Tracing the Impact of Payment Convenience on Deposits: Evidence from Depositor Activeness*

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Abstract

What drives deposit demand? Analyzing 50 billion transactions from 1,400 U.S. banks, we find that depositors *actively* manage their accounts, and greater payment convenience makes deposits less sticky. Depositors experiencing shorter transfer delays move funds more frequently and maintain smaller balances. We develop a new model incorporating random transfer delays to explain these findings and quantify its implications: if all bank deposit transfers were settled next-business-day, deposit transfers would increase significantly while total deposit demand would decline by about 7%. Our findings highlight the important role of payment convenience in shaping deposit demand and influencing deposit franchise value.

Keywords: banking, deposits, payments, convenience.

JEL Codes: G21, E41, E42.

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1. Introduction

Why do people hold deposits, and how do they manage them? Understanding the determinants of deposit demand is critical for bank stability and the effectiveness of monetary policy transmission (Hanson, Shleifer, Stein, and Vishny 2015, Drechsler, Savov, and Schnabl 2017), yet this remains a challenge, partly due to the lack of granular data on depositor behavior. Leveraging new deposit transaction data, our paper offers a detailed characterization of depositor-level money demand and introduces novel measures of payment frictions. Our findings highlight that payment convenience plays a pivotal role in shaping deposit demand. Contrary to conventional wisdom, we show that depositors *actively* manage their bank accounts despite the stability of aggregate deposit demand, and that faster payments, while enhancing deposit convenience, may not necessarily increase bank franchise value.

Our paper builds on the fact that bank deposits underpin the U.S. payment system, yet moving funds across banks or transferring money in and out of banks often comes with significant delays and fees. We show that these frictions discourage deposit transfers and lead people to maintain large balances against unexpected consumption and liquidity needs. Empirically, we find when bank transfers become faster, depositors move more funds between bank accounts *and* in and out of banks while maintaining smaller bank balances. We further find that depositors maintain funds in transactional bank accounts to meet liquidity demands, and it motivates us to build a new deposit management model that explicitly accounts for the delays in bank transfers. In this model, we highlight the role of precautionary deposit demand in prompting depositors to accumulate bank balances. The model matches detrended data moments and aligns well with reduced-form estimates. We then simulate a counterfactual scenario in which all transfers settle by the next business day. We show that uniformly faster payments not only boost transfer volumes significantly but also reduce the necessity for holding large transactional deposit balances. These findings highlight the crucial role of payment efficiency in shaping deposit demand and bank franchise value.

We begin with a comprehensive analysis of depositor behavior using transaction-level data from over one million depositors across more than 1,400 U.S. banks and credit unions. This analysis reveals three new stylized facts that motivate us to measure depositor activeness through their fund transfers among bank accounts. First, from 2014 to 2022, over 95% of retail depositors hold at least two bank accounts. Second, depositors actively manage their portfolios through bank-to-bank deposit transfers (hereafter referred to as *interbank transfers*), which constitute approximately 20% of all transactions. Third, 9% of transactions are fund transfers between a depositor's own accounts, often involving substantial amounts. We systematically track these interbank transfer transactions and introduce a new measure, *deposit turnover*, to assess the activeness of retail depositors. Deposit turnover aggregates the gross flows of funds transferred between a depositor's accounts at different depository institutions, similar to the bank-level payment volume recorded in FedWire.

This transaction-by-transaction approach also allows us to uniquely measure the latency between when a deposit transfer is initiated and when it is credited (hereafter *transfer delays*). By aggregating these transaction-level estimates of delays, we provide a novel empirical measurement of payment frictions in banks at the account and depositor levels.

Our depositor-level analysis first reveals that transfer delays have a significant impact on both deposit turnover and deposit balances: depositors experiencing longer transfer delays are less active in interbank transfers and maintain larger balances. In particular, depositors facing higher consumption uncertainty and greater interest rate dispersion across accounts are more responsive, suggesting that they actively manage deposit transfers and balances to navigate the trade-off between uncertain consumption needs and savings.

Although our unique data on interbank transfer delays justifies our primary focus on interbank deposit transfers, interest rate differentials between typical checking and savings accounts are relatively small. To address this limitation, we extend our baseline empirical analysis to include all deposit inflows and outflows, providing a more comprehensive understanding of the drivers of deposit activity. This broader approach allows us to capture potential fund movements out of banks into higher-yielding nonbank savings vehicles, such as money market funds and brokerage accounts. Our findings robustly indicate that faster transfers are associated with increased deposit flows both into and out of bank accounts, with the effects being more pronounced when consumption volatility is higher. While our data cannot precisely identify the nonbank accounts to and from which depositors move funds, this analysis clarifies the underlying driver of deposit activity: depositors plan for savings but also seek to minimize payment delays and avoid disruptions to consumption. As a result, when payments become faster, depositors reallocate funds more actively to better manage the trade-off between consumption and savings. Consistent with this narrative, we find that as transfer speeds increase, depositors move more funds both between banks and in and out of the banking system when the rate spread between the Fed Funds Rate (FFR) and the interest rates offered on their bank accounts widens.

The negative correlation between transfer delays and depositor activeness could arise from two sources. First, sophisticated or attentive depositors may be more likely to choose efficient bank accounts that allow them to transfer funds across banks faster. Second, after exogenous decreases in transfer delays, depositors may adjust their activity levels and balances as they face less friction and require lower balances in low-interest deposit accounts for their spending needs. Disentangling this second source is important because our policy counterfactuals examine the impact of exogenous changes in payment technologies, such as the universal adoption of a faster technology, like FedNow, which increases payment transfer speed for *all* bank accounts.

To separate out this second source of variation empirically, we exploit a natural experiment in which depositors are exposed to fast payment technologies through their social networks. During the sample period, instant payment applications such as Zelle, Venmo, PayPal, and Cash App experienced rapid growth. More than half of the depositors in our sample received or initiated fund transfers using these platforms. Not all depositors seek faster payments in the same way. To address the potential endogeneity of technology adoption due to depositor characteristics, we focus on a subsample of depositors who have never used these fast payment applications before receiving an inflow of funds through them. We treat the first inflow of funds through these applications as a shock to their access to the technologies. The timing of these inflows is most likely not determined by the depositors themselves but rather influenced by their exposure to these technologies through their peers. We find that the exposure to faster transfer technologies increases depositor activeness and lowers account balances.

Our findings on transfer delays and their impact on depositor activeness and deposit balances motivate us to develop a model that reconciles these observations and further explores the counterfactual of implementing faster payments uniformly across banks. Specifically, we build a new deposit management model to extend the Baumol-Tobin two-account framework by incorporating transfer delays and consumption volatility. In this model, payment convenience of deposits stems from both the transactional and precautionary functions of money, and shorter transfer delays enable depositors to maintain lower balances in low-interest transactional deposit accounts. We characterize the optimal policy using two thresholds and two target balances and derive analytical properties for the special case without consumption growth. The model reproduces our empirical findings qualitatively, where depositors maintain smaller transactional deposit balances and transfer more funds when transfer delays are reduced.

We calibrate this model using detrended moments from our sample of depositors. Specifically, we examine changes in deposit balances and deposit turnover related to facing consumption uncertainty in a zero-consumption-growth environment, which focuses on the precautionary component of deposits rather than total deposits. In the baseline calibration, we use the average interest rate spread between FFR and account-level interest rate observed during the sample period, which is 0.78% annualized, detrended consumption volatility $4,833 for the average depositor, and 2-business-day transfer delays; the model matches average depositor's detrended balances and deposit turnover as observed in the data.

To address important policy questions such as what prevents bank payments from being faster and more efficient and the potential impact if the Federal Reserve mandates all banks to adopt a faster payment system, we examine two counterfactual scenarios to quantify the effects of faster payments on deposit demand: (a) reducing expected transfer delays to one business day; and (b) increasing consumption uncertainty by 26%, matching the post-pandemic rise in consumer debt levels. Under scenario (a), if all bank deposit transfers are expected to complete the next business day, deposit turnover driven by the precautionary motive will increase by more than 40% and depositors will hold approximately 30% less in bank deposits designated for precautionary consumption needs. Since approximately 23% of total deposits are designated for payments and precautionary uses, this leads to an overall decrease in total deposits of around $30\% \times 23\% = 6.9\%$. However, the effects of faster payments in reducing aggregate deposit demand are less pronounced when consumption uncertainty is higher in scenario (b) as liquidity needs increase, reflecting the strong precautionary demand for transactional deposits. Additionally, we sort depositors into quintiles based on average balances. At the cross-section, we find that reducing transfer delays impacts high-balance depositors the most. These depositors decrease their funds held at banks the most and transfer significantly higher amounts between accounts, consistent with our empirical findings.

Overall, our theoretical framework and empirical findings provide a fresh perspective on the role of payments in shaping deposit demand and bank franchise value. Faster payment technologies reduce the transaction costs associated with transferring funds between low-interest transactional accounts and higher-yielding savings accounts, enabling depositors to manage consumption needs without maintaining large transactional balances. While faster payment and transfer services enhance deposit convenience and may help banks attract new depositors, they also diminish the bank's franchise value by increasing deposit activeness and reducing the average size of transactional accounts. This erosion of deposit stickiness could offset the benefits gained from expanding the depositor base. Consequently, banks face a trade-off between attracting new depositors and preserving deposit stability, which may explain their reluctance to adopt faster payment technologies such as FedNow and their preference for slower payment systems. At a broader level, this dynamic also mirrors the historical decline in demand for non-interest-bearing checking deposits following the repeal of Regulation Q and the resulting increased supply of high-rate savings accounts (e.g., Drechsler, Savov, and Schnabl 2021, 2023). In this capacity, our study offers new insights into the design of future payment systems, bank regulation, and monetary policy.

Literature. Focusing on deposits, our paper contributes to the extensive literature on bank funding (e.g., Diamond and Dybvig 1983, Diamond and Rajan 2001, Goldstein and Pauzner 2005, Drechsler, Savov, and Schnabl 2017, Egan, Hortaçsu, and Matvos 2017, Greenwood, Stein, Hanson, and Sunderam 2017, Brunnermeier and Niepelt 2019, Whited, Wu, and Xiao 2022, Hanson, Ivashina, Nicolae, Stein, Sunderam, and Tarullo 2024), particularly in light of recent changes in depositor composition (Acharya, Chauhan, Rajan, and Steffen 2023, Acharya and Rajan 2023, Drechsler, Savov, Schnabl, and Wang 2023, Blickle, Li, Lu, and Ma 2024, Chen, Goldstein, Huang, and Vashishtha 2024). An emerging strand of research finds that deposits at digital banks are more volatile and serve more prominently as a medium of exchange (e.g., Erel, Liebersohn, Yannelis, and Earnest 2023, Jiang, Yu, and Zhang 2023, Koont 2023, Koont, Santos, and Zingales 2023). We contribute novel depositor-level evidence showing that enhanced payment convenience and the adoption of fast payment technologies encourage depositors to move funds more actively and maintain lower balances. These behaviors may have important implications for bank funding, deposit franchise value, and financial stability more broadly.[1]

Our paper also sheds new light on the implications of payment technologies for banking and the real economy. Prior research has shown that bank technology innovations influence borrowing and lending (e.g., Fuster, Plosser, Schnabl, and Vickery 2019, Berg, Burg, Gombović, and Puri 2020, Ghosh, Vallee, and Zeng 2023), bank competition (e.g., Sarkisyan 2023),

[1]Relatedly, Goldstein, Yang, and Zeng (2023) theoretically shows that increased payment convenience can lead to higher payment volume, which complicates bank liquidity management (e.g., Freixas, Parigi, and Rochet 2000, Afonso, Kovner, and Schoar 2011, Duffie 2019, Li and Li 2021, Afonso, Duffie, Rigon, and Shin 2022).

payment media choices (e.g., Massoud, Saunders, and Scholnick 2006, Scholnick, Massoud, Saunders, Carbo-Valverde, and Rodríguez-Fernández 2008, Wang 2023), financial inclusion (e.g., Dubey and Purnanandam 2023, Higgins 2024), and risk-sharing for lower-income households (e.g., Jack and Suri 2014, Balyuk and Williams 2021). We contribute to this literature by providing new evidence and a theoretical framework showing that faster payments allow depositors to maintain smaller transactional and precautionary account balances. This adds to the broader understanding of the determinants of precautionary savings (e.g., Bewley 1983, Parker and Preston 2005, Carroll and Kimball 2006).

Our paper adds to the expansive macroeconomic literature on the demand for money and liquidity (see Lagos, Rocheteau, and Wright 2017, Krishnamurthy and Ma 2024, for surveys). An expanding body of research highlights a convenience yield across various asset classes arising from factors such as search costs, liquidity demand, safety demand, and regulations (e.g., Stein 2012, Kacperczyk and Schnabl 2013, Sunderam 2015, Begenau 2020, Jiang, Krishnamurthy, and Lustig 2021, Acharya and Laarits 2023, Corell, Mota, and Papoutsi 2023, Brunnermeier, Merkel, and Sannikov 2024, Payne and Szőke 2024). We provide microeconomic-based evidence of payment convenience resulting from transfer frictions and demonstrate how these frictions influence both the demand for and the velocity of deposits. To address new evidence on transfer delays, we introduce a variable temporal transaction cost into a two-account money demand model (e.g., Baumol 1952, Tobin 1956, Miller and Orr 1966, Alvarez and Lippi 2009, Kaplan and Violante 2014, Di Tella, Hébert, and Kurlat 2024), presenting a novel addition to this longstanding theoretical framework.

The rest of the paper is organized as follows. Section 2 introduces the key variables and new stylized facts about U.S. depositors. Section 3 empirically tests how payment frictions affect depositor activeness and deposit balances. Section 4 develops a two-account deposit management model with transfer delays. Section 5 calibrates the model and discusses implications of mandating next-day processing for all bank transfers. Section 6 concludes.

2. Data, Measures, and Stylized Facts

In this section, we outline the dataset and detail the construction of key variables, in particular, a new measure for depositor activeness, *deposit turnover*, and a measure of payment friction at the depositor level, *transfer delay*, along with other depositor characteristics inferred from the transaction data. Additionally, we present new stylized facts about how American depositors actively manage their funds, which motivate our subsequent analysis of deposit turnover and transfer delays.

2.1. Data description

We obtain transaction-level de-identified household spending, income, and transfer data from a leading financial analytics firm. The database consolidates transaction data from more than 1,400 U.S. banks and credit unions, spanning American depositors with billions of transactions recorded from January 2014 until October 2022. The databases include savings accounts, checking accounts, credit, and debit card activities but exclude other account types such as brokerages and investments. In particular, deposits and withdrawals are observable for both saving and checking accounts. Each transaction is rich in metadata, including date, amount, category, and often merchant name and location. We use the textual description in the transaction data to extract information on depositors' income, debt, spending, bank transfers, and monthly location through physical transactions.

We focus on the depositors who had ten spending, income, or transfer-related transactions each quarter across 36 quarters out of 40 quarters in sample (Baugh, Ben-David, Park, and Parker 2021, Buda et al. 2022). Because the sample does not include the entire universe of banks, this selection also helps to ensure depositors selected primarily use bank accounts in sample. Importantly, we note that the total deposit balance changes inferred from the data closely match the aggregate trends in the Flow of Funds (Figure 1), suggesting that our sample is representative. We report summary statistics of depositors in sample by the end of the section.

2.2. *Deposit turnover*

We introduce a new measure, *deposit turnover*, to assess how active retail depositors are. Specifically, it measures the total gross amount of funds that a depositor transfers across bank accounts of *different banks* within a given period, similar to the bank-level payment volume reported in FedWire. Higher deposit turnover (larger interbank transfer volume) is associated with higher payment risk (Li and Li 2021, Li, Li, and Sun 2022, Goldstein, Yang, and Zeng 2023).[2]

Figure 2 summarizes the construction of depositor-level interbank deposit turnover, and we detail each step below. Before zooming into the algorithm, we first present two novel stylized facts that motivate our analysis of interbank transfers.

First, most American depositors have more than one bank account. The notion of interbank deposit transfers is only well-defined if depositors possess multiple bank accounts. Although the information about the number of bank accounts per American is limited, a 2019 survey by the Mercator Advisory Group indicated that the average number of bank accounts is 5.3 per person (Reville 2019). And in our sample, as illustrated in Figure 3, it is evident that the majority of depositors hold not just one but several bank and credit card accounts.

Second, the second bank account for more than three quarters of depositors has a sizable balance. Table 1 shows that the mean (median) deposit in the first bank account, ordered by size of account balance, at \$33,159 (\$7,256), the mean (median) deposit in the second bank account at \$17,019 (\$3,425), and the mean (median) deposit in the third bank account at \$7,548 (\$1,699). This suggests that depositors hold significant funds across bank accounts.

Based on these observations, we construct a measure of depositor activeness through depositors' fund transfer activities across bank accounts. For each depositor i, we pull together every transaction from all of their accounts, denoted by $a \in \mathcal{A}_i$. The challenge is

[2] Additionally, the gross outflow of deposits to other banks can be interpreted as the random maturity of deposits. Bolton, Li, Wang, and Yang (2023) and Jermann and Xiang (2023) model deposits as debt contracts with random maturity, where a larger amount of maturing debt within a given period poses a higher risk to the bank.

that our dataset does not tag transactions with unique identifiers across different banks, nor does it tell us which bank each account belongs to. As a result, we cannot simply flag a transaction as an interbank transfer based on account or bank labels.

To get around this, we developed a straightforward algorithm. On any given day t, we start by examining all debit transactions—these include transfers out, ATM or cash withdrawals, and deposits—from every account that depositor i holds, which constitute approximately 20% of all transactions. For each debit transaction on day t, we then search for a matching credit in any of the depositor's other accounts $i.e., a' \in \mathcal{A}_i$, with $a' \neq a$ that occurs within a five-day window, from day t to $t + 5$.

