Sticky Deposits, not Depositors [*]

Bronson Argyle[†] Benjamin Iverson[‡] Jason Kotter[§] Taylor Nadauld[¶]
Christopher Palmer[‖]

December 4, 2024

Abstract

This paper examines deposit stickiness using account-level data from over 10 million accounts across 152 U.S. credit unions. We find significant skewness in deposit distributions, with 10% of depositors controlling 70% of total deposits. Aggregate deposit stickiness is driven by high-balance depositors. Using unexpected changes in Fed Funds rates as exogenous variation in the opportunity cost of holding deposits, we show that low-balance depositors are sensitive to changes in interest rates, but high-balance depositors are not. High-balance depositors are also relatively insensitive to discontinuous interest rate jumps at specific balance thresholds and are more likely to experience periods of prolonged inactivity followed by large reductions in account balances. Our evidence suggests that deposit stickiness is driven by relatively few high-balance accounts that are used as liquidity pools rather than for long-term savings.

Keywords: deposit stickiness, banks, interest rate pass-through

JEL Classification: G21, G51, E43, D14

[*]For helpful comments, we thank Scott Baker, Anthony DeFusco, Mark Egan, Julia Fonseca, Ray Kluender, Elena Loutskina, Brian Melzer, John Mondragon, Amit Seru, Luke Taylor, and seminar participants at BYU and the University of Virginia. Sam Passey and Eric Vorkink provided helpful research assistance. Palmer acknowledges funding from NSF CAREER Grant 1944138.

[†]Marriott School of Business, Brigham Young University. Email: bsa@byu.edu

[‡]Marriott School of Business, Brigham Young University. Email: biverson@byu.edu

[§]Marriott School of Business, Brigham Young University. Email: jasonkotter@byu.edu

[¶]Marriott School of Business, Brigham Young University. Email: taylor.nadauld@byu.edu

[‖]Sloan School of Management, Massachusetts Institute of Technology and NBER. Email: cjpalmer@mit.edu

1 Introduction

Deposit-taking institutions typically invest and lend at long rates while borrowing at short rates, primarily in the form of deposits. The resultant maturity mismatch creates risks that have been at the heart of the modern banking literature, beginning with Diamond and Dybvig (1983) and Kashyap, Rajan, and Stein (2002). Recent contributions to this literature reconcile the puzzle of banks' organizational form by pointing out that the stability of deposits reduces the effective maturity mismatch (Drechsler, Savov, and Schnabl, 2017).[1] Deposit stickiness, arising in part from deposit insurance (Hanson, Shleifer, Stein, and Vishny, 2015), superior services (d'Avernas, Eisfeldt, Huang, Stanton, and Wallace, 2023), and market power (Drechsler, Savov, and Schnabl, 2021), allows banks to manage liquidity risks effectively. While the aforementioned factors explain variation in aggregate deposit stickiness *across* banks, factors influencing individual deposit-level behavior *within* bank remain unexplored.

Using account-level data from over 10.6 million accounts across 152 U.S. credit unions, we document significant skewness in deposit distributions and find heterogeneity in deposit inelasticity. Distinct from the existing literature, we find low-balance depositors *are* sensitive to changes in interest rates, but high-balance depositors are not. There are several dimensions through which deposit skewness and elasticity heterogeneity are important for policy. First, traditional analysis that emphasizes the importance of banking-sector competition may overlook the fact that even in a competitive banking market with each bank holding a small market share of local deposits, banks may act as if they have de facto market power if most of their deposits are concentrated in large-balance accounts. Second, this heterogeneity could help explain geographic patterns in bank branching over time. For example, given that accounts with high balances are less elastic,

[1]Though there is an active debate in the literature about the value of the deposit franchise. See Bolton, Li, Wang, and Yang (2020) and Begenau and Stafford (2021).

banks could have extra incentives to locate branches in high-income areas at the expense of low-income areas. Third, when contractionary monetary policy seeks to stimulate household saving and reduce consumption to curb inflation by raising policy rates, banks may not feel any pressure to pass through interest-rate rate hikes given that the bulk of their deposits are held in sticky large-balance accounts. Moreover, if low-balance depositors have higher marginal propensities to consume, banks optimizing around large-balance accounts may further blunt the effects of monetary policy.

Examining account-level deposit data, we first confirm prior work that the within-depository distribution of deposit account balances is highly skewed.[2] For the average institution in our sample, only around 10% of depositors hold more than $25,000 in an account, but over 70% of an institution's total deposit dollars are held in accounts that hold more than $25,000. Further, roughly 4% of depositors account for over 50% of the average institution's total deposits. Summing up, 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.

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

However, this estimate is at the account level, and hides considerable heterogeneity in the response to interest rate shocks across depositors. The skewness of deposit balances implies that

[2]For example, Michel (2023) finds that while only 1% of bank accounts hold balances in excess of $250,000, these uninsured balances comprise 57% of overall deposits.

the overall, dollar-weighted sensitivity of deposits to federal funds rate surprises ultimately depends on the behavior of the small fraction of depositors with the largest account balances. Our account-level data yield a surprising result that is 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 spreads leads to an insignificant reduction in account balances of about 0.5%. 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, estimated to be 9.2% for a 1 percentage point change in spreads. The disparity between large- and small-balance depositors shows that the average *depositor* is not "sleepy," even if the average *deposit dollar* is.

Why are larger-balance depositors less likely to respond to changes in the deposit spread? Our findings remain if we omit uninsured balances and use bank fixed effects to focus on within-institution variation, ruling out market power or bank solvency effects. We propose two candidate hypotheses. First, larger deposits likely enjoy higher-quality services from their depository institution. Such services could include concierge attention, discounts on affiliated offerings like loans, wealth management, and estate planning, and reduced fees. These extra perks could make depositors reluctant to move deposits even when returns are higher elsewhere. This variation-in-services channel is examined across institutions by d'Avernas et al. (2023). Our elasticity regressions rule out an explanation of institution-level differences in services via the inclusion of account-level fixed effects. However, it is possible that the difference in elasticities across balance size is driven by differences in services that also vary with account balances, for example, if account services are higher quality for accounts above a given balance threshold. A second 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, large-balance deposit accounts are not focused exclusively on earning high returns or gaining access to differentiated banking services but function more like a consumption or investment staging facility. Under this explanation, the demand for liquidity is not correlated with deposit spreads because large transaction timings are mostly idiosyncratic. As a result, deposit flows appear to be "sleepy" when evaluated relative to changes in interest rate spreads. The liquidity pool intuition is consistent with the economics advanced in Fleckenstein and Longstaff (2024). Households are willing to accept lower deposit rates in exchange for the liquidity offered by depository institutions.

