appendix

Figure A1. Interest Rate Discontinuities and the Return on Bunching



Notes: This figure plots the average interest-rate discontinuity (left-hand axis in %) 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	1	19,649.0	111,407,098	10.0
2012	1	20,786.0	122,539,654	10.0
2013	1	20,178.0	136,104,860	10.0
2014	3	23,814.9	115,144,931	13.5
2015	5	21,174.4	110,512,980	13.6
2016	21	51,048.3	276,702,789	22.1
2017	33	55,410.8	329,748,662	23.2
2018	41	59,201.2	404,832,077	26.6
2019	51	52,287.7	304,130,581	58.4
2020	69	53,355.4	304,671,002	52.2
2021	88	55,184.2	547,191,402	46.5
2022	97	56,993.5	648,352,121	45.2
2023	92	47,945.1	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.