If we find a credit transaction on the balance statements of any other account of depositor i on the same day (i.e., $t' - t = 0$), that's our first hint of a same-day transfer across accounts of the same depositor. We then check how close the amounts are. Specifically, if the absolute difference satisfies $0 \leq |D_{iat} - C_{ia't'}| \leq 50$, we take this as evidence that the two transactions are part of a wire transfer, intrabank transfers (i.e., funds transferred between accounts of the same bank), or payments facilitated by rapid payment platforms such as Zelle or Venmo. We choose the upper threshold of $50 because it covers the maximum fees typically seen for wire transfers.[3] In cases where there are multiple candidate credit transactions, we pick the one that comes earliest.

If no same-day match turns up, we extend our search to cover the following business days (up to day $t' \leq t + 5$). Transactions found in this window are most often Automated Clearing House (ACH) transfers, which generally don't have fees or might incur a small fee of up to $10.[4] If debit transaction D_{iAt} and the corresponding credit transaction C_{iAt} meet all

[3] An analysis of the costs associated with wire and ACH transfers across leading U.S. banks informed these thresholds. For details of wire transfer charges, please refer to Appendix B.1.

[4] The Expedited Funds Availability Act (Reg CC) was passed in 1987 to regulate electronic transfers. According to Reg CC, for wire transfers between banks, banks need to ensure the availability of transferred funds within the same day or, at the latest, the next day. However, a regular interbank transfer through ACH does not fall under the definition of an electronic payment within the purview of Reg CC and is exempt from the next-day availability requirement established in section 229.10, leading to variations in processing delays and fees.

conditions, we record the value of D_{iAt} as an interbank transfer, with one exception: the exact same-day matches with no difference in amounts. These are most likely intrabank transfers which are funds moving between accounts at the same bank, and don't affect the overall deposit size or liquidity of the institution. Thus, for each depositor i, we define their interbank deposit turnover as the total volume of debit transactions (that meet our matching criteria) across all their accounts in a given month. Formally, we summarize this as:

$$\text{Interbank Deposit Turnover}_i = \sum_{a \in \mathcal{A}_i} \sum_{t \in \mathcal{T}} D_{iat},$$

where $\mathcal{A}_i$ represents the set of all accounts held by depositor i, and $\mathcal{T}$ denotes the transaction dates within the month. This metric captures the gross volume of fund transfers for each depositor, analogous to the gross volume reported at the bank level in FedWire, capturing the gross payment flow of funds across banks.

During the sample period, ACH transfers account for the majority of interbank deposit turnover. The types of interbank transfers are important because different types of transfers vary significantly in their transfer speeds. While ACH transfers can experience long delays, wire transfers and transfers initiated through fast payment applications are typically processed within a business day with minimal to no delay. Using the meta information and transfer delays for paired deposit transactions, we further report deposit turnover based on the method of transfer used. In the following analysis, we do not consider transfers that are initiated and credited within the same bank; instead, analysis below focus on interbank transfers, and we summarize the main categories of deposit transfer across banks in Figure 4.

Transactions completed with fast payment services such as Zelle, PayPal, Cash App, and Venmo are classified as "Instant App Transfer" transactions. Over time, there has been a noticeable uptick in these types of transactions. Additionally, transactions with metadata that include ATM-related information (physical cash withdrawal, ATM, cash, etc) in their metadata are classified as ATM transactions. These transactions have maintained a low but steady rate of occurrence. All other deposit transfers with a non-zero transaction delay that do not fall into the categories of ATM-related, instant payment application related, or wire, are labeled as interbank transfers, as shown in orange in the graph. Our study does not look into the specifics of choosing wire transfers as a payment method, including the decision-making process regarding the willingness to pay for for superior payment services, leaving this area open for future exploration. Appendix B.1 summarizes fee differences for different payment methods of interbank transfers.

2.3. Transfer delays

To assess the delay in payment processing for each bank account of every depositor every month, we start by analyzing the delay between the debit and credit transactions for each of the paired deposit transactions. We define a payment lag as the difference in transaction dates between a debit transaction D and its paired credit transaction C for a paired deposit transaction,

$$Delay_k = Date(C_k) - Date(D_k),$$

where $Date(D_k)$ is the transaction date of the k^{th} debit transaction and $Date(C_k)$ is the transaction date for the corresponding credit transaction.

We further adjust for weekends by subtracting any weekend days that fall within the delay period, representing the delay in terms of standard business days. Once these individual lags are identified, we compile the data by each account for every month and define the transfer delay as the weighted average of the transfer delays for all accounts within a given month. That is, for each account a in a given month,

$$AvgDelay_{a,t} = \frac{\Sigma_k Delay_k \cdot \mathbf{I}(D_k \text{ is originated from account } a)}{\Sigma_k \mathbf{I}(D_k \text{ is originated from account } a)}.$$

Given these individual account delays for month t, the depositor-month level *transfer delay*, factoring in the monetary values, can be written as:

$$TransferDelay_{Depositor,t} = \frac{\Sigma_a D_{a,t} \times AvgDelay_{a,t}}{\Sigma_a D_{a,t}}.$$

Here, $D_{a,t}$ is the total value of debit transactions originated from account a for paired deposits of the given depositor. This measure gives a representation of each depositor's overall experience with transfer delays taking into account the monetary significance of the transfers.[5]

Based on our notion of transfer delay, Figure 5 shows that American depositors encounter substantial delays when transferring deposits between banks via standard ACH transfer methods. Specifically, delays for regular ACH transfers consistently average around two business days across the sample period. Nevertheless, when considering transactions facilitated by fast payment services, the average delay for interbank transfers decreases to 1.5 days, with a downward trend over time.

Table 2 provides a further breakdown of the average transaction sizes associated with respective transfer delays. In this table, we outline the mean transaction values for each category of delay, measured in days, across depositors over multiple months.

2.4. Other characteristics and constraints of depositors

Account-level interest rates. We impute interest rate from deposit balances from each bank account. Specifically, we compute interest income generated from interests on deposits at the individual account level from transaction records with a description containing the word "interest" and are credited to the account. We manually filter out transactions that might misrepresent interest income such as transaction descriptions associated with bonuses, overdraft fees, loans, and rents. For each month, we compute interest rate for account a of depositor i at month t as

$$i_{i,a,t} = Interest_{i,a,t}/Balance_{i,a,t-1}.$$

One reason that depositors move money across account is that depositors shop for interest rates across bank accounts. We find the rate offered across bank accounts for a given depositor has a relatively large variation (standard deviation of 25bp) compared to the mean (13bp).

[5]We assume the delay in a given account's payment processing is independent of the transaction's value.

We hence construct *Rate Dispersion*$_{it}$ to capture the difference between the highest and lowest rates offered at different bank accounts of depositor i at month t.

Expectation of overdraft. Maintaining a sufficiently positive balance is crucial to avoid penalty such as overdraft fees for depositors. In our model, expectation of penalty fees also acts as a key parameter preventing deposits from turning negative. Although we cannot directly observe a depositor's expectation of overdraft fees, we use two proxies. First, we consider whether a depositor has incurred any overdraft, non-sufficient funds, or returned check fees during the sample period. We track all transactions with descriptions related to these fees and create a dummy variable, *Overdraft Realized*$_i$, which equals one if a depositor has paid such fees at least once. Second, a depositor's decision to opt into overdraft protection services provides a clear indication of their expectation of overdraft fees. Banks often offer this service to help depositors avoid hefty fees. The service is often free if the accounts being protected and the funds being drawn are from the same bank, typically between a checking and a savings account, although some banks may charge a small fee, which is lower than the typical overdraft fee. We capture this by creating a dummy variable, *Overdraft Protected*$_i$, which equals one if the depositor has a bank account with overdraft protection. Table 3 shows that 5% of depositors opt in for overdraft protection services, while 21% have experienced overdrafts during the sample period, suggesting depositors are aware and expect overdraft when facing zero balance, which supports a precautionary motive of deposit holdings.

Salary. We construct salary income from credit transactions that are either categorized under 'Salary/Regular Income' or contain payroll-related terms in their description. We exclude any transactions related to social security, tax refunds, or UI benefits and consider both the transaction category name and specific keywords in the transaction descriptions. We cross-validate the aggregate trend with labor income dynamics of depositors in our dataset to those in the Panel Study of Income Dynamics.

Consumption volatility and stability. Analyzing depositor behavior requires a look at how people adjust their consumption, especially when they face unpredictable income shocks. Driven by a precautionary saving motive, depositors who experience higher consumption uncertainty could adjust their behavior more often. As a result, these depositors are likely to be more responsive to changes in interest rates. We introduce two measures. First, we compute the rolling consumption uncertainty as the 12-month rolling standard deviation of consumption for each depositor; second, we introduce a standardized measure of consumption smoothing efficiency (CSE) to measure to capture each depositor's relative steadiness of consumption regardless of levels of consumption. CSE is defined as the ratio of the rolling mean to the rolling standard deviation of consumption using monthly data from the previous 12 months. It quantifies how effectively depositors maintain consistent consumption patterns with potential fluctuations; in other words, it captures how much average consumption a depositor achieves per unit of consumption variability. A higher value indicates that he gets more average consumption for less volatility, suggesting better consumption smoothing.[6]

In addition, we compute each depositor's residence at the state-city level based on locations they frequent and transactions containing location information, for example, restaurants, gas stations, utility bills, and groceries. In our analysis below, we find similar results with either depositor fixed effects or location fixed effects.

Financial sophistication. To capture financial sophistication, we construct *digital payment ratio*, defined as the ratio between online versus total spending for each depositor. This measure can serve as an indicator of a user's adoption of digital payment methods, reflecting their familiarity with online payments. The *Digital Payment Ratio* highlights a depositor's trust in technology, accessibility to digital platforms, and preference for transactional convenience.

Table 3 provides summary statistics for depositors with active interbank transfers, high-

[6] The concept of CSE is similar to Sharpe ratio. Sharpe ratio measures the risk-adjusted return of an investment by comparing the excess return to its volatility while CSE evaluates the "efficiency" of consumption relative to its variability. While Sharpe ratio gauges financial return achieved per unit of risk, CSE assesses the consistency of consumption per unit of its fluctuation.

lighting substantial variability in deposit turnover, with an average deposit turnover of around $1,488.32 and a standard deviation of $968.10. Dollar-weighted transfer delays also exhibit variability, averaging 2.02 days with a standard deviation of 0.94 days. A contributing factor to the large deposit turnover might be the sporadic nature of deposit transfers; households often remain inactive for several months, and when they do make transfers, the amounts can be significant. Consequently, in the subsequent analysis using lagged transfer delays as a proxy for transfer frictions, we employ a one-year rolling average of transfer delays for each depositor to account for changes over time.

Another factor influencing the rate of deposit turnover is account specialization. Gelman and Roussanov (2024) document evidence of mental accounting as individuals exogenously receive new payment cards temporarily increase total consumption expenditure. Appendix Figure A-4 shows that depositors utilize different bank accounts for specific purposes, which suggests a need to frequently transfer deposits between their own accounts to meet various liquidity requirements. The mean of *Digital Payment Ratio* is 32%, showing the prevalence of online transactions. Additionally, the percentage of depositors using fast payment applications stands at 65%, suggesting a notable adoption of fast payment platforms.

Furthermore, the average deposit balance is $24,774.50 with a standard deviation of $59,139.49, indicating significant variation in the amounts held by depositors. The mean interest rate offered on deposits is 0.09%, with a rate dispersion of 0.13%, reflecting differences in interest rates across different bank accounts.

Finally, *consumption Volatility* has a mean of $3,293.28, indicating variability in monthly consumption expenditures. *Consumption Smoothing Efficiency* has a mean of 2.73, suggesting that, on average, depositors maintain a relatively stable level of consumption relative to fluctuations in income. The variables in the table have been winsorized at the 1% level to account for outliers, including *Transfer Fees*, *Transfer Delay*, *Salary*, *Mean Interest Rate*, *Consumption Volatility*, *Consumption Smoothing Efficiency*, and *Account Balance*.

In addition to the dollar volume of deposit turnover, which is crucial for bank funding, we present an additional set of empirical results using scaled variables. Depositors vary in their wealth; a $1,000 transfer constitutes different proportions for individuals with $1 million compared to those with $2,000 in deposits. To capture the decision of deposit transfers, following Attanasio and Pistaferri (2016), we scale deposit turnover and other depositor-level metrics by each individual's average monthly spending in the preceding year. We show the distribution of scaled deposit turnover in both raw and logarithmic forms in Figure A-5 in Appendix B.4.

3. Transfer Delays and Depositor Behavior

In this section, we empirically examine how transfer delays affect depositor activeness and account balances. We present evidence on deposit movements both between banks and in and out of banks, highlighting the trade-off depositors face between optimizing savings and meeting uncertain consumption needs. Additionally, we introduce a quasi-experiment involving payment technology shocks to disentangle depositors' responses to changes in transfer delays from the effects of depositor-bank sorting based on varying transfer speeds.

3.1. Transfer delays, interbank deposit turnover, and bank balances

Our primary proxy for depositor activity is $\textit{Deposit Turnover}_{i,t}$, defined as the total interbank transfers made by depositor i during month t. We focus on interbank transfers for a depositor in our baseline regressions because our measure of payment delays is most precise at the interbank level for depositors. Specifically, we examine how payment frictions, in the form of transfer delays, affect deposit turnover and deposit balances for depositor i at the end of month t using the following empirical model:

$$Y_{i,t+1} = \beta_0 + \beta_1 \times \textit{Transfer Delay}_{i,t} + \Gamma \times \mathbf{X}_{i,t} + \delta_t + \epsilon_{i,t+1},$$

where the dependent variable Y is either *Deposit Turnover* or *Deposit Balance*. $\textit{Transfer Delay}_{i,t}$ is the dollar-weighted average duration, measured in days, that it takes for depositor i to complete a transfer, calculated as a rolling average over the 12 months leading up to month t to account for the irregular occurrence of transfers and thereby gaps in transfer delay data. $\mathbf{X}_{i,t}$ includes a set of depositor-specific covariates to address other characteristics across depositors that can affect deposit activeness in addition to transfer delays. First, we control for the rolling consumption uncertainty and potential interest income captured by rate dispersion. Second, we consider financial constraints and sophistication, proxied by salary and digital payment ratio, which compares non-physical to total consumption and reflects a depositor's inclination towards newer, faster technologies. We include year-month fixed effects, δ_t, to focus on the cross section of depositors.

We summarize the results in two panels in Table 4. In panel (a), we report how transfer technology drives deposit turnover and balances in dollar amount. In panel (b), to facilitate comparisons across depositors, we present how transfer technologies affect deposit turnover and balances in consumption units per depositor. Specifically, we scale each depositor's measures by their average spending over the past year and apply a log transformation to the dependent variable, which allows the coefficients to be interpreted as semi-elasticities. When accounting for both time fixed effects and depositor-specific controls, an additional day of transfer delay reduces deposit turnover by about 46 dollars and increases deposit balances by about 1,700 dollars; in consumption units, the scaled deposit turnover decreases by 16.4% and the scaled deposit balance increases by 5.2%.

Understanding the drivers of deposit activeness with respect to transfer delays. Having established the baseline relationship between deposit turnover, account balances, and payment delays, we now investigate the underlying economic trade-offs driving these patterns. We hypothesize that the impact of transfer speed on deposit activity reflects a balance between managing uncertain consumption needs and optimizing savings, alongside other economic factors. This motivates us to empirically examine the key determinants influencing the semi-elasticity of deposit turnover and balances with respect to transfer delays. Looking ahead, we develop a formal model in Section 4 to formalize these ideas, which we then use for quantitative analysis.

With respect to deposit turnover, we first run individual regressions for each depositor by regressing their log(*Scaled Deposit Turnover*) on transfer delays. Specifically, for each depositor i, we estimate the following regression: $\log(\textit{Scaled Deposit Turnover}_{i,t+1}) = \beta_i \times \textit{Transfer Delay}_{i,t} + \epsilon_{i,t+1}$, where β_i represents the semi-elasticity of deposit turnover with respect to transfer delays for depositor i. This gives us a cross section of semi-elasticity estimates, which we then regress against depositor-level average characteristics to determine which factors significantly affect the semi-elasticities. Specifically, we run a cross-sectional regression of the semi-elasticity estimates on the standardized depositor characteristics: $\beta_i = \gamma_0 + \sum_k \gamma_k X_{i,k} + \epsilon_i$, where $X_{i,k}$ are the standardized depositor characteristics, including salary, consumption uncertainty, digital payment ratio, and interest rate dispersion. The depositor-level salary, consumption uncertainty, deposit turnover, and balance are scaled by the 12-month moving average of consumption. We conduct the same exercise for account balances as well.

We find that depositors with higher interest rate dispersion and consumption uncertainty are more responsive to changes in transfer delays. Panel (a) in Figure 6 shows that depositors with higher interest rate dispersion or greater consumption uncertainty have lower semi-elasticities of turnover with respect to transfer delays, suggesting they transfer more funds when transfers become faster. On the other hand, the semi-elasticity of account balance with respect to transfer delays is positive, and panel (b) in Figure 6 shows that depositors with larger consumption uncertainty have higher semi-elasticities of balance with respect to transfer delays, i.e., holding more deposits when transfer delays are larger.

The richness of our data further allows us to conduct the same analysis on two specific depositor subgroups: large-sized uninsured depositors and depositors without credit cards. The results, reported in Appendix B.5 in great detail, also align with the trade-off between consumption uncertainty and savings highlighted in the baseline findings.

3.2. *Transfer delays, deposit movements in and out of banks, and rate sensitivity*

To further support the economic rationale that the impact of transfer speed on deposit activity reflects a trade-off between managing uncertain consumption needs and optimizing savings, we extend our baseline empirical analysis in Table 4 and Figure 6 to include all deposit inflows and outflows, both within and outside the banking system. This approach helps address the challenge that interest rate spreads among bank accounts in our sample period are relatively small and allows us to capture potential fund movements into higher-yielding nonbank savings vehicles, such as money market funds and brokerage accounts.