We present two lines of evidence in support of a liquidity pool explanation that are likely to be separate from a differentiated-services explanation. We begin by using a non-parametric analysis of deposit behavior to show that larger deposit accounts more frequently experience large, idiosyncratic 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, the sudden withdrawal behavior is consistent with larger deposits serving as the source of liquidity for large transactions like a car purchase, lumpy educational expense, or a down payment on a home.

To more directly test for large-balance depositor preferences for services, we make use of the fact that many depository institutions offer deposit products whose interest rate varies discontinuously with deposit size; that is, for some products, the offered rate jumps discontinuously at certain dollar amount thresholds.[3] We evaluate bunching behavior around rate thresholds in an effort to disentangle competing explanations of the low elasticity of large-balance accounts. An underlying assumption of a differentiated-services explanation is that the derived utility from services is higher for larger balance depositors, which keeps them sticky. We construct an excess bunching measure as the difference in the bunching around a dollar-amount threshold, e.g.

[3]For example, one of the products in our sample offers a 1 percentage point higher interest rate to depositors that have $5,000 in an account compared to borrowers with $4,999.

$5,000, for products with a rate discontinuity compared to bunching at the same threshold for products without a rate discontinuity. If the lower elasticity of large-balance depositors is due to higher utility from services, we would expect to find weakly higher excess bunching at higher thresholds as large-balance depositors seek to qualify for improved services. The excess bunching analysis described in Section 5.1 shows this is not the case.

Contribution to Literature

The contributions of this paper are two-fold. First, using microdata with an unprecedented level of granularity and breadth, we document a new empirical fact; namely within-bank heterogeneity in depositor stickiness.[4] Second, we propose a new liquidity management hypothesis to explain the observed patterns in deposit behavior.

These new empirical facts and hypothesized mechanism give rise to several policy questions involving bank competition, branching decisions, and monetary policy pass-through. On the competition front, HHI measures of banking concentration that indicate a competitive banking environment could be misleading if institutions with a concentration of high-balance depositors do not have strong incentives to compete for deposits. Regarding branching decisions, credit desserts could persist or be created if depository institutions see little benefit to creating or maintaining branches in geographies with a concentration of small deposit customers. Finally, despite the fact that low-balance depositors are most responsive to interest rate changes and have the highest marginal propensity to consume, high-balance institutions have less incentive to pass through rate changes. These implications are explored in contemporaneous work.

The insights from our analysis are consistent with Egan, Lewellen, and Sunderam (2022) that banks build valuable deposit franchises. The importance of the deposit franchise affects both monetary policy pass-through and how banks manage their balance sheets (Drechsler, Savov, and

[4]Notable prior work using deposit level 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.

Schnabl, 2017, 2021). The value of a deposit franchise, however, necessarily relies on deposits that do not respond when rising rates are not passed-through to depositors (e.g., Driscoll and Judson, 2013; Duquerroy, Matray, and Saidi, 2020). Market power (Drechsler, Savov, and Schnabl, 2021) or search costs (Duffie and Krishnamurthy, 2016) are the most prominent explanations for cross-sectional variation in the pass-through of market rates to deposits. The behavior of large-dollar depositors is also relevant to a literature focused on the behavior of uninsured depositors and the risks to bank stability (Jiang, Matvos, Piskorski, and Seru, 2024).

Previous papers advance differing explanations for deposit stickiness at the bank level. Services provided to depositors likely play an important role (d'Avernas et al., 2023). A liquidity management explanation of *within-bank* differences in deposit stickiness coexists comfortably with a services explanation for differences in aggregate deposit stickiness *across* banks.[5] Liquidity management is also not at odds with contemporaneous work by Lu, Song, and Zeng (2024) showing that, *conditional on transacting*, depositors value technological efficiency and higher interest rate spreads. By focusing on the full deposit base, rather than conditioning on account transactions, we show that many depositors are, in fact, sensitive to the opportunity cost of holding deposits, but these small-balance depositors only make up a minority of the total dollars held in deposit accounts. Further, in our setting, market power cannot be the friction preventing large-balance depositors from taking advantage of interest rate discontinuities as many of these individuals do not move funds from one account to another *within the same institution* to take advantage of higher interest rates (see a related argument in Adams, Hunt, Palmer, and Zaliauskas, 2021). Of course, this does not mean that market power and search costs do not play any role in aggregate deposit stickiness. However, our contribution is to show that the relatively small set of depositors who hold most of the funds in financial institutions are inattentive to interest rate changes, and

[5]Though it could also be the case that the composition of depositors and their liquidity pool behaviors also contributes to differences in aggregate stickiness across banks.

that this inattention is likely due to these accounts being used to temporarily hold liquidity.

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 over 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 total demand deposits ranging between $111 million and $650 million. Credit unions are small relative to large banks; however, they make up an important part of the U.S. financial system. 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 Table 1, 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 91 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 19,000 to nearly 43,000, while the average total retail demand deposit balance per institution grew from $115 million to $600 million.

For each financial institution in our data, we have monthly data on every deposit account held at that institution. The data includes more than 10.6 million accounts owned. Financial institutions in our sample offer a surprisingly 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 41 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, as well as whether or not the account is jointly owned and the name(s) associated with the account. Based on both names and account types, we exclude all business/commercial accounts from our sample.[6] Consequently, our final sample is limited to retail depositors.

In addition to balances and names, we see the account holder's address (aggregated to the census tract level), age, gender, and for a subset of depositors, credit scores. 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 2 shows the distribution of depositor characteristics in our institution-account-month panel. Approximately half of the depositors are male, with an average age of 48 years and an interquartile range from 33 to 63 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.[7] Despite these differences, our overall sample appears to be broadly representative of the U.S. adult population.

[6] Specifically, we drop all account-types with "Business" in the description, as well as any accounts with names that contain …Because large accounts are more likely to be owned by businesses, we also drop all accounts with balances greater than $1 million.

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

2.1 Documenting Deposit Skewness

Most accounts in our data are relatively small. The average balance in a demand deposit account is \$10,916, while the median balance is only \$1,181. These accounts pay very low interest rates; the average rate from 2011 to 2023 is about 8 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.[8] However, Table 3 reveals that there is a noticeable jump in account balances post-COVID. The average account balance increased from \$7,376 pre-2020 to \$13,987 post-2020—an increase of nearly 90%. This increase in balances does not appear to be driven by changes in depositor demographics, which have remained relatively stable, despite a slight upward trend in age over the past two years.

A striking feature of financial institutions' total demand deposit exposure is its extreme skewness. In 2023, 3.8% of accounts held 50% of all deposits, and 25.5% of accounts held 90% of deposits. Table 4 shows that this skewness has remained relatively stable over time; the percentage of accounts holding 50% of total demand deposits has fluctuated between 3.3% and 4.5%. 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 exceed the insurable limit of \$250,000, these accounts hold 14.4% of total balances. Over the last two 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.