To this end, we examine how interest rates and transfer delays influence the allocation of deposits into and out of any given bank account a for a given depositor i at time t:

$$\begin{aligned}\%\textit{Account balance}_{i,a,t+1} = \beta_0 + \beta_1 \times \textit{Rate Spread}_{i,a,t} + \beta_2 \times \textit{Transfer Delay}_{i,a,t} \\ + \beta_3 \times (\textit{Rate Spread}_{i,a,t} \times \textit{Transfer Delay}_{i,a,t}) + \Gamma \times \mathbf{X}_{i,a,t} + \delta_{i,t} + \epsilon_{i,a,t+1},\end{aligned}$$

where $\%\textit{Account balance}_{i,a,t+1}$ is the change in the balance of account a for depositor i at time $t+1$ over total deposits held by depositor i across all deposit accounts at time t. We note that our dataset primarily tracks bank accounts, meaning we lack direct information on non-bank savings or brokerage accounts, such as money market funds or other high-yield alternatives. However, $\%\textit{Account balance}_{i,a,t}$ serves as an imperfect proxy and an upper bound for all transfers into and out of a transactional bank account a at time t, including potential movements between that account and non-bank savings or brokerage accounts. Thus, we are able to examine how such fund transfers respond to transfer delays as well as changes in competitive interest rates.

Particularly, to capture such competitive interest rates, $\textit{Rate Spread}_{i,a,t}$ is the standardized average rate spread between effective Fed Funds Rate and account level interest rate over the past 12 months of account a for depositor i in month t. In addition, $\textit{Transfer Delay}_{i,a,t}$ is the standardized average transfer delays over the past 12 months of account a for depositor i in month t, also calculated as a rolling average. The interaction term $\textit{Rate Spread}_{i,a,t}$ ×

Transfer Delay$_{i,a,t}$ captures the interaction effect between interest rates and transfer delays on deposit allocation. We also include a set of control variables $\mathbf{X}_{i,a,t}$ that account for other factors influencing deposit allocation, including the account-level consumption volatility (12-month rolling standard deviation over the rolling mean of consumption), the proportion of income from social security and unemployment insurance received through account a to the depositor's total income across accounts, the proportion of gross investment flows in account a to the depositor's total investment across accounts,[7] the shares of credit card payments in the depositor's total credit card payments, and ATM withdrawals in account a out of total transactions in credit card payments and ATM withdrawals across accounts. These factors capture other account non-pecuniary characteristics on services, including access to credit card rewards, ATM services, direct deposit services, and integration with brokerage and wealth management. Fixed effects $\delta_{i,t}$ absorb time and depositor level variations.

Table 5 presents the results. First, higher account-level rate spreads are linked to lower balances in transactional bank accounts: controlling for depositor and time fixed effects, a one-standard-deviation increase in the rate spread (approximately 80 basis points) coincides with a 15% reduction in account balances. However, this effect is dampened when payment transfers are slower, reflecting depositors' unwillingness to move funds out of transactional accounts if doing so is cumbersome. Moreoever, the relationship is even more pronounced for depositors with heightened precautionary motives: in Columns (4) to (6), focusing on individuals whose consumption volatility lies above the median, we find that such depositors respond more strongly to rate spreads, and delays further magnify the friction that limits outflows. All these observations are consistent with the baseline results in Table 4 and Figure 6 and suggest that deposit activeness indeed reflects a trade-off between managing uncertain consumption needs and optimizing savings.

In reality, many daily expenditures are not directly handled from bank accounts; credit

[7]The gross investment flows are more informative than net investment flows at the depositor level as a measure of depositor activeness (Blickle, Li, Lu, and Ma 2024).

cards, which on average account for around 30% of total spending, is another important payment channel for many depositors. Because credit cards act much like lines of credit and permit flexible repayment schedules, the uncertainty of any waiting period for fund transfers becomes less important (Akerlof and Milbourne 2199). Consistent with this view, Columns (7) and (8) in Table 5 suggest that accounts experiencing heavier credit card usage are subject to a weaker dampening effect of payment delays on depositors' sensitivity to rate spreads.

In sum, at the account level and focusing on all transfers into and out of a bank account, our findings suggest that faster transfers are associated with increased deposit flows both into and out of bank accounts, with the effects being more pronounced when consumption volatility is higher. At the same time, depositors become more responsive to rate spreads as payment speeds increase, an insight that helps explain why banks, benefiting from higher rate spreads, may be reluctant to adopt faster payment infrastructures that could make deposit outflows more sensitive to rate differentials. Looking forward, we provide further quantitative results consistent with these reduced-form observations in Section 5 using a calibrated model that incorporates these trade-offs.

3.3. Causal relationship: Access to fast payments and depositor behavior

To further establish a causal relationship between transfer delays and depositor behavior, we address potential endogeneity concerns arising from depositor self-selection into accounts with shorter transfer delays. We exploit a natural experiment that leverages exogenous exposure to faster payment technologies through depositors' social networks.

Our identification relies on the exogenous adoption of fast payment applications such as Zelle, PayPal, Venmo, and Cash App through social interactions. Prior literature has documented that social networks and peer interactions significantly impact financial decisions, including investment choices (Hong, Kubik, and Stein 2004, Hirshleifer 2020), product adoption (Bailey et al. 2022), housing decisions (Bailey, Cao, Kuchler, and Stroebel 2018), and risk-taking behavior (Roussanov 2010). We search through all transactions of each depositor, and consider the first incoming fund transfer facilitated by Zelle, PayPal, Venmo, and Cash App as an exogenous *payment technology shock* resulting from peer interactions.

Fast payment applications are relevant for transfer delays. While these platforms offer standard transfer options with delays comparable to traditional bank transfers (Appendix B.1), empirically, Figure 7 shows that interbank transfers facilitated through fast payment applications experience significantly shorter delays, typically settling on the same or the following business day. This suggests that depositors primarily use fast payment applications to expedite fund transfers.

The validity of our instrument hinges on the assumption that the *timing* of the initial receipt of a fast payment inflow is exogenous to the depositor's own characteristics and deposit behavior. While the formation of social networks may be endogenous, the exact timing of when a depositor first receives an unsolicited payment via fast payment technology is plausibly exogenous. To isolate the impact of exogenous exposure to faster payment technology rather than endogenously adopting the technology, we focus on depositors who receive an initial inflow through fast payment technologies prior to initiating outflow transactions through fast payment technologies. In our sample, we have 193,787 such depositors who fit this criterion, representing approximately 24% of all adopters of these technologies. The majority of depositors (approximately 76%) began using these platforms by making payments to others before receiving any inbound transactions. By focusing on those who receive funds first, we mitigate concerns that their adoption decision is driven by their own proactive choice, and instead capture the influence of their social network's adoption.

As an example, consider depositor i, who has never used Zelle prior to date t. On date t, depositor i receives an unsolicited incoming Zelle transfer from depositor j, who is part of depositor i's social network (e.g., a friend, family member, or colleague). To access the funds, depositor i must install and register with Zelle, thereby adopting the fast payment technology. This incoming transfer acts as an exogenous shock to depositor i's access to faster payment services, independent of depositor i's prior preferences or characteristics.

Consequently, depositor i is now more likely to utilize Zelle for future transactions, potentially increasing their activeness and reducing their reliance on holding larger deposit balances.

Figure 8 shows that the treated depositors exhibit similar pre-adoption trends compared with the control group, which includes depositors who had used fast payment technology for outflows before their first inflow of funds via these platforms. Figure 9 reports a series of covariate balance tests between depositors who adopted fast payment applications via social interactions and the rest, and finds that the differences in their characteristics are insignificant. We additionally report the distribution of the depositors' balances in the treated and control groups in Figure A-6.

Using the exposure to first payment via social network as an instrument, we estimate a two-stage least squares:

$$Transfer\ Delay_{i,t} = \gamma_0 + \gamma_1 I(\widehat{Post\ First\ Inflow})_{i,t} + \gamma_2 \mathbf{X}_{i,t} + \delta_t + \varepsilon_{i,t},$$

$$Y_{i,t+1} = \beta_0 + \beta_1 \widehat{Transfer\ Delay}_{i,t} + \beta_2 \mathbf{X}_{i,t} + \delta_t + \epsilon_{i,t+1}.$$

For each depositor, we find his first *incoming* fund transaction facilitated by Zelle, PayPal, Venmo, and Cash App and record the month of that transaction as τ_i. The indicator $I(\widehat{Post\ First\ Inflow})_{i,t}$ equals one for month t if $t \geq \tau_i$ and depositor i has not made any outflow via fast payment applications prior to month τ_i. $Transfer\ Delay_{i,t}$ is the dollar-weighted transfer delays for depositor i using the 12-month moving average for each month t. In the second stage, we estimate the effect of transfer delays due to the technology shock on deposit turnover and deposit balances, using the predicted transfer delays in the first stage; i.e., the dependent variable Y is *Deposit Turnover* and *Deposit Balance*. We include time-fixed effects and depositor-level controls in both stages to focus on the cross-sectional heterogeneity of depositors. Time-varying depositor-level controls $\mathbf{X}_{i,t}$ include salary, consumption uncertainty, interest rate dispersion, digital payment ratio, as in previous sections, along with the size of money first deposited via fast payment platforms.

To further investigate whether exposure to fast payment platforms influences depositors' transfer delays through increased usage of outgoing transfers, we extend our analysis by introducing an intermediary step. We employ a Three-Stage Least Squares estimation approach to test if depositors begin to initiate outgoing transfers via these platforms after receiving their first inflow. Specifically, we estimate the following three regressions:

$$I(\textit{Post First Outflow})_{i,t} = \zeta_0 + \zeta_1 I(\textit{Post First Inflow})_{i,t} + \zeta_2 \mathbf{X}_{i,t} + \delta_t + v_{i,t},$$

$$\textit{Transfer Delay}_{i,t} = \gamma_0 + \gamma_1 \widehat{I(\textit{Post First Outflow})}_{i,t} + \gamma_2 \mathbf{X}_{i,t} + \delta_t + \varepsilon_{i,t},$$

$$Y_{i,t+1} = \beta_0 + \beta_1 \widehat{\textit{Transfer Delay}}_{i,t} + \beta_2 \mathbf{X}_{i,t} + \delta_t + \epsilon_{i,t+1}.$$

The first equation models how receiving funds via fast payment platforms for the first time ($I(\textit{Post First Inflow})_{i,t}$) influences a depositor's likelihood of initiating outgoing transfers using the same platforms ($I(\textit{Post First Outflow})_{i,t}$), where $I(\textit{Post First Inflow})_{i,t}$ is the dummy variable for exposure to technology as in the 2SLS, and $I(\textit{Post First Outflow})_{i,t}$ is a dummy variable equal to 1 if depositor i has initiated an outgoing transfer via fast payment platforms by time t, and 0 otherwise. $\mathbf{X}_{i,t}$ controls for time-varying depositor-level controls, including salary, consumption uncertainty, interest rate dispersion, digital payment ratio, and the amount first received via fast payment platforms, and time-fixed effects to control for common trends. Using the predicted values $\widehat{I(\textit{Post First Outflow})}_{i,t}$ from the first stage, the second equation estimates the effect of adopting technology for transfer outflows through exposure on transfer delays. The third equation assesses how changes in transfer delays, influenced by technology adoption, affect deposit turnover and deposit balance. By introducing this intermediary step, the 3SLS approach allows us to disentangle the pathways through which exposure to fast payment platforms impacts depositor behavior. Specifically, it tests whether the initial exposure to fast payment through receiving funds prompts the use of these technologies for outgoing transfers, subsequently reducing transfer delays and influencing deposit turnover and balances.

Table 6 shows the impact of transfer delays on deposit balances and deposit turnover, using various estimation methods. In columns (1), (2), and (4), the dependent variable is the depositor's scaled balance in the final stage, while columns (7) to (9) report the final-stage results for scaled deposit turnover. We report the results on raw values of balances and turnover in Table A-5.

Column (1) finds that longer transfer delays lead depositors to hold higher balances. However, this estimate may be biased due to unobserved depositor characteristics sorting into bank accounts with different transfer delays. To address potential endogeneity, we adopt an instrumented regression. In the first stage (column (3)), we instrument *Transfer Delay* with the depositor's exposure to fast payment technologies via social networks ($\mathbf{I}_{\text{Post First Inflow}}$). The instrument significantly reduces transfer delays, confirming its relevance. In the second stage (column (2)), the coefficient on *Transfer Delay* remains positive and significant, though smaller in magnitude compared to the OLS estimate. This result suggests that, after controlling for endogeneity, longer transfer delays causally lead to higher deposit balances.

The 3SLS estimates in columns (4) to (6) further strengthen this finding by simultaneously modeling the potential feedback between deposit balances and the adoption of fast payment technologies. Column (5) shows that depositors are more likely to use fast payment technologies for outgoing transactions after being exposed through incoming funds, indicating a behavioral shift prompted by the technology shock. Column (4) confirms that longer instrumented transfer delays increase deposit balances, reinforcing the causal interpretation.

For deposit turnover, the OLS estimation in column (7) indicates that longer transfer delays significantly reduce depositor activeness. A one-day increase in transfer delay leads to a decrease in deposit turnover, suggesting that payment frictions discourage frequent interbank transfers. The 2SLS and 3SLS estimations in columns (8) and (9) corroborate this negative relationship with similar magnitudes, implying that shorter transfer delays facilitate more active fund management among depositors.

Limitations and Potential Bias. While our instrumental variable approach mitigates some endogeneity concerns, there are limitations that could introduce bias. First, later adopters of fast payment technologies might naturally experience shorter transfer delays due to improvements in banking infrastructure over time, independent of their technology use. This could confound our results if the decreasing trend in transfer delays is correlated with unobserved depositor characteristics. However, as illustrated in Figure 5, transfer delays remain relatively stable around a mean of two days throughout the sample period, suggesting that temporal trends are unlikely to bias our estimates significantly. Additionally, we consider the staggered adoption of Zelle by banks starting in 2019 (Balyuk and Williams 2021). Restricting our sample to depositors exposed to Zelle post-2019 (i.e., those with τ_i after 2019), we find robust evidence that the results remain consistent and exhibit slightly larger magnitudes (Table A-5).

Second, our instrumental variable estimates reflect the LATE for depositors who adopted fast payment technologies through peer interactions—approximately 24% of technology adopters. A significant portion of depositors (about 40%) never used fast payment technologies. Despite controlling for observable depositor characteristics, unmeasured factors such as individual preferences for technology could influence both the likelihood of adopting fast payment technologies and changes in deposit balances or turnover. If these non-adopters differ systematically from adopters—for example, some individuals may be reluctant to adopt new technologies, even when their friends propose to pay via Venmo—our results may not be generalizable to the entire population of depositors. Third, fast payment applications often impose limits on instant transfers, as summarized in Appendix B.1. These caps might constrain the ability of depositors to fully adjust their behavior in response to reduced transfer delays. Consequently, our estimates could be biased downward, underestimating the true effect of faster payments on depositor behavior.

While our study provides evidence of a causal relationship between transfer delays and depositor behavior, the limitations suggest caution in interpreting the results. In Section 5, we use a simple inventory model of deposit demand to provide guided estimates on the effect of fast payments on the average depositor by matching aggregate data moments.

4. A Model of Deposit Demand with Transfer Delays

To reconcile our empirical findings and further quantify the impact of payment convenience on banks' deposit balances and depositor activity, in this section we develop a new deposit management model in the spirit of Alvarez and Lippi (2009) and Kaplan and Violante (2014), incorporating both transfer delays and consumption volatility. The model illustrates how payment convenience emerges from both the transactional and precautionary functions of money, showing that shorter transfer delays allow depositors to maintain lower balances in low-interest deposit accounts while increasing fund transfers. Our key theoretical contribution is the explicit incorporation of uncertain transfer delays, an important factor omitted in existing liquidity management models. Our model predictions align closely with our empirical analysis in Section 3. In Section 5, we further calibrate the model and conduct counterfactual analyses to evaluate the effects of faster payment technologies on banking and monetary policy.

Time is modeled as continuous. A representative depositor with discount rate β is endowed with two bank accounts, account C and account S, which are offered by different banks, starting at time $t = 0$. Motivated by the evidence of account specialization discussed earlier, and without loss of generality, we assume that deposits in bank account C are non-interest-bearing yet are used by the depositor for spending and pay interest-bearing liabilities, while deposits in bank account S are interest-bearing with an exogenous interest rate of $r > 0$. As in Alvarez and Lippi (2009), suppose the total repayment amount is exogenous: let $g > 0$ denote the constant flow of new consumption from bank account C. Different from their setup, we further assume that the net consumption flow c (total spending minus income) follows a Brownian motion, $dc = -gdt + \sigma dw$, where w is a standard Wiener process, and $g > 0$ and $\sigma > 0$ are the drift and volatility, respectively. Additionally, denote by m the balance of bank account C, which, as we will show, is a crucial state variable in the model. It is important to note that the assumption of account C being non-interest-bearing is not critical. What is essential is that the two accounts offer different interest rates, and we hence also refer to r as the interest rate spread in this simple two-account model.

To model deposit turnover and its determinants, we assume that the depositor can transfer funds between the two bank accounts in either direction: from account C to account S or vice versa. Importantly, to account for payment and transfer delays, as previously discussed, we assume that once an outgoing payment is initiated from one bank account, the corresponding incoming payment to the other account is processed only after a delay, modeled by an independent Poisson process with rate κ. Importantly, these deposits in transfer can neither earn interest earnings nor be used for interest repayments. This captures the potential losses due to delays in deposit transfers.

Additionally, we assume that when $m = 0$, meaning bank account C has a zero balance, a deposit transfer from bank account S to account C incurs no delays but does involve a penalty $b > 0$, irrespective of the transfer size. This penalty can be interpreted as the total costs associated with payday borrowing, overdrafting, or any mental cost of lack of liquidity. Technically, this assumption also aids in tractability by ruling out defaults and ensuring non-negativity of account balances in bank account C. This helps introduce a straightforward boundary condition, as we will specify below. Notably, however, in our model, the balance of bank account S is not required to be non-negative, capturing potential borrowing or shorting positions.

Under this setup, the depositor chooses a sequence of voluntary deposit transfers x_j made at t_j and processed at uncertain time $t_i^{'}$ in order to minimize the expected present cost of interest losses, subject to occurrence of the penalty cost when involuntary transfers y_k are made at t_k, when the balance in account C hits 0:

$$V(m) = \min_{x_j, t_j} E_0 \left[r \int_0^\infty m(t) e^{-\beta t} dt + r \sum_j E_{t_j} \left[\int_{t_j}^{t_j'} 1_{x_j > 0} x_j e^{-\beta t} dt \right] + b \sum_k e^{-\beta t_k} \right],$$

where positive (negative) transfers indicate a transfer from account S to account C (from account C to account S). The first term captures the expected interest losses due to carrying a positive deposit balance in account C rather than in account S, the second term captures the additional expected interest losses due to delayed transfers from S to C, where the expectation is taken with respect to the Poisson process that governs transfer delays, and the third term captures expected penalties.

Accordingly, the law of motion for m is given by

$$dm(t) = -gdt + \sigma dw + \sum_j \left(1_{x_j>0} x_j \delta_{t'_j} + 1_{x_j<0} x_j \delta_{t_j} \right) + \sum_k y_k \delta_{t_k} \,,$$

where an incoming transfer into account C incurs a delay before being processed while an outgoing transfer out of account C immediately leaves, and δ is the Dirac's delta function defined at the respective time.

We seek to identify an optimal deposit turnover policy characterized by two thresholds and two optimal targets for m: $0 < \underline{m} \le m^* < m^{**} \le \overline{m}$. This policy minimizes the shadow cost of maintaining a non-interest-bearing balance in bank account C to meet interest repayments. Specifically, the lower threshold $\underline{m}$ represents the lowest allowable balance in bank account C, below which the depositor decides to replenish the account after a successful transfer from bank account S, thereby increasing the balance in account C to the target balance m^*. The upper threshold $\overline{m}$ represents the balance in bank account C above which the depositor opts to transfer funds to bank account S, thereby reducing the balance in account C to the optimal target m^{**}. Assuming that the optimal turnover policy follows this form and that the value function $V(m)$ is differentiable, it must satisfy the HJB conditions:

$$\beta V(m) = \begin{cases} rm - \left(gV'(m) - \frac{1}{2}\sigma^2 V''(m)\right) + \kappa(V(m^*) - V(m)) + r(m^* - m), & 0 \le m \le \underline{m}, \\ rm - \left(gV'(m) - \frac{1}{2}\sigma^2 V''(m)\right), & \underline{m} \le m \le \overline{m}, \\ rm - \left(gV'(m) - \frac{1}{2}\sigma^2 V''(m)\right) + \kappa(V(m^{**}) - V(m)), & m \ge \overline{m}, \end{cases}$$

where the first term rm gives the carry cost of balance in account C, the second term $gV'(m) - \frac{1}{2}\sigma^2 V''(m)$ gives the change in the value function due to the use of deposit balance to repay interest liabilities per unit of time conditional on no transfers, and the third term gives the expected change in the value function conditional on a successful transfer with probability κ. The fourth term in the region $m < \underline{m}$ represents the additional expected interest cost due to the transfer delay when replenishing the account balance from m to m^*; since the carry cost rm already accounts for the cost of holding funds in account C, there is no additional expected interest cost due to the transfer delay when $m > \overline{m}$.

Our setup differs significantly from existing models of money demand and liquidity management, and it is worth discussing how we solve the model, with particular focus on the roles of uncertain transfer delays and consumption volatility. Due to the dual sources of uncertainty, namely, random transfer delays and stochastic consumption, the characteristic equations for the HJB conditions in the action regions have two real roots; as a result, the optimal deposit policy generally cannot be solved in closed form.[8] We follow Constantinides and Richard (1978) in analyzing a limiting case where consumption has no drift ($g = 0$) and the discount rate approaches zero ($\beta \to 0$). Even under this simplification, the introduction of uncertain transfer delays in our framework leads to value functions in the action regions that satisfy transcendental equations with two exponential terms, unlike the degenerate homogeneous solution typically found in the existing literature. Despite this challenge, we are able to derive analytical properties of the optimal policy $(\underline{m}, m^*, m^{**}, \bar{m})$ as functions of (r, κ, σ, b), as summarized in the results below. Detailed analytical properties of m^* and m^{**} and their proofs are provided in Appendix A.

Proposition 1 (Balances)**.** *The optimal deposit thresholds m^* and m^{**} satisfy $m^* = \underline{m}$ and $m^{**} = \overline{m}$, and they all decrease as the efficiency of the transfer technology increases (i.e., κ increases). This effect is amplified when the interest rate spread r is higher. Moreover, depositors with greater consumption volatility σ maintain higher balances and experience a larger decrease in balances as κ increases.*

[8] Without the Brownian term in consumption, Alvarez and Lippi (2009) derived a closed-form solution by introducing a random transfer cost. In an earlier draft of this work, we excluded consumption uncertainty and obtained a similar closed-form solution with stochastic transfer delays by assuming a sufficiently large initial balance. This is because Poisson arrivals of transfers can also be interpreted as a form of variable transfer cost.

Proposition 2 (Turnover)**.** *The expected transfers between accounts increase with more efficient transfer technology (κ), and the effect is amplified when interest rate spread r is higher. Depositors with greater consumption volatility σ experience a larger increase in deposit turnover as κ increases.*

Propositions 1 and 2 offer new insights that align with our key empirical findings in Section 3: deposit turnover is influenced by payment delays conditional on depositor's consumption uncertainty and interest rate spreads, as shown in Table 4, Figure 6, and Table 5.

The intuition for Proposition 1 is as follows. As fund transfers become more efficient, depositors need to hold less in low-interest balances in account C to support their consumption needs, since they can access funds from higher-interest accounts more quickly. When the interest rate spread r is higher, representing better outside investment opportunities, depositors further reduce their holdings in account C to maximize returns elsewhere. Depositors with higher consumption volatility σ keep larger balances in account C as a precautionary measure to meet unpredictable transactional demands. And as transfer technology improves, these depositors can reduce their balances more significantly as faster transfers affect their ability to manage consumption volatility the most.

Turning to Proposition 2, the intuition behind the increase of the expected deposit transfer size when m deviates from the target S-s band with respect to transfer efficiency lies in the interaction between the size of individual transfers and their frequency. As κ increases, the expected time until a transfer is cleared decreases, leading to more frequent successful transfers. This means that transfers occur more often within any given time interval. At the same time, the reduced waiting time for completion implies that the balance m has less opportunity to deviate significantly from the threshold due to the randomness inherent in Brownian motion. Consequently, the expected size of each individual transfer decreases with higher κ. However, the effect of increased frequency dominates the reduction in individual transfer size. The higher rate of transfer completions results in an overall increase in the total expected transfer per unit time. Similarly, the expected transfer is also influenced by both the interest rate spread r and the volatility σ of the account balance. Depositors with larger σ have account balance m fluctuating more widely. The high volatility increases the likelihood that m will deviate significantly from the target S-s band before a transfer is completed. When transfers do occur, these depositors also respond more actively to correct for the more substantial deviations.

It is worth noting that in the optimal depositing rule, the lower threshold $\underline{m}$ coincides with m^*, and the upper threshold $\underline{m}$ coincides with m^{**}. Intuitively, the absence of fixed transaction costs eliminates the incentive to adjust cash balances only when reaching certain thresholds; instead, any deviation from optimal cash balances should be corrected immediately but the adjustment size would depend on expected transfer delays. However, the inaction region between m^* and m^{**} remains non-zero because the costs associated with transfers at the lower and upper thresholds differ from each other.

As another benchmark to understand the model mechanisms, we consider the limiting case where $\kappa \to 1$, when transfers between the two accounts become instantaneous. In this scenario, the model reduces to a special case of the Alvarez and Lippi (2009) model, characterized by zero transfer fees and the constant opportunity to freely transfer funds. Additionally, depositors are more inclined to actively manage their deposits when there is greater interest rate spread across accounts or higher consumption uncertainty. This is because shifting deposits offers potential gains from higher interest earnings and savings by avoiding costs associated with delayed transfers, as discussed in Kaplan and Violante (2014). Specifically, greater interest rate spread makes deposits in bank account S a more attractive store of value, while higher consumption uncertainty increases the value of liquidity in bank account C.

It is also useful to compare our solution to the standard Baumol-Tobin model, where inaction in transactions is driven by transaction costs, or equivalently, transfer fees in the context of deposits. To highlight the novel aspect of transfer delays, as documented in Section

2, we explicitly model delays in deposit transfers while abstracting away from transfer fees. There are fundamental differences between transfer delays and transfer fees. An immediate consequence of these differing frictions is that delays are costly because they prevent depositors from optimizing their deposit portfolios by transferring funds between different bank accounts, not because they make the transfers themselves inherently costly. The expected costs induced by waiting are endogenous, depending on the size of the transfer. Transfer fees, on the other hand, impose exogenous costs whenever a transfer is made. These distinctions between transfer delays and transfer fees also have important implications for the timing of deposit turnover. From this perspective, transfer delays naturally postpone the adjustment of deposit balances following a shock, whereas transfer fees, which allow for instantaneous transfers, are much less likely to cause such delays in reality without imposing other frictions.

5. Quantification: Payment Convenience and Deposit Demand

In this section, we calibrate and quantify the model developed in Section 4 to examine a counterfactual scenario in which payments become faster across the banking sector. This analysis helps address key policy questions, such as the potential impact if the Federal Reserve mandated all banks to adopt FedNow. Moreoever, even without regulatory requirements compelling all banks to adopt faster payments, banks may seek a competitive edge by offering faster transfers to promote deposit convenience, especially since much of the necessary infrastructure is already in place (Duffie 2020). What prevents the payment landscape from being faster and more efficient? To address these questions, we assess how deposit turnover and account balances would change if all bank deposit transfers were completed within one business day. Our findings suggest that implementing uniform next-day payments could significantly reduce aggregate deposit demand, providing a rationale for why U.S. banks have been reluctant to adopt fast payment technologies.

5.1. Faster payments, consumption uncertainty, and aggregate deposit demand

We first calibrate the benchmark model outlined in Section 4 to match key data moments and evaluate the impact of mandating all transfers to be cleared the next business day on deposit balances and depositor activeness. Specifically, the optimal deposit policy in the presence of transfer delays and consumption uncertainty follows an S-s rule characterized by two thresholds. We derive these thresholds and simulate the paths of balances and deposit turnover under varying levels of interest rates and consumption uncertainty.

Our model emphasizes uncertainties in transfer delays and consumption while abstracting from consumption growth. To focus on the dynamics of deposit balances and turnover without the influence of long-term growth trends, we detrend the data moments using a 12-month moving average during calibration. Detrending is commonly used in macroeconomic studies to isolate business cycle fluctuations (Kydland and Prescott 1982); in our case, especially given that we calibrate the model at a daily frequency, long-run growth effects are likely to be small and negligible. After detrending, the average depositor exhibits daily consumption uncertainty of $E(\sigma)/28 = \$4,822/28 \approx \$172.21$, an average deposit balance of $E(m) \approx \$5,766$, and deposit turnover of $E\left(\sum|X|\right) = \$1,426$. As previously discussed, the penalty b for hitting a zero balance captures the total costs associated with payday borrowing, overdrafts, or the mental cost of lack in liquidity. We hold b constant throughout the quantification exercises to ensure that depositors do not maintain negative balances.

We begin by examining the behavior of the average depositor using an average transfer delay of two business days (i.e., $\kappa \approx 0.24$). Panel (a) in Figure 10 illustrates how the depositor's balance evolves over a month, based on 10,000 simulations and using parameter values consistent with our data: an average rate spread of 0.78%, a two-business-day transfer delay, and daily consumption uncertainty of approximately \$172.21. The results show that the average deposit balance is \$5,939 and the average deposit turnover is \$1,647, closely matching the empirical median deposit balance (\$5,766) and median deposit turnover (\$1,426) observed in our sample.

Based on the calibrated model, the primary contribution of our quantification exercise lies in examining a counterfactual scenario in which payment technology, or equivalently, bank transfers, becomes faster. Panel (b) in Figure 10 illustrates a case where all fund transfers into account C are completed with a one-business-day transfer delay (i.e., $\kappa \approx 0.5$). Under this counterfactual, the average precautionary and transactional deposit balance in account C declines by 30%, or by the amount of \$1,764, to \$4,175, while deposit turnover volume rises by 57% to \$2,525, consistent with Propositions 1 and 2. This substantial decrease in deposit balance and increase in deposit turnover suggests larger and more volatile gross deposit flows, raising concerns about payment fragility and financial stability (Li and Li 2021, Goldstein, Yang, and Zeng 2023, Cipriani, Eisenbach, and Kovner 2024). Beyond directly eroding deposit franchise value, heightened deposit flow volatility may also affect banks' demand for reserves (Lopez-Salido and Vissing-Jorgensen 2024), placing additional pressures on monetary policy implementation.

Consistency with the reduced-form estimates. The calibration results indicate a 30% reduction in deposits held for transactional and precautionary purposes when transfer delays are expected to be one business day shorter, which aligns with the reduced-form analyses in Section 3. On average, detrended deposits account for approximately 23% of total deposits, encompassing deposits held for payment and precautionary purposes. Consequently, the expected average reduction in total deposits based on the calibration is calculated as $30\% \times 23\% = 6.9\%$. This is comparable in magnitude to the reduced-form estimates of $4 \sim 6\%$ in Table 4 and Table 6.

Interaction with consumption volatility. With the same transfer technology, our quantification shows that depositors with higher transactional demand (i.e., greater consumption uncertainty) tend to hold larger deposit balances. While these depositors reduce their total deposits by a larger amount when payment efficiency improves, they still maintain relatively high balances to accommodate their larger, uncertain spending needs, consistent with

Propositions 1 and 2.

To illustrate this, we consider a scenario in which aggregate consumer debt in 2024 has increased by 26% relative to pre-pandemic levels, implying greater consumption uncertainty due to higher debt repayment obligations. We simulate the introduction of faster payments alongside a 26% increase in consumption uncertainty. Compared to Panel (a) in Figure 10, Panel (c) shows that higher consumption uncertainty significantly increases the deposits held in transactional accounts, raising the average target balance from $5,939 to $7,550. As a benchmark, recall that when transfers become uniformly faster, the average target balance declines by $1,764 under low consumption uncertainty as in Panel (b). However, now, Panel (d) reveals that heightened consumption uncertainty amplifies this effect, with the account balance decreasing by $2,242 under uniformly faster transfers. Despite this larger decline, the average target balance remains relatively high at $5,308, reflecting a relatively strong precautionary demand for deposits in the presence of high consumption uncertainty.

The role of interest rate spread. At the same time, our quantification shows that changes in the interest rate spread have minimal impact on deposit balances. As illustrated in Figure A-1, even when the rate spread increases from 78 to 200 basis points, the target deposit balance declines only slightly. Given our earlier discussion on depositors holding funds in transactional accounts as a precaution against unexpected consumption needs, this finding suggests that precautionary deposit demand outweighs the incentives for interest shopping under our calibrated model parameters. Intuitively, while a wider rate spread may encourage depositors to shift some funds from low-rate transactional accounts to high-yield savings accounts, the necessity of maintaining liquidity to buffer against uncertain consumption shocks keeps transactional balances relatively stable.

In summary, we find that a policy mandating all bank deposit transfers to clear by the next business day would significantly reduce transactional deposit balances and increase deposit turnover. However, despite the larger magnitude of these changes, deposit balances remain relatively high when depositors face elevated consumption uncertainty. These findings suggest that the impact of fast payment technologies on bank funding costs and franchise value depends critically on the degree of uncertainty in aggregate consumption.

5.2. *Faster payments and the cross section of depositors*

To further examine the heterogeneous effects of faster payments on different depositors, we categorize depositors into quintiles based on their average deposit balance over the sample period. The first quintile represents those with the lowest balances, while the fifth quintile includes those with the highest. Additionally, we define an "uninsured" subsample comprising depositors who, at any point during the sample period, held balances exceeding $250,000 in any bank account. Consistent with the previous analyses, consumption volatility σ is empirically measured by calculating the volatility of detrended balances for each depositor over the sample period and then averaging across depositors within each subsample. Transfer delay is measured in business days: a delay of 2 (or 1) business days corresponds to 2.8 (or 1.4) calendar days, with κ set to 0.24 (or 0.5) accordingly. We continue to use an annualized interest rate spread of 0.78% (i.e., 78 basis points), denoted as $r = 0.78\%/365$. Data moments are detrended using 12-month moving averages, and model moments are computed from 10,000 simulations.

For each subsample, we first compute the target balances using the approximation of m^*. We then simulate the evolution of the deposit balance m over one year, reporting the average and volatility. The benchmark calibration (shown in columns (2), (5), and (8) of Table 7) closely aligns with the empirical mean and variance of deposit balances, as well as the average deposit turnover, for each subsample in the data (shown in columns (1), (4), and (7) of Table 7).

To assess the impact of faster transfers on the cross-section of deposits, columns (3), (6), and (9) of Table 7 present a counterfactual scenario in which all bank transfers are settled by the next business day, effectively reducing transfer delays to one day. Under this scenario, total precautionary and transactional deposit balances decline by approximately 30%, while average monthly deposit turnover per depositor increases by about 40%. Notably, depositors with higher balances, particularly uninsured depositors, experience the largest changes in both balances and turnover in dollar terms. This finding suggests a plausible reason why larger banks, which hold a greater share of large-size deposits, may be especially reluctant to adopt fast payment technologies (Duffie 2020).