To provide further insight into the characteristics of depositors with large balance accounts, Table 5 presents summary statistics by account size. Not surprisingly, larger accounts are more likely to be jointly owned. 20% of accounts above \$250,000 are jointly owned, compared to only 14% of accounts with balances below \$200. Additionally, higher balance accounts tend to be

[8]This growth is primarily driven by deposits into accounts with balances under \$1,000 (see Table 5).

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

A key advantage of our data is that we can estimate the elasticity of deposit balances to prevailing interest rates at the account-level, which to the best of our knowledge has never been done before. By examining the heterogeneity in account-level sensitivity to interest rate changes, we shed light on the economic drivers of deposit stickiness. We estimate the account-level elasticity using regressions of the following form:

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

for account i at financial institution j in month t.[9] 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.[10] 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 (α_i) to absorb any fixed account (or individual) characteristics that influence deposit behavior.

The 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

[9]We exclude accounts with balances of less than $5 from our sample.

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

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.[11] 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.

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.[12] 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.

[11]The rate is a trivial transformation of the contract price, since the price is equal to 100 minus the implied average rate. We obtain Fed Funds futures prices from Bloomberg.

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

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

$$\text{Deposit Spread}_{i,j,t} = \beta\,\text{FF\_Surprise}_t + \alpha_q + \alpha_i + \varepsilon_{i,j,t}. \tag{3}$$

This instrument is clearly relevant, as 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:

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

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

4 Heterogeneity in Deposit Elasticity

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 in the previous section 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 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, and this is true 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 Elasticity

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 effect further restricts the comparison to balance changes within the same year-quarter, thus controlling for broader economic conditions and trends. Table 7 reports the results. The estimate in Column (1) indicates that a one percentage point exogenous increase in deposit spreads leads to an 8.9% decrease in deposit balances. This semi-elasticity of -8.9 is similar to, but somewhat larger than, the -5.3 semi-elasticity reported by Drechsler, Savov, and Schnabl (2017) in aggregate commercial bank data.

We next 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 4). 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 7. We find that the negative elasticity between deposit balances and spreads is driven by accounts 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.

These results suggest that the average deposit *account* is much less "sticky" than the average deposit *dollar*. For the vast 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. In the next section, we explore the reasons behind this phenomenon.

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, 2022), 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.[13] Thus, 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? It must be the case that these services are insti-

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

tution specific (d'Avernas et al., 2023; Zhang, Muir, and Kundu, 2024), otherwise a high-balance depositor would be indifferent between institutions, and would prefer a higher interest rate. But it also must be the case that the utility derived from these institution-specific services varies by balance, to explain the difference in elasticities documented above. We are agnostic as to both the relationship between services and balances, and the utility functions of high- and low-balance depositors. Thus, the key assumption for a services explanation is that high-balance depositors manifest lower interest rate elasticities because they derive higher utility from services than low-balance depositors.[14] We show evidence in section 5.1 that contradicts this explanation.

Consequently, we introduce a new hypothesis: large 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 non-savings purpose and are held short-term, 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 frequently used in this way. The liquidity pool hypothesis 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.

[14]The other two possible relationships, i.e., that derived utility for high-balance depositors is the same or lower than that of low-balance depositors, 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 deposit dollars would not be more elastic with respect to rate changes.

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 interest rates increase sharply. These discontinuities are relatively common, occurring in 5% of products in our sample. 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 sharp interest rate discontinuities provide strong 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. We would actually expect *more* bunching at higher balances as the derived utility increases.

To test these predictions, we need to identify the extent of bunching driven by interest rate changes. Because previous studies document the use of round-number heuristics in financial settings (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 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 1. 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 1 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 represents "excess bunching" caused by interest rate breaks. A different way of visualizing this excess bunching is shown in Figure 2. Each panel shows a scatter plot of the number of account-months in $2 increment within the $100 window surrounding a threshold. Red dots indicate accounts with an interest rate break, while blue 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 red dots, consistent with interest rate breaks leading to excess bunching.

To formally test the statistical significance of the excess bunching depicted in Figure 1, 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. We are effectively integrating under the curves in Figure 2 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. Thus, for each month, for all products with (and for all products without) a rate break at the threshold, we have the fraction of the accounts in the window that is above the threshold.

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

$$\text{Fraction of Window}_t = \beta\, \text{Bunch Dummy}_t \times \mathbb{I}_{has\_break_t} + \gamma\, \text{Bunch Dummy}_t + \delta_{\mathbb{I}_{has\_break_t} \times t} + \varepsilon_t, \quad (5)$$

where Bunch Dummy is an indicator variable equal to one for the bin above the interest rate threshold (i.e., Bunch Dummy = $\mathbb{I}_{balance \in [break, break+\$100]}$) and $\mathbb{I}_{has\_break}$ is an indicator variable equal to one for the products that have an interest rate break at a given threshold. $\delta_{\mathbb{I}_{has\_break_t} \times t}$ represents fixed effects for month t separately for products with and without a break. These fixed effects absorb macroeconomics trends that might vary by month and between products with and without breaks. Finally, we cluster standard errors at the month level. γ represents the amount of bunching, i.e. the fraction of the accounts in the window that have balances to the right of the threshold, for products without an interest rate break. This is the bunching due to an innate preference to target above the salient threshold. β represents the bunching due to the interest rate break in excess of the innate bunching.

We estimate Equation 5 for interest rate thresholds of $1,000, $5,000, $10,000, $25,000, and $50,000. Table 8 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 7 and suggest that depositors with lower balances pay attention to interest rates and adjust their account balances accordingly.

In contrast, higher thresholds show no evidence of excess bunching. Columns (4) and (5) of Table 8 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.

Importantly, 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. Effectively 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

To further examine the role of liquidity, we categorize accounts into two groups: small-balance accounts, defined as those with balances that never exceed $25,000 during our sample period, and large-balance accounts, which at some point exceed this threshold. We then analyze the likelihood of experiencing a material drawdown, defined as a balance reduction of at least 75% over a single month.

Table 9 summarizes the prevalence of various drawdown events across the two groups. Among small-balance accounts, 28% experience a 75% drawdown at some point during our sample. In comparison, 33% of large-balance accounts experience a drawdown of this magnitude, and the 5 percentage point difference is statistically significant. This divergence becomes even more pronounced for more extreme drawdowns. Small-balance accounts experience a 95% drawdown with only a 5% probability, whereas large-balance accounts are more than three times as likely (16%) to experience such a severe balance reduction.

This evidence suggests two things. First, accounts are frequently used as liquidity pools, evidenced by the prevalence of large, sudden drawdowns across all accounts. Second, large-balance accounts are much more likely to serve as liquidity pools than small-balance accounts. 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 large-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 depositors 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 over 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. Understanding this behavior is important for developing strategies that enhance the resiliency of banks to interest rate shocks. By providing a granular analysis of deposit flows and their responsiveness to interest rate changes, we contribute to the broader discourse on financial institution risk management.

References

Adams, Paul, Stefan Hunt, Christopher Palmer, and Redis Zaliauskas, 2021, Testing the effectiveness of consumer financial disclosure: Experimental evidence from savings accounts, *Journal of Financial Economics* 141, 122–147.

Argyle, Bronson S, Taylor D Nadauld, and Christopher J Palmer, 2020, Monthly payment targeting and the demand for maturity, *The Review of Financial Studies* 33, 5416–5462.

Bauer, Michael D, and Eric T Swanson, 2023, A reassessment of monetary policy surprises and high-frequency identification, *NBER Macroeconomics Annual* 37, 87–155.

Begenau, Juliane, and Erik Stafford, 2021, Limits to bank deposit market power, Technical report, HBS Working Paper.

Bolton, Patrick, Ye Li, Neng Wang, and Jinqiang Yang, 2020, Dynamic banking and the value of deposits, Technical report, National Bureau of Economic Research.

Collier, Benjamin L, Cameron Ellis, and Benjamin J Keys, 2021, The cost of consumer collateral: Evidence from bunching, Working Paper 29527, National Bureau of Economic Research.

Cortés, Kristle Romero, Mandeep Singh, David H. Solomon, and Philip E. Strahan, 2023, The stench of failure: How perception affects house prices, Working Paper, Available at https://ssrn.com/abstract=4296494.

d'Avernas, Adrien, Andrea L Eisfeldt, Can Huang, Richard Stanton, and Nancy Wallace, 2023, The deposit business at large vs. small banks, Working Paper 31865, National Bureau of Economic Research.

Diamond, Douglas W, and Philip H Dybvig, 1983, Bank runs, deposit insurance, and liquidity, *Journal of Political Economy* 91, 401–419.

Drechsler, Itamar, Alexi Savov, and Philipp Schnabl, 2017, The deposits channel of monetary policy, *The Quarterly Journal of Economics* 132, 1819–1876.

Drechsler, Itamar, Alexi Savov, and Philipp Schnabl, 2021, Banking on deposits: Maturity transformation without interest rate risk, *The Journal of Finance* 76, 1091–1143.

Driscoll, John C., and Ruth A. Judson, 2013, Sticky deposit rates, FEDS Working Paper 2013-80, Federal Reserve Board.

Duffie, Darrell, and Arvind Krishnamurthy, 2016, Passthrough efficiency in the fed's new monetary policy setting, in Richard A. Babson, ed., *Designing Resilient Monetary Policy Frameworks for the Future, A Symposium Sponsored by the Federal Reserve Bank of Kansas City*, 21–102, Federal Reserve Bank of Kansas City, Jackson Hole, Wyoming.

Duquerroy, Anne, Adrien Matray, and Farzad Saidi, 2020, Sticky deposit rates and allocative effects of monetary policy, Working Paper 794, Banque de France.

Egan, Mark, Stefan Lewellen, and Adi Sunderam, 2022, The cross-section of bank value, *The Review of Financial Studies* 35, 2101–2143.

Flannery, Mark J, 1982, Retail bank deposits as quasi-fixed factors of production, *The American Economic Review* 72, 527–536.

Flannery, Mark J, and Christopher M James, 1984, The effect of interest rate changes on the common stock returns of financial institutions, *The Journal of Finance* 39, 1141–1153.

Fleckenstein, Matthias, and Francis A Longstaff, 2024, Is maturity-transformation risk priced into bank deposit rates?, Technical report, National Bureau of Economic Research.

Gertler, Mark, and Peter Karadi, 2015, Monetary policy surprises, credit costs, and economic activity, *American Economic Journal: Macroeconomics* 7, 44–76.

Gorodnichenko, Yuriy, and Michael Weber, 2016, Are sticky prices costly? Evidence from the stock market, *American Economic Review* 106, 165–199.

Gürkaynak, Refet S, Brian Sack, and Eric T Swanson, 2005, Do actions speak louder than words? the response of asset prices to monetary policy actions and statements, *International Journal of Central Banking* 1, 55–93.

Hannan, Timothy H., and Allen N. Berger, 1991, The rigidity of prices: Evidence from the banking industry, *The American Economic Review* 81, 938–945.

Hanson, Samuel G, Andrei Shleifer, Jeremy C Stein, and Robert W Vishny, 2015, Banks as patient fixed-income investors, *Journal of Financial Economics* 117, 449–469.

Hutchison, David E, and George G Pennacchi, 1996, Measuring rents and interest rate risk in imperfect financial markets: The case of retail bank deposits, *Journal of Financial and Quantitative Analysis* 31, 399–417.

Indarte, Sasha, 2023, Financial Crises and the Transmission of Monetary Policy to Consumer Credit Markets, *The Review of Financial Studies* 36, 4045–4081.

Iyer, Rajkamal, and Manju Puri, 2012, Understanding bank runs: The importance of depositor-bank relationships and networks, *American Economic Review* 102, 1414–1445.

Iyer, Rajkamal, Manju Puri, and Nicholas Ryan, 2016, A tale of two runs: Depositor responses to bank solvency risk, *The Journal of Finance* 71, 2687–2726.

Jiang, Erica Xuewei, Gregor Matvos, Tomasz Piskorski, and Amit Seru, 2024, Monetary tightening and us bank fragility in 2023: Mark-to-market losses and uninsured depositor runs?, *Journal of Financial Economics* 159, 103899.

Kahn, Charles, George Pennacchi, and Ben Sopranzetti, 1999, Bank deposit rate clustering: Theory and empirical evidence, *The Journal of Finance* 54, 2185–2214.

Kashyap, Anil K, Raghuram Rajan, and Jeremy C Stein, 2002, Banks as liquidity providers: An explanation for the coexistence of lending and deposit-taking, *The Journal of Finance* 57, 33–73.

Kuttner, Kenneth N, 2001, Monetary policy surprises and interest rates: Evidence from the fed funds futures market, *Journal of Monetary Economics* 47, 523–544.

Lu, Xu, Yang Song, and Yao Zeng, 2024, The making of an alert depositor: How payment and interest drive deposit dynamics, *Available at SSRN 4699426* .

Michel, N., 2023, Fewer than one percent of accounts are above the fdic limit, *Cato Institute* .