6. Conclusion

Depositors are active, and payment frictions, specifically long transfer delays, reduce depositor activeness and lead to large deposit balances. Using novel transaction-level data, we show that depositors actively manage their funds across multiple bank accounts, with higher interest rate spread leading to an increase of deposit outflows, and transfer delays dampen the effect of rates on deposit balances. Leveraging a natural experiment that exploits exogenous exposure to fast payment technologies via social networks, we show that the adoption of fast payment technologies increases depositor activeness and reduces deposit balances.

To understand these dynamics, we extend the classic Baumol-Tobin framework by incorporating transfer delays. Our analyses suggest that if all bank transfers are expected to be cleared the next business day, deposit transfers would increase significantly, while total deposit demand would drop by about 7%. These effects depend on consumption uncertainty, highlighting the interplay between payment technologies and economic conditions.

These findings have important implications for banks and policymakers. While universally faster payments improve convenience for depositors, they may unexpectedly undermine the traditional franchise value of deposits, a key source of stable bank funding, potentially challenging banks' liquidity management and profitability. Policymakers should consider how payment innovations affect monetary aggregates and the transmission of monetary policy, as changes in transfer delays change the level of aggregate deposit demand.

While we highlight the significant effects of payment convenience in deposit demand, several avenues for future research remain. The reasons behind the sizable interbank transfers are not yet fully understood; preliminary analysis suggests depositors optimize fund allocation across various liquid, transactional accounts consistent with mental accounting. Our findings also suggest that depositor heterogeneity offers a promising path for providing empirically grounded perspectives on the longstanding debates regarding money demand. The finding that depositors with varying levels of liquid wealth value payment convenience differently raises further questions about the redistributional effects of monetary policy and the welfare implications of inflation, particularly in the context of a rapidly evolving payment landscape.

References

Acharya, Viral V, Rahul S Chauhan, Raghuram Rajan, and Sascha Steffen. 2023. "Liquidity Dependence And The Waxing And Waning of Central Bank Balance Sheets." 6

Acharya, Viral V, and Toomas Laarits. 2023. "When Do Treasuries Earn The Convenience Yield?: A Hedging Perspective."Technical report, National Bureau of Economic Research. 7

Acharya, Viral V, and Raghuram Rajan. 2023. "Liquidity, Liquidity Everywhere, Not A Drop To Use–Why Flooding Banks With Central Bank Reserves May Not Expand Liquidity." *Journal of Finance* forthcoming. 6

Afonso, Gara, Darrell Duffie, Lorenzo Rigon, and Hyun Song Shin. 2022. "How Abundant Are Reserves? Evidence From The Wholesale Payment System." 6

Afonso, Gara, Anna Kovner, and Antoinette Schoar. 2011. "Stressed, Not Frozen: The Federal Funds Market In The Financial Crisis." *Journal of Finance* 66 (4). 6

Akerlof, George A, and Ross D Milbourne., "Irving Fisher On His Head II: The Consequences of The Timing of Payments For The Demand For Money." *The Quarterly Journal of Economics* 95 (1). 22

Alvarez, Fernando, and Francesco Lippi. 2009. "Financial Innovation And The Transactions Demand For Cash." *Econometrica* 77 (2). 7, 28, 31, 33

Attanasio, Orazio P, and Luigi Pistaferri. 2016. "Consumption Inequality." *Journal of Economic Perspectives* 30 (2). 17, A-20

Bailey, Michael, Ruiqing Cao, Theresa Kuchler, and Johannes Stroebel. 2018. "The Economic Effects of Social Networks: Evidence From The Housing Market." *Journal of Political Economy* 126 (6). 22

Bailey, Michael, Drew Johnston, Theresa Kuchler, Johannes Stroebel, and Arlene Wong. 2022. "Peer Effects In Product Adoption." *American Economic Journal: Applied Economics* 14 (3). 22

Balyuk, Tetyana, and Emily Williams. 2021. "Friends And Family Money: P2P Transfers And Financially Fragile Consumers." 7, 27

Baugh, Brian, Itzhak Ben-David, Hoonsuk Park, and Jonathan A Parker. 2021. "Asymmetric Consumption Smoothing." *American Economic Review* 111 (1). 8

Baumol, William J. 1952. "The Transactions Demand For Cash: An Inventory Theoretic Approach." *The Quarterly Journal of Economics* 66 (4). 7

Begenau, Juliane. 2020. "Capital Requirements, Risk Choice, And Liquidity Provision In A Business-Cycle Model." *Journal of Financial Economics* 136 (2). 7

Berg, Tobias, Valentin Burg, Ana Gombović, and Manju Puri. 2020. "On The Rise of Fintechs: Credit Scoring Using Digital Footprints." *Review of Financial Studies* 33 (7). 6

Bewley, Truman. 1983. "A Difficulty With The Optimum Quantity of Money." *Econometrica*. 7

Blickle, Kristian, Jian Li, Xu Lu, and Yiming Ma. 2024. "The Dynamics of Deposit Flightiness And Its Impact On Financial Stability." *Available at SSRN 4873784*. 6, 21

Bolton, Patrick, Ye Li, Neng Wang, and Jinqiang Yang. 2023. "Dynamic Banking And The Value of Deposits." *Journal of Finance* forthcoming. 9

Brunnermeier, Markus K, Sebastian Merkel, and Yuliy Sannikov. 2024. "Safe Assets." *Journal of Political Economy* 132 (11). 7

Brunnermeier, Markus K, and Dirk Niepelt. 2019. "On The Equivalence of Private And Public Money." *Journal of Monetary Economics* 106. 6

Buda, Gergely, Stephen Hansen, Vasco Carvalho, Alvaro Ortiz, Tomasa Rodrigo, and Jose Rodriguez Mora. 2022. "National Accounts In A World of Naturally Occurring Data: A Proof of Concept For Consumption." 8

Carroll, Christopher, and Miles Kimball. 2006. "Precautionary Saving And Precautionary Wealth." 7

Chang, Briana, Ing-Haw Cheng, and Harrison G Hong. 2023. "The Fundamental Role of Uninsured Depositors In The Regional Banking Crisis." A-22

Chen, Qi, Itay Goldstein, Zeqiong Huang, and Rahul Vashishtha. 2024. "Liquidity Transformation And Fragility In The US Banking Sector." *Journal of Finance* 79 (6). 6, A-22

Cipriani, Marco, Thomas M Eisenbach, and Anna Kovner. 2024. "Tracing Bank Runs In Real Time." *FRB of New York Staff Report* (1104). 36

Constantinides, George M, and Scott F Richard. 1978. "Existence of Optimal Simple Policies For Discounted-Cost Inventory And Cash Management In Continuous Time." *Operations Research* 26 (4). 31, A-1

Corell, Felix, Lira Mota, and Melina Papoutsi. 2023. "Service Flows In Euro Area Corporate Bonds." *Available at SSRN*. 7

Di Tella, Sebastian, Benjamin M Hébert, and Pablo Kurlat. 2024. "Aggregation, Liquidity, And Asset Prices With Incomplete Markets."Technical report, National Bureau of Economic Research. 7

Diamond, Douglas W., and Philip H. Dybvig. 1983. "Bank Runs, Deposit Insurance, And Liquidity." *Journal of Political Economy* 91 (3) 401–419. 6, A-22

Diamond, Douglas W, and Raghuram G Rajan. 2001. "Liquidity Risk, Liquidity Creation, And Financial Fragility: A Theory of Banking." *Journal of Political Economy* 109 (2). 6

Drechsler, Itamar, Alexi Savov, and Philipp Schnabl. 2017. "The Deposits Channel of Monetary Policy." *The Quarterly Journal of Economics* 132 (4). 1, 6

Drechsler, Itamar, Alexi Savov, and Philipp Schnabl. 2021. "The Financial Origins of The Rise And Fall of American Inflation." *Working Paper*. 6

Drechsler, Itamar, Alexi Savov, and Philipp Schnabl. 2023. "Credit Crunches And The Great Stagflation." 6

Drechsler, Itamar, Alexi Savov, Philipp Schnabl, and Olivier Wang. 2023. "Banking On Uninsured Deposits." 6, A-22

Dubey, Tamanna, and Amiyatosh Purnanandam. 2023. "Can Cashless Payments Spur Economic Growth?". 7

Duffie, Darrell. 2019. "Digital Currencies And Fast Payment Systems." 6

Duffie, Darrell. 2020. "Interoperable Payment Systems And The Role of Central Bank Digital Currencies." 34, 39

Dávila, Eduardo, and Itay Goldstein. 2023. "Optimal Deposit Insurance." *Journal of Political Economy* 131 (7). A-22

Egan, Mark, Ali Hortaçsu, and Gregor Matvos. 2017. "Deposit Competition And Financial Fragility: Evidence From The US Banking Sector." *American Economic Review* 107 (1). 6

Erel, Isil, Jack Liebersohn, Constantine Yannelis, and Samuel Earnest. 2023. "Monetary Policy Transmission Through Online Banks." 6

Freixas, Xavier, Bruno M Parigi, and Jean-Charles Rochet. 2000. "Systemic Risk, Interbank Relations, And Liquidity Provision By The Central Bank." *Journal of Money, Credit And Banking*. 6

Fuster, Andreas, Matthew Plosser, Philipp Schnabl, and James Vickery. 2019. "The Role of Technology In Mortgage Lending." *Review of Financial Studies* 32 (5). 6

Gelman, Michael, and Nikolai Roussanov. 2024. "Managing Mental Accounts: Payment Cards And Consumption Expenditures." *Review of Financial Studies.* 16

Ghosh, Pulak, Boris Vallee, and Yao Zeng. 2023. "FinTech Lending And Cashless Payments." *Journal of Finance* forthcoming. 6

Goldstein, Itay, and Ady Pauzner. 2005. "Demand–Deposit Contracts And The Probability of Bank Runs." *Journal of Finance* 60 (3). 6

Goldstein, Itay, Ming Yang, and Yao Zeng. 2023. "Payments, Reserves, And Financial Fragility." 6, 9, 36

Greenwood, Robin, Jeremy C Stein, Samuel G Hanson, and Adi Sunderam. 2017. "Strengthening And Streamlining Bank Capital Regulation." *Brookings Papers On Economic Activity* 2017 (2). 6

Hanson, Samuel G, Victoria Ivashina, Laura Nicolae, Jeremy C Stein, Adi Sunderam, and Daniel K Tarullo. 2024. "The Evolution of Banking In The 21st Century: Evidence And Regulatory Implications." *Brookings Papers On Economic Activity* 27. 6

Hanson, Samuel, Andrei Shleifer, Jeremy C. Stein, and Robert W. Vishny. 2015. "Banks As Patient Fixed-Income Investors." *Journal of Financial Economics* 117 (3). 1

Harrison, J Michael. 2013. *Brownian Models of Performance And Control.* Cambridge University Press. A-1

Higgins, Sean. 2024. "Financial Technology Adoption: Network Externalities of Cashless Payments In Mexico." *American Economic Review.* 7

Hirshleifer, David. 2020. "Presidential Address: Social Transmission Bias In Economics And Finance." *Journal of Finance* 75 (4). 22

Hong, Harrison, Jeffrey D Kubik, and Jeremy C Stein. 2004. "Social Interaction And Stock-Market Participation." *Journal of Finance* 59 (1). 22

Jack, William, and Tavneet Suri. 2014. "Risk Sharing And Transactions Costs: Evidence From Kenya's Mobile Money Revolution." *American Economic Review* 104 (1). 7

Jermann, Urban, and Haotian Xiang. 2023. "Dynamic Banking With Non-Maturing Deposits." *Journal of Economic Theory* 209. 9

Jiang, Erica Xuewei, Gregor Matvos, Tomasz Piskorski, and Amit Seru. 2023. "Monetary Tightening And US Bank Fragility In 2023: Mark-To-Market Losses And Uninsured Depositor Runs?". A-22

Jiang, Erica Xuewei, Gloria Yu, and Jinyuan Zhang. 2023. "Bank Competition Amid Digital Disruption: Implications For Financial Inclusion." 6

Jiang, Zhengyang, Arvind Krishnamurthy, and Hanno Lustig. 2021. "Foreign Safe Asset Demand And The Dollar Exchange Rate." *Journal of Finance* 76 (3). 7

Kacperczyk, Marcin, and Philipp Schnabl. 2013. "How Safe Are Money Market Funds?" *The Quarterly Journal of Economics* 128 (3). 7

Kaplan, Greg, and Giovanni L Violante. 2014. "A Model of The Consumption Response To Fiscal Stimulus Payments." *Econometrica* 82 (4). 7, 28, 33

Koont, Naz. 2023. "The Digital Banking Revolution: Effects On Competition And Stability." 6

Koont, Naz, Tano Santos, and Luigi Zingales. 2023. "Destabilizing Digital 'Bank Walks'." 6

Krishnamurthy, Arvind, and Yiming Ma. 2024. "The Demand And Supply of Safe And Liquid Assets." *Annual Review of Financial Economics* forthcoming. 7

Kydland, Finn E, and Edward C Prescott. 1982. "Time To Build And Aggregate Fluctuations." *Econometrica*. 35

Lagos, Ricardo, Guillaume Rocheteau, and Randall Wright. 2017. "Liquidity: A New Monetarist Perspective." *Journal of Economic Literature* 55 (2). 7

Li, Ye, and Yi Li. 2021. "Payment Risk And Bank Lending: The Tension Between The Monetary And Financing Roles of Deposits." 6, 9, 36

Li, Ye, Yi Li, and Huijun Sun. 2022. "The Network Structure of Money Multiplier." 9

Lopez-Salido, David, and Annette Vissing-Jorgensen. 2024. "Reserve Demand, Interest Rate Control, And Quantitative Tightening." 36

Massoud, Nadia, Anthony Saunders, and Barry Scholnick. 2006. "The Impact of ATM Surcharges On Large Versus Small Banks: Is There A Switching Effect?" *Journal of Business* 79 (4). 7

Miller, Merton H, and Daniel Orr. 1966. "A Model of The Demand For Money By Firms." *The Quarterly Journal of Economics* 80 (3). 7

Parker, Jonathan A, and Bruce Preston. 2005. "Precautionary Saving And Consumption Fluctuations." *American Economic Review* 95 (4). 7

Payne, Jonathan, and Bálint Szőke. 2024. "Convenience Yields And Financial Repression." 7

Reville, Peter. 2019. "ATM Banking: It's Not Just About Cash Withdrawal Anymore." *Mercator Advisory Group-North American PaymentsInsights.* 9

Roussanov, Nikolai. 2010. "Diversification And Its Discontents: Idiosyncratic And Entrepreneurial Risk In The Quest For Social Status." *Journal of Finance* 65 (5). 22

Sarkisyan, Sergey. 2023. "Instant Payment Systems And Competition For Deposits." 6

Scholnick, Barry, Nadia Massoud, Anthony Saunders, Santiago Carbo-Valverde, and Francisco Rodríguez-Fernández. 2008. "The Economics of Credit Cards, Debit Cards And ATMs: A Survey And Some New Evidence." *Journal of Banking and Finance* 32 (8). 7

Stein, Jeremy C. 2012. "Monetary Policy As Financial Stability Regulation." *The Quarterly Journal of Economics* 127 (1). 7

Sunderam, Adi. 2015. "Money Creation And The Shadow Banking System." *Review of Financial Studies* 28 (4). 7

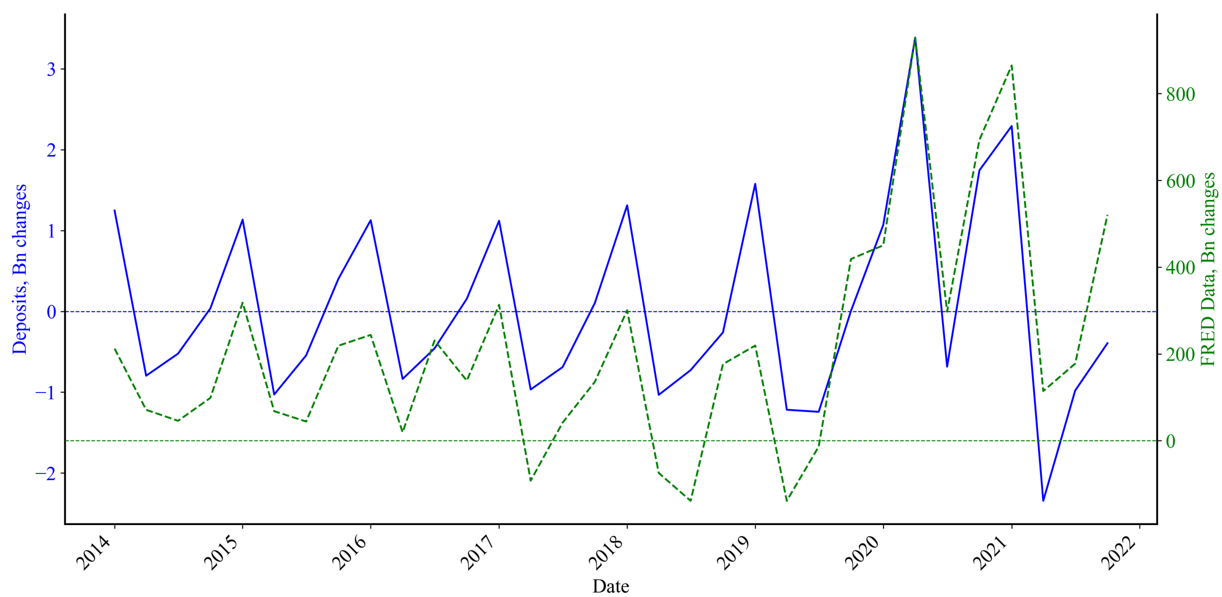
Tobin, James. 1956. "The Interest-Elasticity of Transactions Demand For Cash." *Review of Economics And Statistics* 38 (3). 7

Wang, Lulu. 2023. "Regulating Competing Payment Networks." 7

Whited, Toni M, Yufeng Wu, and Kairong Xiao. 2022. "Will Central Bank Digital Currency Disintermediate Banks?" *Available at SSRN 4112644.* 6

Figures and Tables

Figure 1: Aggregate deposit in the sample and in Flow of Funds



This plot compares total deposits from our sample with aggregate deposit data from FRED. The left axis displays changes in deposit balances from our data, while the right axis shows changes in household checkable deposits and currency total transactions from FRED.