NAFCU, 2022, Report on credit unions, Available at https://www.nafcu.org/sites/default/files/NAFCU_Report_on_Credit_Unions_2022_0.pdf.

Nakamura, Emi, and Jón Steinsson, 2018, High-frequency identification of monetary non-neutrality: the information effect, *The Quarterly Journal of Economics* 133, 1283–1330.

Neumark, David, and Steven A Sharpe, 1992, Market structure and the nature of price rigidity: Evidence from the market for consumer deposits, *The Quarterly Journal of Economics* 107, 657–680.

Sakaguchi, Hiroaki, John Gathergood, and Neil Stewart, 2024, Round number preferences and left-digit bias: Evidence from credit card repayments, *Working Paper* .

Wang, Yifei, Toni M. Whited, Yufeng Wu, and Kairong Xiao, 2022, Bank market power and monetary policy transmission: Evidence from a structural estimation, *The Journal of Finance* 77, 2093–2141.

Yankov, Vladimir, 2022, In search of a risk-free asset: Search costs and sticky deposit rates, Working Paper, Available at https://papers.ssrn.com/abstract=2044882.

Zhang, Jinyuan, Tyler Muir, and Shohini Kundu, 2024, Diverging banking sector: New facts and macro implications, Working Paper, Available at https://ssrn.com/abstract=4798818.

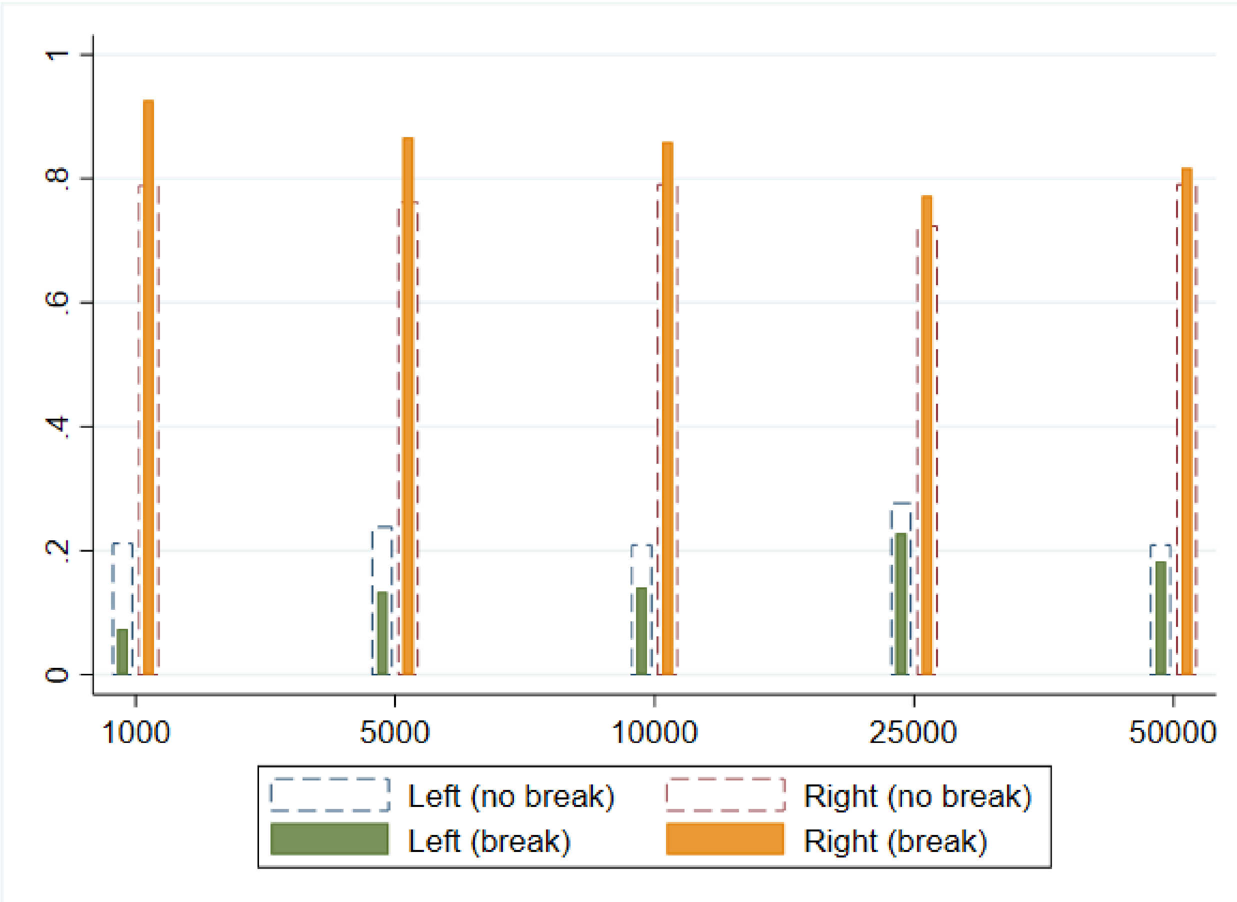

Figure 1. Excess Bunching. This figure shows the fraction of account-months in a ± $100 window around various balance thresholds. The solid bars include the subset of accounts that have a discontinuous interest rate break at the indicated threshold, while the dashed bars include all accounts that have 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").

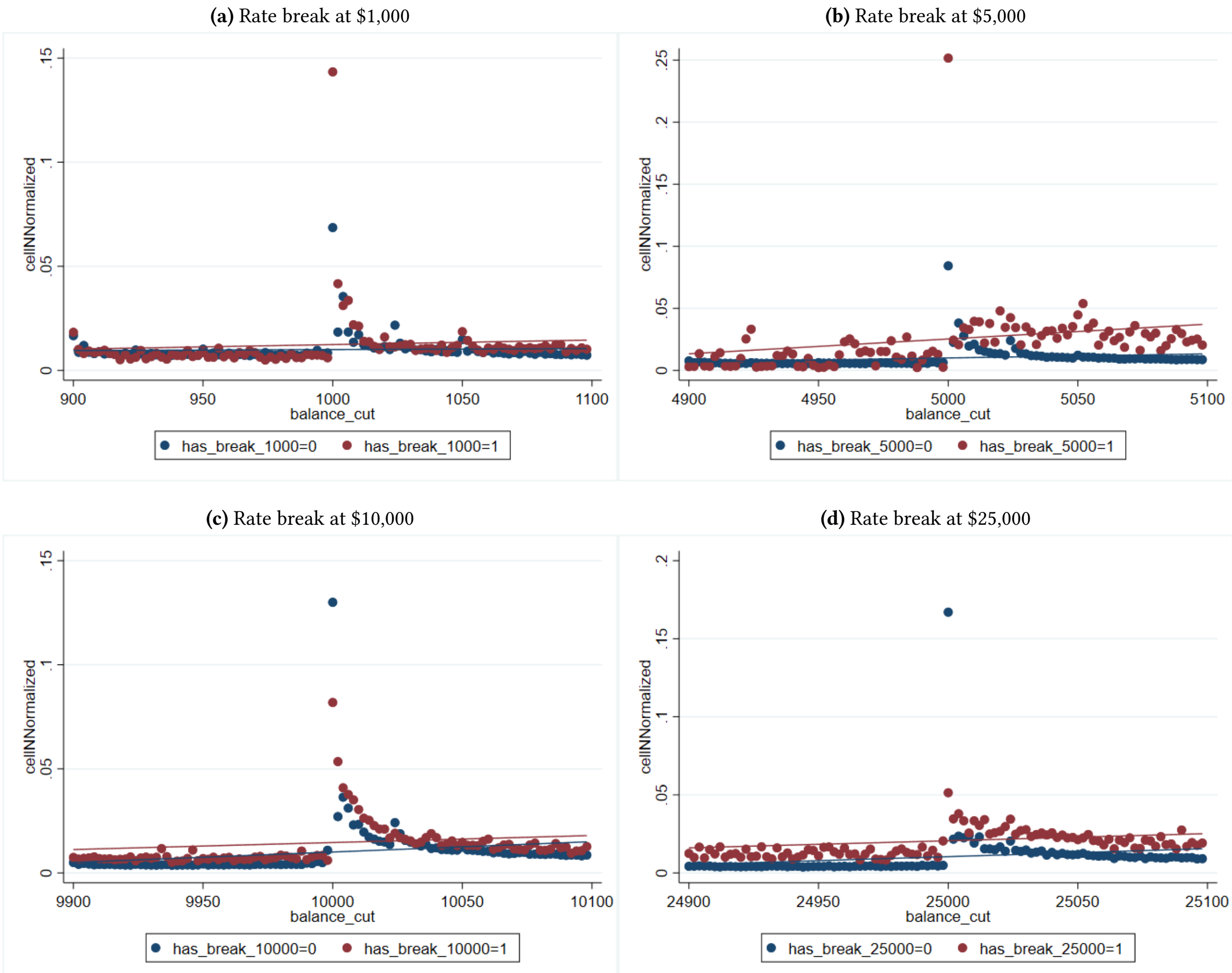

Figure 2. Account Bunching Around Balance Thresholds. This figure plots the distribution of account-months in $2 increments within the $100 window above and below each indicated balance threshold. Red dots represent the subset of products that offer a discontinuous interest rate break at the balance threshold, while blue dots include all products without such a break. (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,

Table 1: Demand Deposit Growth

Year	Number of Unique Institutions	Average # of Accounts per Institution	Average Total Balance per Institution	Average # of Unique Products per Institution
2011	1.0	14,893.3	111,407,098	10.0
2012	1.0	15,331.8	122,539,654	10.0
2013	1.0	15,598.0	136,104,860	10.0
2014	2.7	18,997.4	115,144,931	13.2
2015	5.4	16,251.1	110,507,756	12.5
2016	19.9	39,674.5	283,541,548	20.8
2017	31.5	45,214.8	338,346,795	23.4
2018	39.5	41,374.1	301,381,997	24.7
2019	50.0	40,919.3	303,370,785	44.2
2020	69.3	37,828.4	304,081,965	42.7
2021	88.1	40,681.8	546,915,162	39.6
2022	96.2	44,492.0	646,134,353	39.5
2023	91.3	42,883.8	600,182,918	41.3

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

Table 2: Characteristics of Demand Deposit Accounts

	N	Mean	SD	p25	p50	p75
Balance ($)	142,937,634	10,916.37	45,258.371	300.8500	1,181.2300	5,043.6600
Balance_delta (%)	132,287,903	1.01	24.141	-0.1239	0.0001	0.1389
Interest Rate	142,937,634	0.00	0.003	0.0000	0.0001	0.0010
Deposit Spread (%)	141,314,425	1.71	1.474	0.2300	1.4000	2.6200
$\mathbb{I}_{\text{male}}$	86,807,074	0.51	0.50	0.00	1.00	1.00
$\mathbb{I}_{\text{white}}$	105,886,362	0.79	0.403	1.00	1.00	1.00
$\mathbb{I}_{\text{joint}}$	142,937,634	0.16	0.370	0.00	0.00	0.00
Credit Score	79,040,627	736.94	83.80	689.00	757.333	802.50
Age	124,477,128	48.14	19.511	33.00	49.00	63.00

This table reports summary statistics for demand deposit accounts. *Balance* is the month-end dollar amount in the account; *Balance_delta* is the percentage change in the month-to-month balance, and *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. $\mathbb{I}_{\text{male}}$ is a dummy equal to one if the account holder is male. $\mathbb{I}_{\text{white}}$ is a dummy equal to one if the account holder is white (imputed race). $\mathbb{I}_{\text{joint}}$ 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 3: Trends in Demand Deposit Characteristics

Year	Balance ($)	Balance_delta (%)	Interest Rate	Deposit Spread (%)	$\mathbb{I}_{male}$	$\mathbb{I}_{white}$	$\mathbb{I}_{joint}$	Credit Score	Age
2011	7,480	0.71	0.00032	0.39	.	.	0.01	.	.
2012	7,993	1.84	0.00031	0.24	.	.	0.01	.	.
2013	8,726	0.64	0.00031	0.29	.	.	0.01	.	.
2014	6,061	0.77	0.00038	0.48	.49	0.92	0.13	758.1	45.6
2015	6,800	0.74	0.00082	0.67	.51	0.83	0.12	753.3	46.5
2016	7,147	1.47	0.00077	0.79	.5	0.75	0.23	743.2	47.9
2017	7,483	0.88	0.00146	1.32	.51	0.79	0.18	742.7	47.2
2018	7,284	0.88	0.00162	2.38	.51	0.80	0.15	739.5	47.5
2019	7,414	0.97	0.00121	1.74	.51	0.80	0.17	740.8	47.4
2020	8,038	1.10	0.00048	0.27	.5	0.80	0.16	733.9	46.4
2021	13,444	1.07	0.00042	0.27	.51	0.80	0.16	732.4	48.1
2022	14,522	0.98	0.00102	3.03	.5	0.79	0.16	734.8	49.7
2023	13,996	0.85	0.00157	4.28	.5	0.78	0.15	733.7	50.1

This table reports summary statistics for all demand deposit accounts. *Balance* is the month-end dollar amount in the account; *Balance_delta* is the percentage change in the month-to-month balance, and *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. $\mathbb{I}_{male}$ is a dummy equal to one if the account holder is male. $\mathbb{I}_{white}$ is a dummy equal to one if the account holder is white (imputed race). $\mathbb{I}_{joint}$ 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.