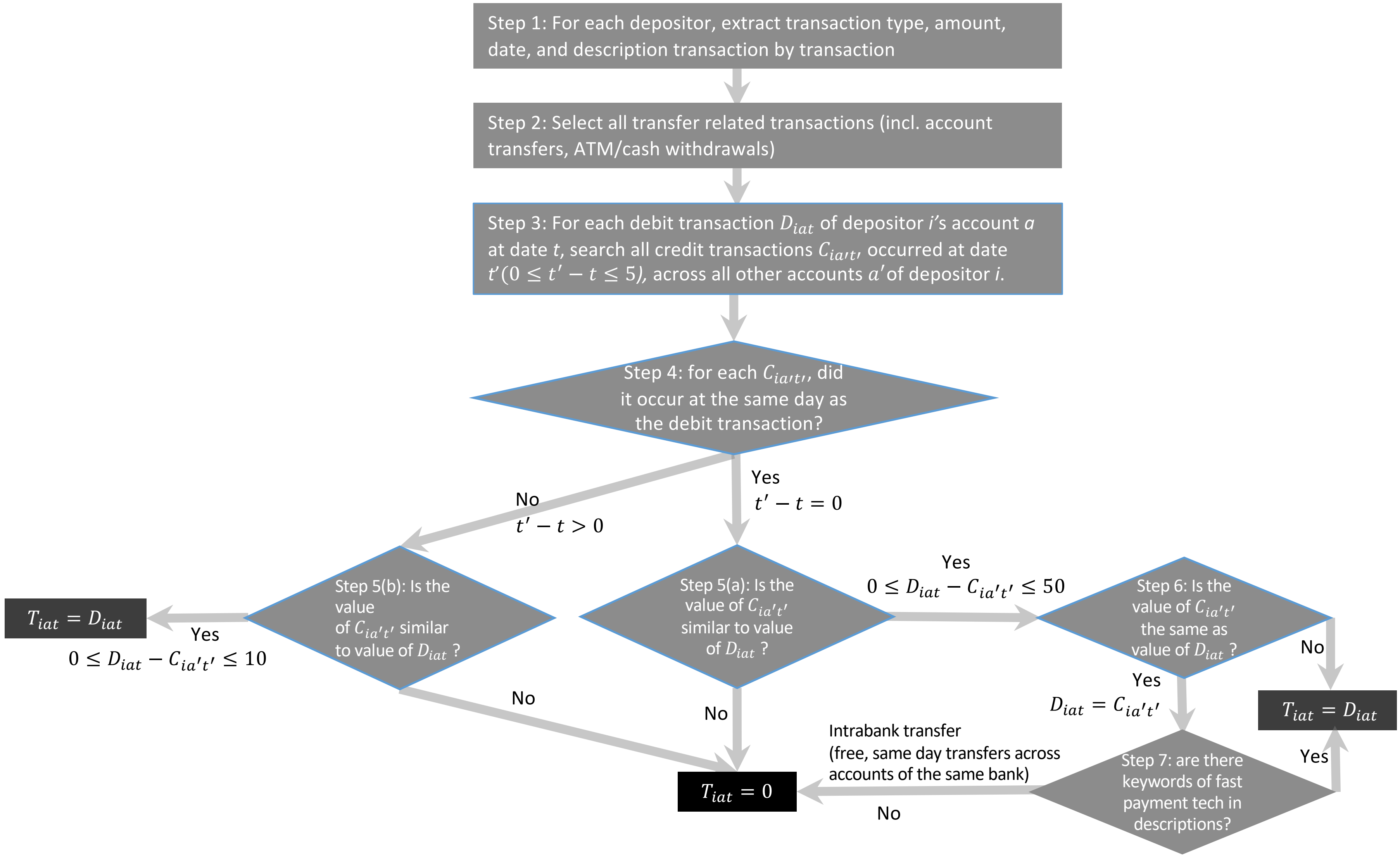
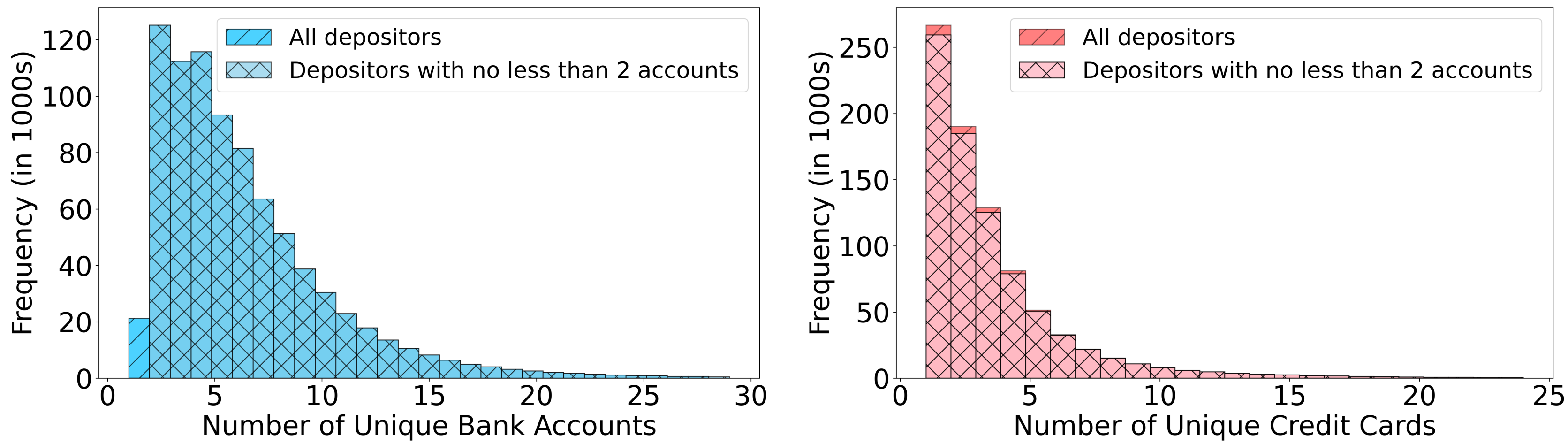


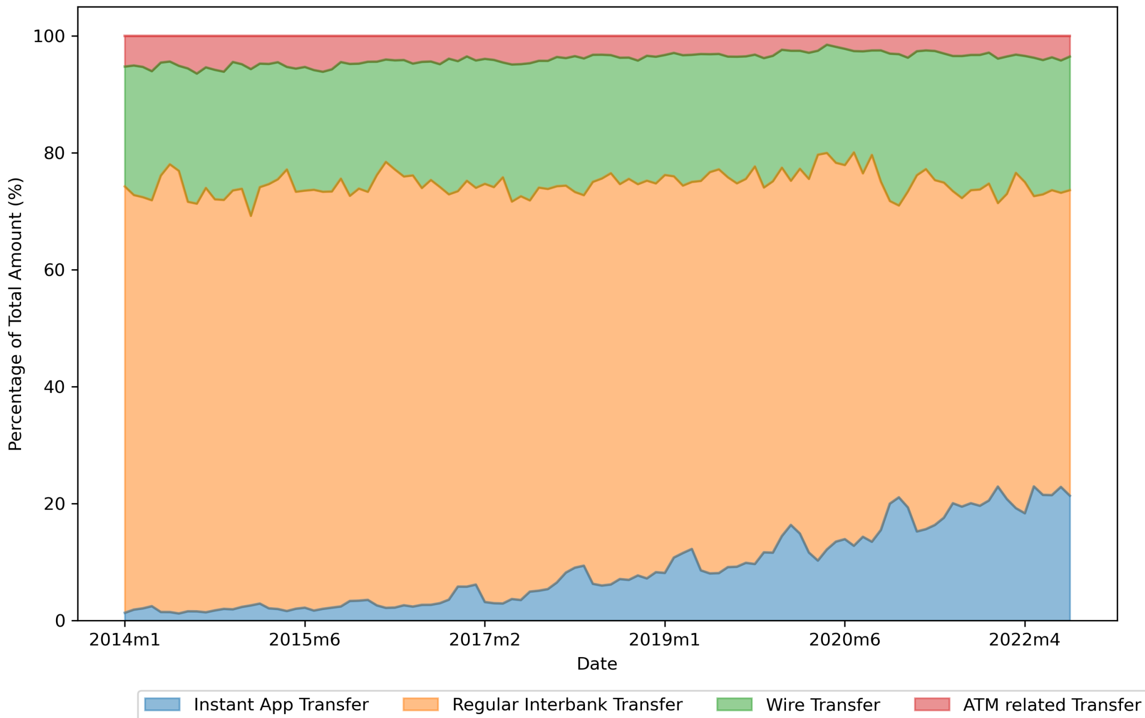
Figure 2: Flow diagram on delay / interbank transfer identification algorithm

Figure 3: Bank accounts and credit cards per depositor



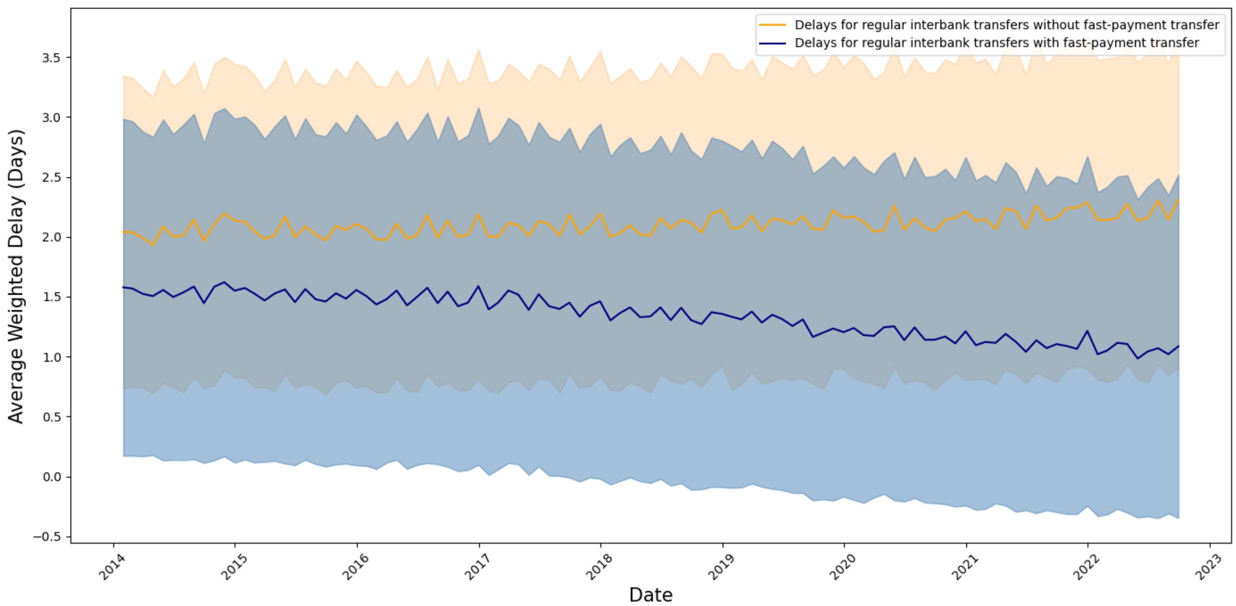
These two plots present the distributions of the average numbers of bank accounts (including checking and savings accounts; histogram on the left) and credit cards (histogram on the right) for depositors in our sample from 2013 to 2022. More than 95% of the depositors in our sample have at least two bank accounts, underscoring the relevance of the deposit turnover.

Figure 4: Types of interbank turnover



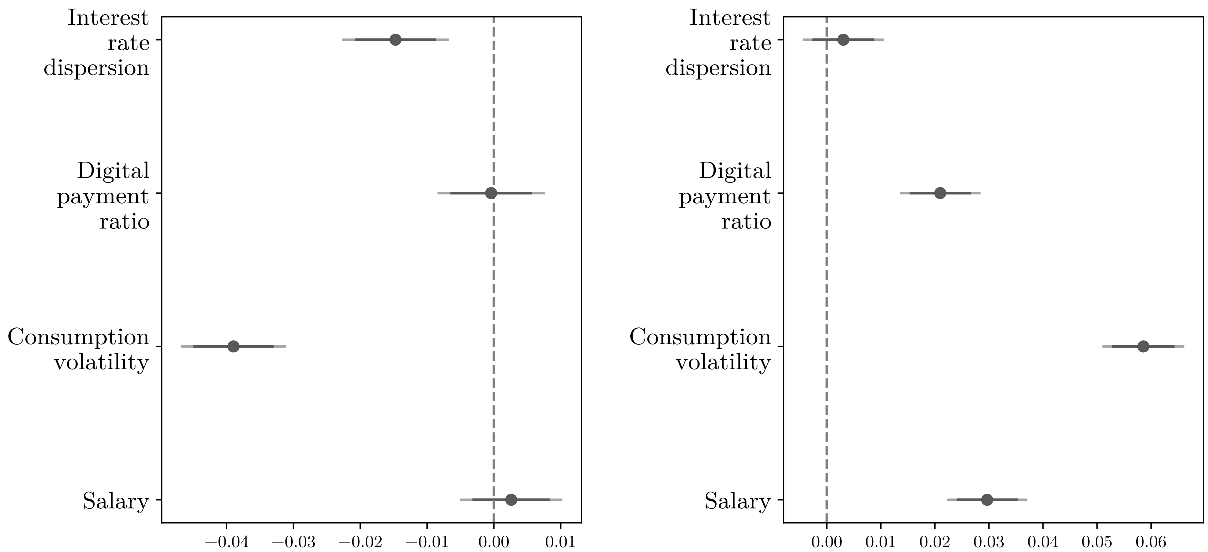
This graph delineates multiple types of interbank transfers in our sample between 2015 and 2022. Depositors have the option to reallocate deposits between accounts held at the same financial institution or to transfer assets to an alternate bank. Transactions marked with fast payment services (such as Zelle, PayPal, Cash App, and Venmo) are classified as "Instant App Transfer" (blue at the bottom). Transactions that are processed on the same day, involve a non-zero difference in debit and credit amounts, and do not utilize instant payment services are inferred as wire transfers in green (transactions without any amount difference and are cleared within the same day are considered intrabank transfers). Those containing ATM-related details in their descriptions are classified as ATM transactions and marked in red. The chart classifies all other transactions as regular (ACH) interbank transfers, represented in the lower middle of the graph in orange.

Figure 5: Transfer delays over time



This graph shows the average weighted delay in interbank deposit transfers from 2014 to 2022, computed using the dollar-weighted transfer delays across interbank deposit transfer transactions for each depositor at any given month. Interbank transfers include transfers between different banks that have any transfer delay, and instant transfers facilitated by services such as Zelle, Cash App, and Venmo, along with a limited selection of transactions identified with ATM-related details. The blue line represents the average delay over time. The shaded area indicates the standard deviation, suggesting significant variation in transfer delay times in the cross section of depositors, despite the relatively stable average delay over time.