Table 4: Demand Deposit Skewness

Year	Fraction of Accounts Representing X% of Total Deposits			Fraction of Accounts with Balances above		Fraction of Deposits held in Accounts with Balances above	
	50%	75%	90%	\$25,000	\$250,000	\$25,000	\$250,000
2011	0.043	0.138	0.288	0.063	0.001	0.581	0.057
2012	0.044	0.137	0.290	0.070	0.001	0.603	0.064
2013	0.045	0.137	0.288	0.079	0.002	0.627	0.070
2014	0.042	0.132	0.292	0.058	0.001	0.554	0.059
2015	0.035	0.112	0.258	0.060	0.002	0.606	0.091
2016	0.034	0.107	0.251	0.065	0.002	0.634	0.098
2017	0.033	0.105	0.246	0.069	0.003	0.651	0.114
2018	0.033	0.106	0.249	0.068	0.003	0.645	0.105
2019	0.035	0.109	0.252	0.070	0.003	0.643	0.102
2020	0.041	0.130	0.289	0.062	0.003	0.580	0.093
2021	0.043	0.128	0.279	0.087	0.006	0.645	0.117
2022	0.037	0.113	0.249	0.102	0.008	0.715	0.159
2023	0.038	0.113	0.255	0.103	0.008	0.703	0.144

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 5: Characteristics of Demand Deposit Accounts by Account Size

Balance Bin	Balance ($)	Balance_delta (%)	Interest Rate	Deposit Spread (%)	$\mathbb{I}_{\text{male}}$	$\mathbb{I}_{\text{white}}$	$\mathbb{I}_{\text{joint}}$	Credit Score	Age	Fraction of Observations
$50 - $200	106.74	3.67	0.00082	1.70	0.51	0.77	0.14	713.8	43.5	0.19
$200 - $500	331.51	1.33	0.00082	1.71	0.49	0.77	0.15	716.8	44.1	0.15
$500 - $1,000	711.07	0.63	0.00081	1.70	0.49	0.78	0.16	720.9	45.1	0.13
$1,000 - $5,000	2,356.22	0.20	0.00088	1.70	0.50	0.80	0.17	741.5	48.5	0.29
$5,000 - $10,000	7,010.82	0.06	0.00104	1.69	0.52	0.81	0.18	762.7	52.3	0.09
$10,000 - $25,000	15,594.33	0.02	0.00125	1.72	0.52	0.82	0.19	771.9	55.2	0.08
$25,000 - $50,000	34,894.49	0.01	0.00148	1.77	0.53	0.82	0.19	777.9	58.4	0.04
$250,000 - $1,000,000	154,677.52	-0.02	0.00184	1.83	0.54	0.84	0.20	776.2	61.0	0.04

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; *Balance_delta* is the percentage change in the month-to-month balance, and *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. $\mathbb{I}_{\text{male}}$ is a dummy equal to one if the account holder is male. $\mathbb{I}_{\text{white}}$ is a dummy equal to one if the account holder is white (imputed race). $\mathbb{I}_{\text{joint}}$ 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 6: Effects of Fed Funds Futures Surprises on Deposit Spreads

	1	2	3	4
FF_Surprise	5.5064***	2.1247***	2.2527***	2.2323***
	(1.2866)	(0.1726)	(0.1531)	(0.1703)
Observations	142,096,567	132,169,961	132,169,961	131,363,412
R-squared	0.0367	0.9432	0.9523	0.966
Quarter FEs	NO	YES	YES	YES
Institution FEs	NO	NO	YES	NO
Account FEs	NO	NO	NO	YES

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 7: Elasticity of Deposit Balances to Spreads

Sample	Full	Low Balance	High Balance	Full
	1	2	3	4
Deposit Spread	-0.0886***	-0.0917***	-0.0051	-0.0926***
	(0.0183)	(0.019)	(0.0041)	(0.018)
High Balance Dummy (HBD)				0.097***
× Deposit Spread				(0.019)
Observations	131,363,412	121,229,347	9,881,662	132,090,290
R-squared	-0.0002	-0.0004	0.0001	-0.0004
Quarter FEs	YES	YES	YES	YES
Account FEs	YES	YES	YES	YES

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 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 8: Deposit Balance Bunching

	1	2	3	4	5
Threshold	\$1000	\$5000	\$10000	\$25000	\$50000
Bunch Dummy × $\mathbb{I}_{has\_break}$	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	0.987	0.951	0.980	0.989	0.993
Month × $\mathbb{I}_{has\_break}$ FEs	YES	YES	YES	YES	YES

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 ≤ threshold ± \$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. *Bunch Dummy* is an indicator variable equal to one if the bin is above the threshold (i.e. *Bunch Dummy* = $\mathbb{I}_{balance \in [threshold, threshold+\$100]}$). $\mathbb{I}_{has\_break} = 1$ for products that have a rate discontinuity at a given threshold. The interaction of *Bunch Dummy* and $\mathbb{I}_{has\_break}$ 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 × $\mathbb{I}_{has\_break}$ 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 9: Likelihood of Drawdown of Small vs. Large Account

	Account Type		
	Small Balance	Large Balance	Diff
$\mathbb{I}[drawdown\_of\_75\%)]$	0.28	0.33	0.05***
	(0.45)	(0.47)	
$\mathbb{I}[drawdown\_of\_80\%)]$	0.23	0.30	0.06***
	(0.43)	(0.46)	
$\mathbb{I}[drawdown\_of\_90\%)]$	0.12	0.22	0.09***
	(0.33)	(0.42)	
$\mathbb{I}[drawdown\_of\_95\%)]$	0.05	0.16	0.10***
	(0.23)	(0.37)	

This table reports, at the account level, the likelihood that an account experiences a sudden large drawdown. We define a drawdown event (i.e., $\mathbb{I}[drawdown\_of\_x\%)]$) 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). 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

Table A1: Time Deposit Growth

Year	Number of Unique Institutions	Average # of Accounts per Institution	Average Total Balance per Institution	Average # of Unique Products per Institution
2011	1.0	2,431.0	48,545,561	4.0
2012	1.0	2,164.3	42,768,603	4.0
2013	1.0	1,982.5	41,117,858	4.0
2014	2.7	2,359.9	48,895,638	18.5
2015	5.9	1,962.1	39,263,010	20.9
2016	19.5	3,516.3	83,207,325	31.9
2017	31.1	3,861.2	97,327,090	30.4
2018	39.0	3,394.3	86,260,094	27.5
2019	50.5	3,880.8	103,798,394	30.5
2020	73.4	4,070.7	126,868,610	32.3
2021	93.4	3,521.7	127,042,344	28.8
2022	98.8	3,107.9	113,030,429	28.6
2023	94.0	3,614.6	140,500,791	30.8

This table reports the average number of time deposit accounts, the total time deposit balance, and the number of time deposit products for the financial institutions in our sample each year from 2011 to 2023. The underlying observations are at the *institution-month* level and averaged within a given year and then averaged across institutions.