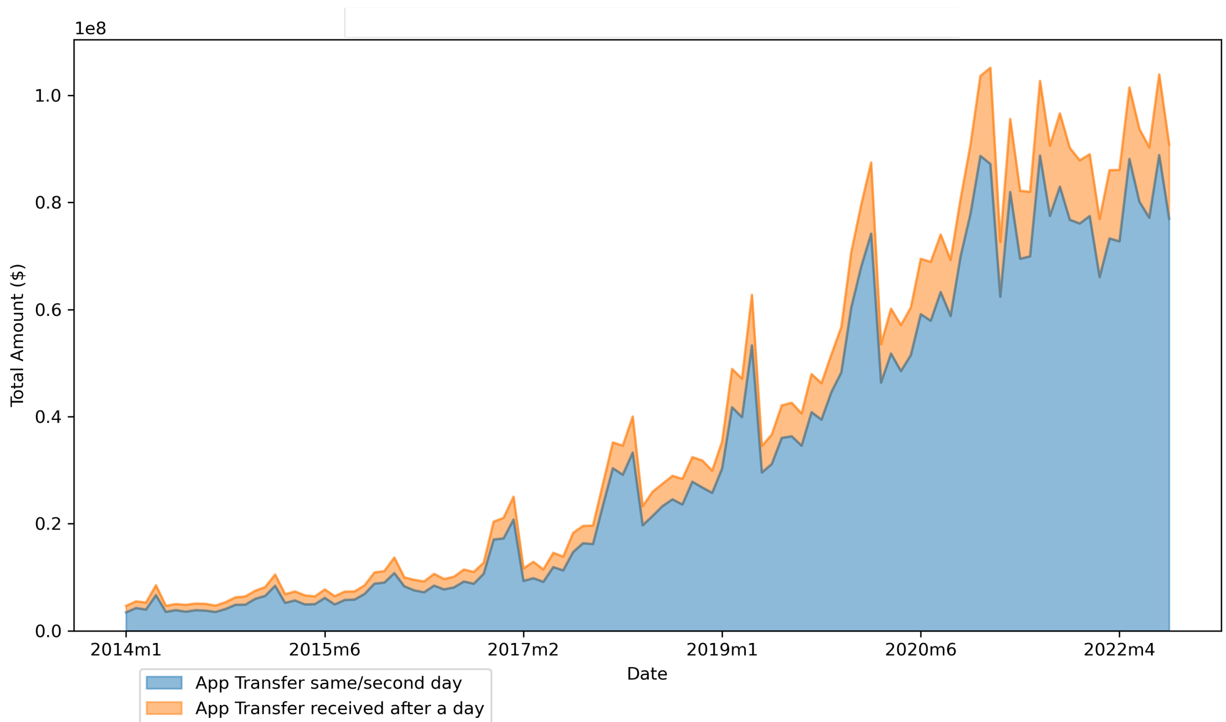
Figure 6: Factors affecting semi-elasticity of deposits to transfer delays



(a) Turnover semielasticity (b) Balance semielasticity

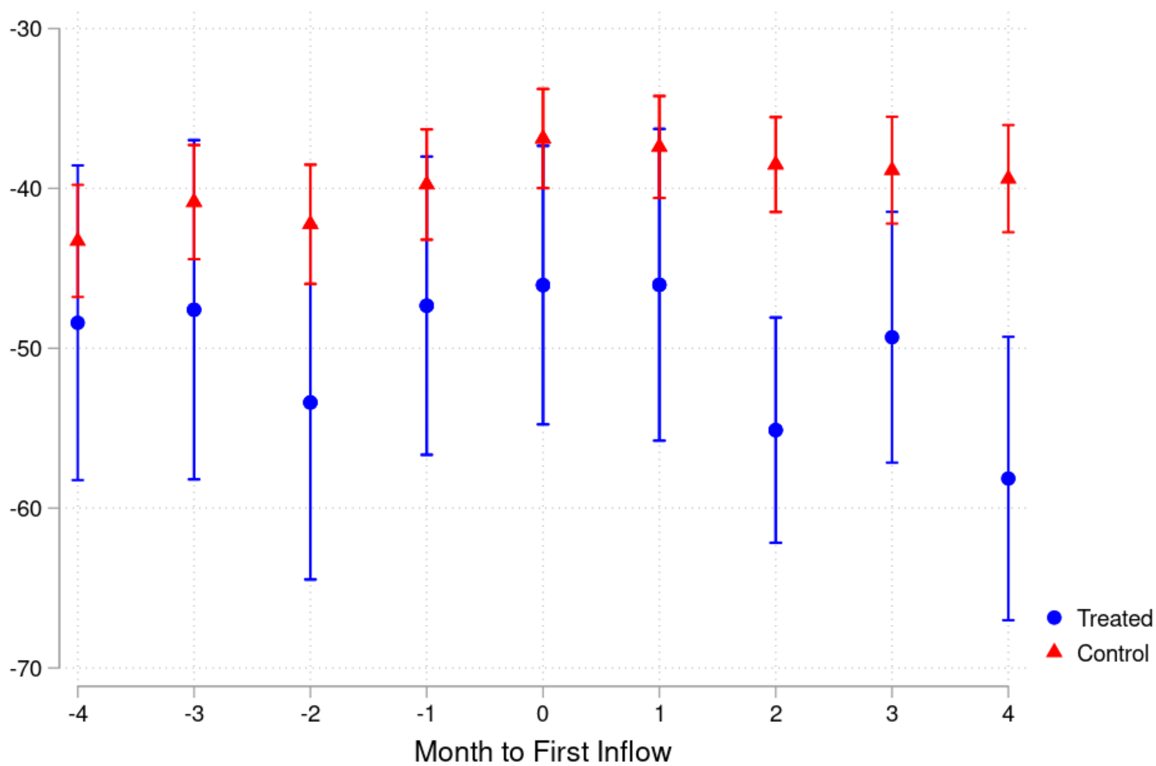
Panel (a) plots the regression coefficients of: $\beta_i = \gamma_0 + \sum_k \gamma_k X_{i,k} + \epsilon_i$, where $X_{i,k}$ include standardized variables such as salary, consumption uncertainty, digital payment ratio, and interest rate dispersion, and β_i represents the semi-elasticity of deposit turnover with respect to transfer delays from individual regressions for each depositor by regressing their log(*Scaled Deposit Turnover*) on transfer delays: $\log(\textit{Scaled Deposit Turnover}_{i,t+1}) = \beta_i \times \textit{Transfer Delay}_{i,t} + \epsilon_{i,t+1}$. Panel (b) plots the regression coefficients of: $\beta'_i = \gamma_0 + \sum_k \gamma_k X_{i,k} + \epsilon_i$, where β'_i represents the semi-elasticity of deposit turnover with respect to transfer delays from individual regressions for each depositor by regressing their log(*Scaled Deposit Balance*) on transfer delays: $log(\textit{Scaled Deposit Balance}_{i,t+1}) = \beta'_i \times \textit{Transfer Delay}_{i,t} + \epsilon_{i,t+1}$, The depositor-level salary, consumption uncertainty, deposit turnover, and balance are scaled by the 12-month moving average of consumption. Thick bands are 99% confidence intervals, and thin bands are 95% confidence intervals.

Figure 7: Transfer delays and fast payment applications



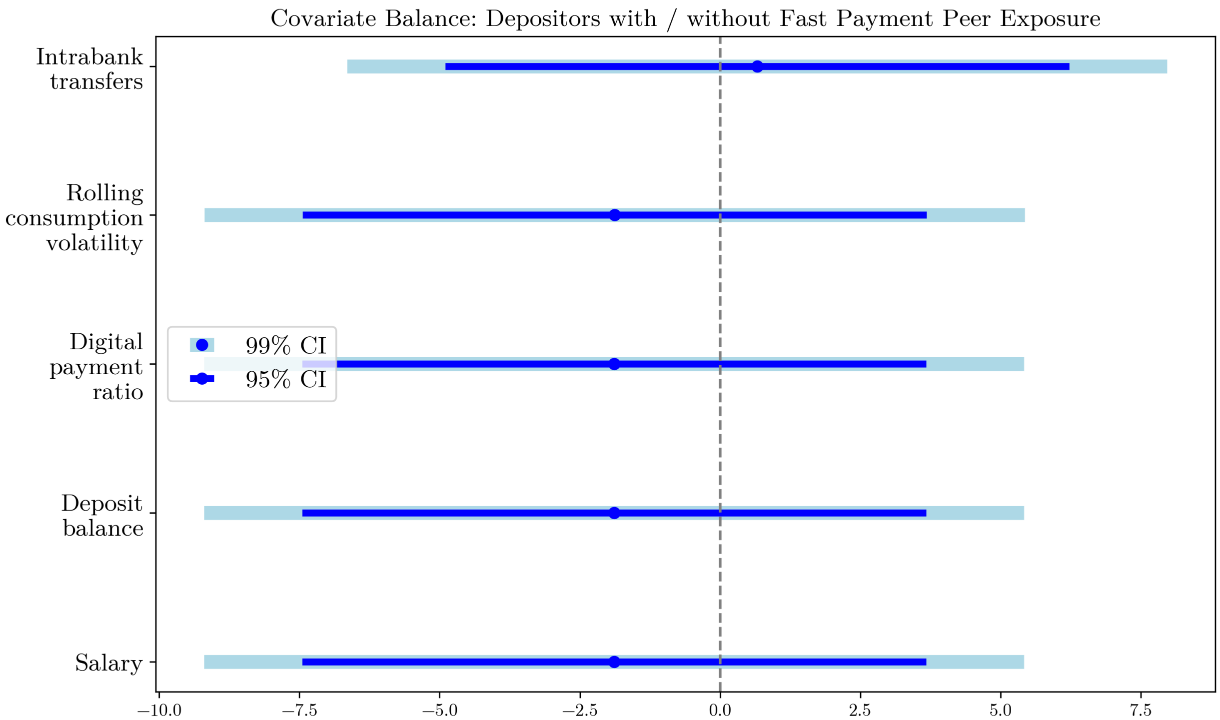
This graph highlights that a significant proportion of interbank transfers leveraging fast payment applications are completed within the same or the next business day, spanning the sample period from 2014 to 2022.

Figure 8: Depositors in treated and control groups have similar trends



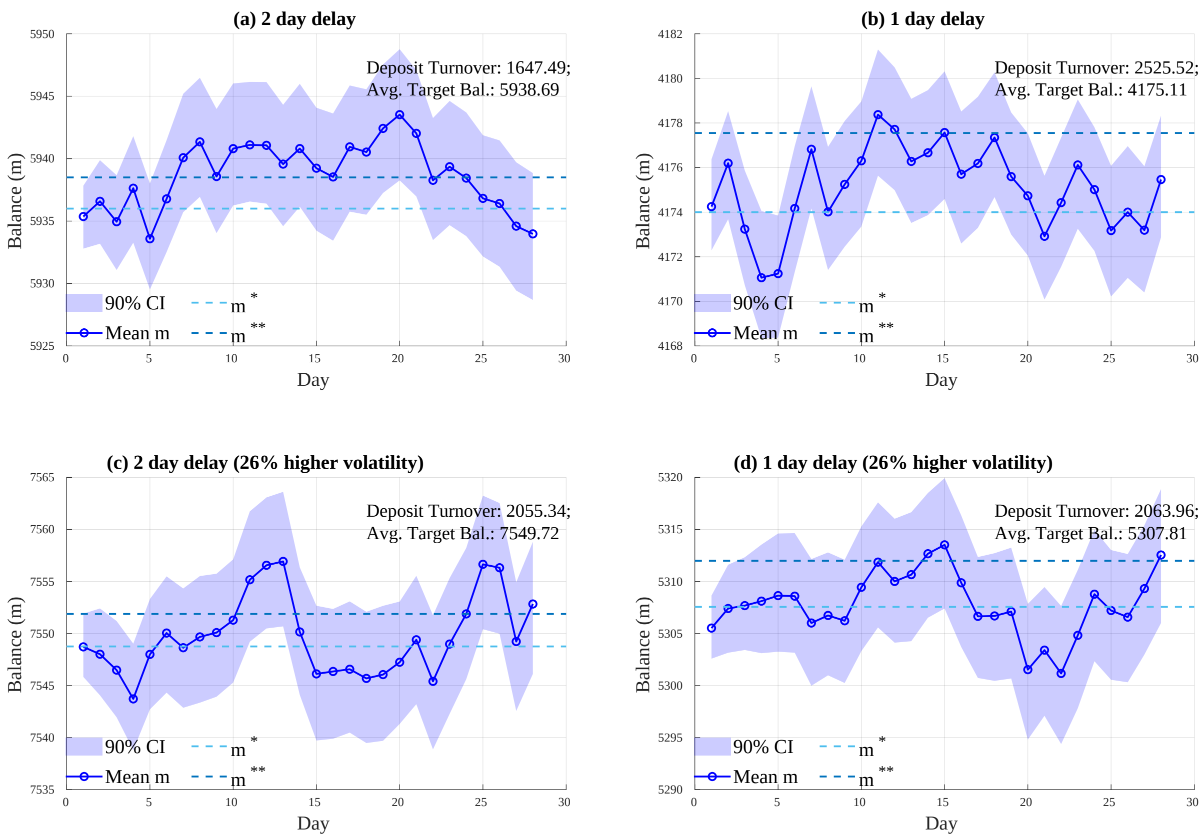
This figure displays the coefficients of *Transfer Delay* from regressions of *Deposit Turnover* on *Transfer Delay*. The regressions include time-varying depositor-level controls such as salary, consumption uncertainty, interest rate dispersion, digital payment ratio, and fixed effects for calendar dates (year-month) relative to the first receipt of incoming funds from fast payment technologies (the treatment). The treated group consists of depositors who had no fund outflows through fast payment technology prior to the treatment, while the control group includes depositors who had used fast payment technology for outflows before their first inflow of funds via these platforms. We plot the 95% confidence intervals with clustered standard errors.

Figure 9: Covariate balance between depositors who accessed fast payments via network exposure and depositors who used fast payments before they receive the first inflow funds.



This figure plots the coefficients and 95% (in dark bands) and 99% (in light bands) confidence intervals of individually estimated and normalized regressions of: $\mathbf{X}_{i,t} = \beta I(Treated_{i,t})$. $I(Treated_{i,t})$ equals one if depositor i who had no transactions related to fast payment technologies receives incoming funds via fast payments during month t. All variables are normalized to have mean zero and standard deviation of one.

Figure 10: Deposit balance evolution with transfer delays



These figures summarize the evolution of deposit balance for the representative average depositor in data from 10,000 simulations. Confidence intervals are computed from bootstrapped SEs with a sample size of 1,000. We first obtain the target balances from the approximation in the limiting case with zero consumption growth and discounting rate $\frac{\sqrt{\kappa}\sigma\cdot\mathcal{W}\left(-\frac{\sqrt{2}b\kappa\sqrt{\kappa}}{r\sigma}\right)}{\sqrt{2\kappa}}$ from Appendix A. In the benchmark case in Figure (a), we set daily volatility $\sigma = 4,822/28 \approx \$172.21$, a 2 business day transfer delay ($\kappa \sim 0.24$) and 0.78% annualized interest rate spread ($r = 0.78\%/365$); b represents the expectation of overdraft fees and the foregone emergency consumption, and we set $b = 20E(\sigma)$. We then simulate the evolation of m for 28 periods. In Figure (b), (c), and (d), we use $\kappa = 0.5$ for 1 business day delays. In Figure (b) and (d), we change consumption uncertainty σ to $\sigma = 1.26\% \cdot 4,822/28 \approx \$216.99$.

Table 1: Depositors hold funds across multiple bank accounts

	Count	Mean ($)	SD ($)	25% ($)	50% ($)	75% ($)
1st	1,239,948	33,159	54,493	2,311	7,256	33,802
2nd	948,253	17,019	37,868	1,195	3,425	11,187
3rd	725,458	7,548	22,335	540	1,699	4,800
4th	580,548	4,311	15,508	268	965	2,783
5th	442,935	2,931	12,233	158	619	1,864
6th	345,733	2,203	10,444	95	412	1,324

This table summarizes the distribution of average account balances across depositors in sample between 2014 and 2022. Accounts are ordered by size of account balances; i.e., 1*st* refers to the deposit account with the largest balance.

Table 2: Average amount by transfer delay

Delay (in days)	Mean ($)	SD ($)	Median ($)	10% ($)	90% ($)	Count
0	1255.12	3408.49	375.00	80.00	2813.00	89,373,597
1	713.00	2393.69	150.00	64.00	1500.00	2,318,511
2	861.74	3051.32	120.00	55.00	1747.06	556,687
3	582.94	2207.45	110.00	54.73	1000.00	725,244
4	527.28	2885.20	103.83	54.00	945.00	582,282
5	400.31	1877.87	102.50	53.00	507.00	340,330

This table presents a further breakdown of the average transaction sizes associated with different transfer delays and summarizes transaction values corresponding to each duration of delay (in days), aggregating data across all depositors and spanning various months during the sample period of 2014 to 2022.

Table 3: Summary statistics

	Mean ($)	SD ($)	Median ($)	10% ($)	90% ($)	Count
Deposit Turnover	1488.32	968.10	1300.51	295.43	3131.25	516279
Deposit Balance	24774.50	59139.49	5739.74	1141.68	59638.70	516279
Transfer Fees	4.33	3.95	3.61	0.00	9.77	516279
Transfer Delay	2.02	0.94	1.87	1.00	3.25	312888
Salary	2858.60	3514.82	1600.59	0.00	7679.74	516279
Rate Dispersion (%)	0.13	0.25	0.04	0.00	0.33	516279
Digital Payment Ratio	0.32	0.27	0.29	0.09	0.60	516279
Mean Interest Rate (%)	0.09	0.19	0.04	0.01	0.20	516279
Consumption Volatility	3293.28	3807.26	2141.13	816.05	6665.25	516279
Consumption Smoothing Efficiency	2.73	1.41	2.56	1.09	4.55	516237
% with Overdraft Protection	0.05	0.23	0.00	0.00	0.00	516279
% Overdrafted	0.21	0.41	0.00	0.00	1.00	516279
% with Outflows from Fast Payment Apps	0.61	0.49	1.00	0.00	1.00	516279
% used Fast Payment Apps	0.65	0.48	1.00	0.00	1.00	516279
% with ATM	0.21	0.41	0.00	0.00	1.00	516279

This table summarizes key variables in the cross section of depositors for the months between 2014 and 2022 when depositors initiated interbank deposit transfers. Transfer Fee are inferred as the difference of between the outflow amount and inflow amount for each pair of deposit transfer transactions for interbank transfers, and reported using the monthly average for each depositor in dollar amount. Transfer Delay is the average business days between the debit transaction and credit transaction for each pair of deposit transfer transactions for interbank transfers weighted by the dollar amount of outflows from each account. Salary is the monthly labor income identified through direct deposits and transfers from employers. Rate Dispersion is the difference between the highest and lowest interest rates (annualized) offered at different bank accounts of depositor i at month t. We additionally report the average annualized interest rate in depositors' checking and savings accounts, the Mean Interest Rate, along with their Interest Income, the income earned from interest on deposits in bank accounts. digital payment ratio is the share of online versus total consumption for each depositor. Deposit Turnover is the total dollar amount transferred across bank accounts in different banks for a given month. Consumption Smoothing Efficiency is the ratio of the rolling mean to the rolling standard deviation of consumption using monthly data from the previous 12 months, as a measure of how consistently a depositor maintains their consumption levels relative to fluctuations in income. Account Balance reports the end of month balance for each account for months when depositors initiated an interbank transfer. The last five rows summarize the percentage of depositors who 1) opt in overdraft protection transfer services, as an indicator of overdraft fee expectation; 2) use fast payment apps to receive or transfer out funds; 3) use fast payment applications to transfer funds out to other bank accounts of his, as an indicator of fast payment technology adoption; 4) were charged at least once an overdraft fee, non-sufficient funds fee, or returned check fee during the sample period. The following variables are winsorized at the 1% level to account for outliers: Transfer Fees, Transfer Delay, Salary, Interest Rate, Interest Income, Financial Obligations, Deposit Turnover, digital payment ratio, Consumption Smoothing Efficiency, and Account Balance.