Table A2: Characteristics of Time Deposit Accounts

	N	Mean	SD	p25	p50	p75
Balance ($)	12,707,969	31,857.10	69,169.493	2,560.4000	10,000.0000	28,431.8900
Balance_delta (%)	11,657,421	0.05	3.375	0.0000	0.0009	0.0028
Interest Rate	12,707,969	0.01	0.011	0.0040	0.0100	0.0210
Deposit Spread (%)	12,577,725	0.32	1.737	-0.7600	0.1220	1.3650
$\mathbb{I}_{\text{male}}$	7,559,653	0.46	0.499	0.0000	0.0000	1.0000
$\mathbb{I}_{\text{white}}$	8,984,186	0.86	0.342	1.0000	1.0000	1.0000
$\mathbb{I}_{\text{joint}}$	12,707,969	0.15	0.355	0.0000	0.0000	0.0000
Credit Score	6,082,483	781.42	61.581	767.0000	802.0000	817.0000
Age	11,072,556	61.94	21.148	54.0000	67.0000	76.0000

This table reports summary statistics for time deposit accounts. *Balance* is the month-end dollar amount in the account; *Balance_delta* is the percentage change in the month-to-month balance, and *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. $\mathbb{I}_{\text{male}}$ is a dummy equal to one if the account holder is male. $\mathbb{I}_{\text{white}}$ is a dummy equal to one if the account holder is white (imputed race). $\mathbb{I}_{\text{joint}}$ 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 A3: Trends in Time Deposit Characteristics

Year	Balance ($)	Balance_delta (%)	Interest Rate	Deposit Spread (%)	$\mathbb{I}_{male}$	$\mathbb{I}_{white}$	$\mathbb{I}_{joint}$	Credit Score	Age
2011	19,969.38	0.00	0.00615	-0.19	.	.	0.00	.	.
2012	19,761.40	0.90	0.00576	-0.31	.	.	0.01	.	.
2013	20,740.41	0.00	0.00570	-0.25	.	.	0.01	.	.
2014	20,718.95	0.00	0.01068	-0.56	0.42	0.96	0.06	779.7	57.5
2015	20,010.80	0.00	0.00773	-0.07	0.44	0.88	0.31	754.9	56.7
2016	23,663.06	0.12	0.00805	0.05	0.44	0.83	0.29	781.4	58.2
2017	25,206.26	0.04	0.01029	0.44	0.45	0.86	0.19	783.9	60.4
2018	25,413.32	0.04	0.01275	1.24	0.46	0.87	0.15	783.1	61.3
2019	26,746.35	0.06	0.01728	0.10	0.47	0.88	0.15	784.3	61.0
2020	31,166.06	0.05	0.01630	-1.32	0.47	0.87	0.12	781.7	61.1
2021	36,074.34	0.03	0.01053	-0.75	0.46	0.86	0.13	778.8	62.5
2022	36,368.85	0.03	0.01043	2.07	0.46	0.85	0.14	779.5	63.9
2023	38,870.83	0.06	0.02098	2.33	0.47	0.85	0.14	780.3	63.6

This table reports summary statistics for all time deposit accounts. *Balance* is the month-end dollar amount in the account; *Balance_delta* is the percentage change in the month-to-month balance, and *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. $\mathbb{I}_{male}$ is a dummy equal to one if the account holder is male. $\mathbb{I}_{white}$ is a dummy equal to one if the account holder is white (imputed race). $\mathbb{I}_{joint}$ 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.

Table A4: Time Deposit Skewness

	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	0.108	0.268	0.490	0.219	0.003	0.696	0.043
2012	0.106	0.265	0.485	0.217	0.003	0.696	0.041
2013	0.105	0.261	0.483	0.224	0.005	0.710	0.064
2014	0.108	0.271	0.495	0.235	0.004	0.711	0.052
2015	0.113	0.277	0.501	0.277	0.009	0.733	0.073
2016	0.097	0.243	0.449	0.252	0.007	0.745	0.077
2017	0.095	0.238	0.440	0.243	0.009	0.741	0.085
2018	0.092	0.231	0.429	0.233	0.007	0.741	0.089
2019	0.090	0.226	0.421	0.239	0.008	0.753	0.099
2020	0.091	0.224	0.416	0.258	0.013	0.775	0.114
2021	0.091	0.224	0.413	0.269	0.018	0.786	0.126
2022	0.090	0.221	0.410	0.273	0.018	0.794	0.132
2023	0.091	0.221	0.410	0.301	0.022	0.820	0.156

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

Table A5: Characteristics of Time Deposit Accounts by Account Size

Balance Bin	Balance ($)	Balance_delta (%)	Interest Rate	Deposit Spread (%)	$\mathbb{I}_{male}$	$\mathbb{I}_{white}$	$\mathbb{I}_{joint}$	Credit Score	Age	Fraction of Observations
$50 - $200	112.73	0.85	0.00408	1.16	0.43	0.81	0.2	714	39.8	0.03
$200 - $500	329.26	0.42	0.0054	1.1	0.43	0.81	0.19	735.2	44	0.03
$500 - $1,000	657.78	0.07	0.00998	0.66	0.46	0.83	0.15	752.2	44.9	0.06
$1,000 - $5,000	2421.39	0.02	0.01181	0.41	0.44	0.85	0.16	775.2	55.1	0.23
$5,000 - $10,000	6645.18	0.01	0.0136	0.27	0.44	0.87	0.14	787.6	64	0.16
$10,000 - $25,000	15139.55	0	0.01414	0.23	0.46	0.87	0.15	791.3	68.1	0.21
$25,000 - $50,000	33810.17	0	0.01501	0.17	0.48	0.88	0.13	792.3	70.1	0.11
$250,000 - $1,000,000	133900.52	0	0.01638	0.06	0.53	0.87	0.14	793.5	70.4	0.17

This table reports summary statistics for all time deposits, split based on the underlying account balance. *Balance* is the month-end dollar amount in the account; *Balance_delta* is the percentage change in the month-to-month balance, and *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. $\mathbb{I}_{male}$ is a dummy equal to one if the account holder is male. $\mathbb{I}_{white}$ is a dummy equal to one if the account holder is white (imputed race). $\mathbb{I}_{joint}$ 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.