Table 4: Transfer delays and depositor behavior

	(a) In dollars				(b) Scaled by the moving average of spending			
	(i) Deposit Turnover		(ii) Deposit Balance		(iii) Deposit Turnover		(iv) Deposit Balance	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Delay	-45.74***	-46.00***	995.8***	1701.8***	-0.147***	-0.164***	0.0421***	0.0521***
	(0.521)	(0.553)	(139.1)	(139.8)	(0.00988)	(0.0111)	(0.00492)	(0.00748)
Depositor Controls	N	Y	N	Y	N	Y	N	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
N	14667809	13411352	13421141	13411352	2481766	923141	923253	467217
Adj. R^2	0.00685	0.0163	0.00683	0.0905	0.0293	0.0804	0.00414	0.0169

This table examines how transfer delays affect depositor activeness and deposit balances using the following empirical model:

$$Y_{i,t+1} = \beta_0 + \beta_1 \times \textit{Transfer Delay}_{i,t} + \beta_2 \times \mathbf{X}_{i,t} + \delta_t + \epsilon_{i,t+1},$$

where the dependent variables are *Deposit Turnover*$_{i,t+1}$—the total interbank transfers during month $t+1$ for depositor i—and $Bal_{i,t+1}$, the deposit balance at the end of month $t+1$. *Transfer Delay*$_{i,t}$, is the dollar-weighted average duration in days it takes for depositor i to complete a transfer, calculated as a 12-month rolling average. The vector $\mathbf{X}_{i,t}$ includes depositor-specific covariates such as rolling consumption uncertainty, interest rate dispersion (capturing potential interest income), salary, and digital payment ratio (the ratio of non-physical to total consumption, reflecting a depositor's inclination towards newer, faster technologies).

Panel (a) reports how transfer delays impact deposit turnover and balances in dollar amounts. Panel (b) scales each depositor's measures by their average spending over the past year and applies a logarithmic transformation to the dependent variable, allowing coefficients to be interpreted as semi-elasticities. Standard errors are two way clustered at date and depositor levels. and are reported in parentheses. *, **, and *** indicate statistical significance level at 10%, 5%, and 1%.

Table 5: Interest, delays, and deposit allocation in and out of bank accounts

	%Account Balance							
	Full			High-Volatility Depositors			Credit Card Usage	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rate Spread	-15.95***	-15.97***	-17.57***	-23.70***	-23.72***	-25.76***	-16.99***	-17.66***
	(0.171)	(0.171)	(0.184)	(0.381)	(0.382)	(0.406)	(0.180)	(0.185)
Transfer Delay		0.0972***	-0.0125		0.108***	0.0264*	-0.0299***	-0.104***
		(0.00795)	(0.00800)		(0.0142)	(0.0142)	(0.0100)	(0.0103)
Rate Spread × Transfer Delay		0.0516***	0.0548***		0.0288***	0.0301***	0.109***	0.110***
		(0.00607)	(0.00607)		(0.0103)	(0.0103)	(0.00714)	(0.00716)
Rate Spread × Transfer Delay							-0.119***	-0.118***
× Credit Card Share							(0.0133)	(0.0133)
Depositor FE	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Account Controls	N	N	Y	N	N	Y	N	Y
N	13972539	13972539	13972539	5609342	5609342	5609342	13972539	13972539
Adj. R^2	0.0273	0.0273	0.0296	0.0269	0.0269	0.0288	0.0279	0.0296

%Account Balance denotes the change in a depositor's account balance relative to their total deposits across all accounts. A value of 1 for %ΔDeposit indicates a 1% increase in the account's balance as a share of the depositor's total deposit balance. The key predictors of interests are the standardized 12-month average interest rate spread between effective Fed Funds rate and account level interest rates, $\textit{Transfer Delay}_{i,a,t}$ at account level, along with their interaction term. Control variables include account-level consumption volatility, income proportions from social security and unemployment insurance, gross investment flows, and the shares of credit card payments and ATM withdrawals. We include fixed effects for depositor and time. Columns 1-3 present results for the full depositor sample, while Columns 4-6 focus on depositors with higher than median consumption volatility. Additionally, Columns 7–8 use a triple diff-in-diff interacting payment delays and rate spread with share of credit card spending out of all spending; additional omitted controls include interactions between share of credit card spending and rate spread and payment delays and share of credit card spending. *, **, and *** indicate statistical significance level at 10%, 5%, and 1%.

Table 6: Scaled deposit balance and fast payment adoption

	(a) Deposit Balance						(b) Deposit Turnover		
	OLS	2SLS		3SLS			OLS	2SLS	3SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Transfer Delay	0.0507***	0.0127***		0.0514***			-0.140***	-0.111***	-0.140***
	(0.00179)	(0.00131)		(0.00151)			(0.0108)	(0.00327)	(0.00401)
$\mathbf{I}_{PostFirstInflow}$			-0.119***			0.956***			
			(0.00106)			(0.000301)			
$\mathbf{I}_{PostFirstOutflow}$					-0.00637***				
					(0.00209)				
Depositor Controls	Y	Y		Y			Y	Y	Y
Month FE	Y	Y		Y			Y	Y	Y
N	3123249	4231442		3123177			528699	702972	528692

This table summarizes the impact of transfer delays on deposit balances and deposit turnover, using various estimation methods. Columns 1 to 6 report results where the dependent variable is the depositor's scaled balance, while columns 7 to 9 present results for scaled deposit turnover. Column 1 presents OLS estimates of the effect of transfer delays on deposit balances. Column 2 reports the 2SLS results, where we instrument *Transfer Delay* with the depositor's exposure to fast payment technologies via social networks ($I(\text{Post First Inflow})_{i,t}$). Column 3 shows the first stage of the 2SLS, where *Transfer Delay* is regressed on the instrument.

Columns 4 to 6 present the 3SLS estimates, which further model the potential feedback between deposit balances and the adoption of fast payment technologies. Specifically, in the first stage, we estimate whether receiving funds via fast payment platforms ($I(\text{Post First Inflow})_{i,t}$) influences a depositor's likelihood of initiating outgoing transfers using the same platforms ($I(\text{Post First Outflow})_{i,t}$). We then use the predicted values of $I(\text{Post First Outflow})_{i,t}$ to understand how it affects *Transfer Delay*, and subsequently how *Transfer Delay* affects the dependent variable.

We estimate the following equations: $I(\text{Post First Outflow})_{i,t} = \zeta_0 + \zeta_1 I(\text{Post First Inflow})_{i,t} + \zeta_2 \mathbf{X}_{i,t} + \delta_t + v_{i,t}$, $\text{Transfer Delay}_{i,t} = \gamma_0 + \gamma_1 I(\widehat{\text{Post First Outflow}})_{i,t} + \gamma_2 \mathbf{X}_{i,t} + \delta_t + \varepsilon_{i,t}$, $Y_{i,t+1} = \beta_0 + \beta_1 \widehat{\text{Transfer Delay}}_{i,t} + \beta_2 \mathbf{X}_{i,t} + \delta_t + \epsilon_{i,t+1}$.

$Y_{i,t}$ is the dependent variable (deposit balances or deposit turnover), $I(\text{Post First Inflow})_{i,t}$ is a dummy variable equal to one if depositor i has received funds via fast payment platforms by time t, and zero otherwise. $I(\text{Post First Outflow})_{i,t}$ is a dummy variable equal to one if depositor i has initiated an outgoing transfer via fast payment platforms by time t, and zero otherwise.

For each depositor, we identify their first incoming fund transaction facilitated by Zelle, PayPal, Venmo, or Cash App, and record the month of that transaction as τ_i. The indicator $I(\text{Post First Inflow})_{i,t}$ equals one for month t if $t \geq \tau_i$ and depositor i has not initiated any outflow via fast payment applications prior to month τ_i. $\text{Transfer Delay}_{i,t}$ is measured as the dollar-weighted transfer delays for depositor i using a 12-month moving average for each month t. We include time-fixed effects (δ_t) and depositor-level controls ($\mathbf{X}_{i,t}$) in all stages to focus on the cross-sectional heterogeneity of depositors. The controls include salary, consumption uncertainty, interest rate dispersion, digital payment ratio, and the amount first received via fast payment technologies. All standard errors are clustered by date and are reported in parentheses. *, **, and *** indicate statistical significance level at 10%, 5%, and 1%. The first-stage F-statistics is 79.49.

Table 7: Uniformly faster transfers and the cross section of depositors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	
	Mean of Deposit Balance			SD of Deposit Balance			Deposit Turnover			σ
	Data	Model		Data	Model		Data	Model		Data
1st Quint.	728	768.73	543.27	2324	2617.76	1498.14	887.77	823.08	1206.69	*676*
2nd Quint.	1403	1488.25	1047.91	2562	2906.48	1658.77	993.21	913.91	1350.41	*1276*
3rd Quint.	2521	2725.88	1918.37	2866	3251.74	1854.87	1034.77	1027.12	1521.92	*2282*
4th Quint.	5089	5344.7	3758.94	3284	3727.4	2126.32	1052.87	1179.58	1752.17	*4359*
5th Quint.	17943	18807.08	13217.41	3973	4506.42	2573.6	1088.62	1430.9	2129.89	*14625*
Uninsured	21101	22578.17	15865.48	4679	5306.99	3031.06	1812	1685.07	2508.51	*17439*
Delay	*2.01*	*2*	*1*	*2.01*	*2*	*1*	*2.01*	*2*	*1*	

The depositors are divided into quintiles sorted by their average deposit balance in the sample period; the 1st Quintile has the lowest balance, and 5th Quintile has the highest balance; additionally, we report another "uninsured" subsample of depositors with more than 250k balances in any bank account at any time during the sample period. The data moments are detrended using 12-month moving averages, and model moments are computed from 10,000 simulations. Additional parameters from data are reported in the table in *Italic*. *Consumption volatility* σ is empirically measured from the data using detrended balance volatility during the sample period for each depositor and then taking the average; *Delay* is measured in business days where 2 (/1) business days maps into 2.8 (/1.4) calendar days and $\kappa = 0.24$ ($/\kappa = 0.5$). We use the average annualized interest rate spread in sample for interest rate; b represents the expectation of overdraft fees and the foregone emergency consumption, and we set $b = 20E(\sigma)$. For each subsample, we first obtain the target balances from the approximation in the limiting case with zero consumption growth and discounting rate $\frac{\sqrt{\kappa}\sigma\cdot\mathcal{W}\left(-\frac{\sqrt{2}b\kappa\sqrt{\kappa}}{r\sigma}\right)}{\sqrt{2\kappa}}$ from Appendix A. We then simulate the evolution of m for a year and report the average and the volatility.

Internet Appendix for

Tracing the Impact of Payment Convenience on Deposits: Evidence from Depositor Activeness

Xu Lu Yang Song Yao Zeng

A. Theory Appendix

A.1. Deriving optimal policy for a patient depositor without consumption growth

In our set up with consumption uncertainty and payment uncertainty, the optimal policy cannot be solved in closed form in general. Despite the absence of fixed costs, our model differs from the instantaneous control problem carefully analyzed by Harrison (2013), as the inclusion of transfer delays renders the time spent outside the inaction region with positive probability in the ergodic state. Constantinides and Richard (1978) demonstrate that in a simpler setting with uncertain consumption and asymmetric transaction costs, there is no general closed-form solution available. To facilitate empirical analysis and model calibration, we consider an intuitive special case involving a patient depositor (letting $\beta \to 0$) and negligible consumption growth (letting $g \to 0$). Under these conditions, we derive an explicit solution that guides our empirical tests and calibration.

HJB conditions

Inaction region ($\underline{m} \leq m \leq \overline{m}$): In this region, we have the HJB condition:

$$0 = rm + \frac{1}{2}\sigma^2 V''(m).$$

Integrate with respect to m:

$$V(m) = -\frac{rm^3}{3\sigma^2} + C_1 m + C_2,$$

where C_1 and C_2 are constants.

Upper action region ($m \geq \overline{m}$): We have the HJB condition:

$$\frac{1}{2}\sigma^2 V''(m) - \kappa V(m) = -rm - \kappa V(m^{**}).$$

The homogeneous equation is:

$$V''(m) - \frac{2\kappa}{\sigma^2} V(m) = 0,$$

with solution

$$V_h(m) = C_3 e^{\frac{\sqrt{2\kappa}}{\sigma} m} + C_4 e^{-\frac{\sqrt{2\kappa}}{\sigma} m}.$$

Assuming a particular solution of the form: $V_p(m) = Am + K$, then

$$-\kappa(Am + K) = -rm - \kappa V(m^{**}).$$

Equate coefficients we have:

$$-\kappa A = -r \implies A = \frac{r}{\kappa},$$
$$-\kappa K = -\kappa V(m^{**}) \implies K = V(m^{**}).$$

That is, $V_p(m) = \frac{r}{\kappa} m + V(m^{**})$. Therefore, the general solution is:

$$V(m) = V_p(m) + V_h(m) = \frac{r}{\kappa} m + V(m^{**}) + C_3 e^{\frac{\sqrt{2\kappa}}{\sigma} m} + C_4 e^{-\frac{\sqrt{2\kappa}}{\sigma} m}.$$

Lower action region ($0 \leq m \leq \underline{m}$): Similarly to the upper action region, we have the Bellman equation:

$$0 = rm^* + \frac{1}{2}\sigma^2 V''(m) + \kappa \left(V(m^*) - V(m) \right).$$

Following the same steps as in the lower action region, the general solution is:

$$V(m) = \frac{r}{\kappa} m^* + V(m^*) + C_5 e^{\frac{\sqrt{2\kappa}}{\sigma} m} + C_6 e^{-\frac{\sqrt{2\kappa}}{\sigma} m}.$$

Additionally, we have the optimality conditions at m^* and m^{**}:

$$V'(m^*) = r, \quad V'(m^{**}) = 0.$$

The continuity and smooth pasting and super contact at the lower and upper thresholds indicate that at $m = \underline{m}$:

$$V_{\text{lower}}(\underline{m}) = V_{\text{inaction}}(\underline{m}), \quad V'_{\text{lower}}(\underline{m}) = V'_{\text{inaction}}(\underline{m}), \quad V''_{\text{lower}}(\underline{m}) = V''_{\text{inaction}}(\underline{m}),$$

and that at $m = \overline{m}$:

$$V_{\text{upper}}(\overline{m}) = V_{\text{inaction}}(\overline{m}), \quad V'_{\text{upper}}(\overline{m}) = V'_{\text{inaction}}(\overline{m}), \quad V''_{\text{upper}}(\overline{m}) = V''_{\text{inaction}}(\overline{m}).$$

Finally the boundary condition at $m = 0$:

$$V(0) = V(m^*) + b.$$

The limiting condition that $V(m)|_{m\to\infty} < \infty$ implies $C_3 = 0$.

The optimal deposit rule and Proof of Proposition 1

Using the optimality conditions, the smooth pasting, the high and super contact conditions at thresholds, and the boundary conditions along with the limited value funtion as $m \to \infty$, we can solve for $(\underline{m}, m^*, m^{**}, \overline{m})$ as functions of r, κ, and σ. In the main text, we show the analytical properties and here we derive the closed-form conditions.

First of all, since $V'(m)$ remains finite as $m \to \infty$, we have $C_3 = 0$. From the inaction region solution, the first derivative is:

$$V'(m) = -\frac{rm^2}{\sigma^2} + C_1.$$

Relation between m^{**} and m^* through the optimality conditions indicates:

$$V'(m^*) = -\frac{r(m^*)^2}{\sigma^2} + C_1 = r \implies C_1 = r + \frac{r(m^*)^2}{\sigma^2},$$

$$V'(m^{**}) = -\frac{r(m^{**})^2}{\sigma^2} + C_1 = 0 \implies C_1 = \frac{r(m^{**})^2}{\sigma^2}.$$

Thus,

$$m^{**} = \sqrt{m^{*2} + \sigma^2}.$$

Relation between $\underline{m}$ and m^* through value matching and super contact gives:

$$C_5 A_1 + C_6 A_1^{-1} = -\frac{r\underline{m}^3}{3\sigma^2} + C_1 \underline{m} - \frac{r}{\kappa} m^* + \frac{r(m^*)^3}{3\sigma^2} - C_1 m^*,$$

$$C_5 A_1 + C_6 A_1^{-1} = -\frac{r}{\kappa} \underline{m},$$

where $A_1 = e^{\sqrt{\frac{2\kappa}{\sigma^2}}\underline{m}}$. Define $\delta_1 \equiv m^* - \underline{m}$, we can solve δ_1 from the cubic equation

$$-\frac{r(m^* - \delta_1)^3}{3\sigma^2} - \frac{r}{\kappa}\delta_1 + \frac{r(m^*)^3}{3\sigma^2} - C_1\delta_1 = 0,$$

where the three solutions are

$$\delta_1^i = 0,\ \delta_1^{ii} = \left(\frac{3}{2}m^* - \sqrt{\frac{9\,m^{*2}}{4\sigma^4} + \frac{(3+\frac{3}{\kappa})}{\sigma^2}}\right)\sigma^2,\ \delta_1^{iii} = \left(\frac{3}{2}\,m^* + \sqrt{\frac{9\,m^{*2}}{4\sigma^4} + \frac{(3+\frac{3}{\kappa})}{\sigma^2}}\right)\sigma^2.$$

Note that $0 \le \delta_1 \le m^*$, $\delta_1^{ii} < 0$, and $\delta_1^{iii} > m^*$. Thus, $\delta_1 = 0$ is the solution, i.e.,

$$m^* = \underline{m}.$$

Similarly, by solving the value matching and super contact at threshold $\overline{m}$ and denoting $\delta_2 = \overline{m} - m^{**}$, we have $r(m^{**3} - (m^{**} + \delta_2)^3)/(3\sigma^2) + (rm^{**2}/\sigma^2)\delta_2 = 0$, where the only non-negative solution of δ_2 is zero, i.e.,

$$m^{**} = \overline{m}.$$

We then solve the value of m^* through the value matching, high contact condition at $\underline{m}$, and the boundary condition and eliminate C_5 and C_6 with $\delta_1 = 0$. Define $\lambda = \sqrt{(2\kappa)/\sigma^2}$, then

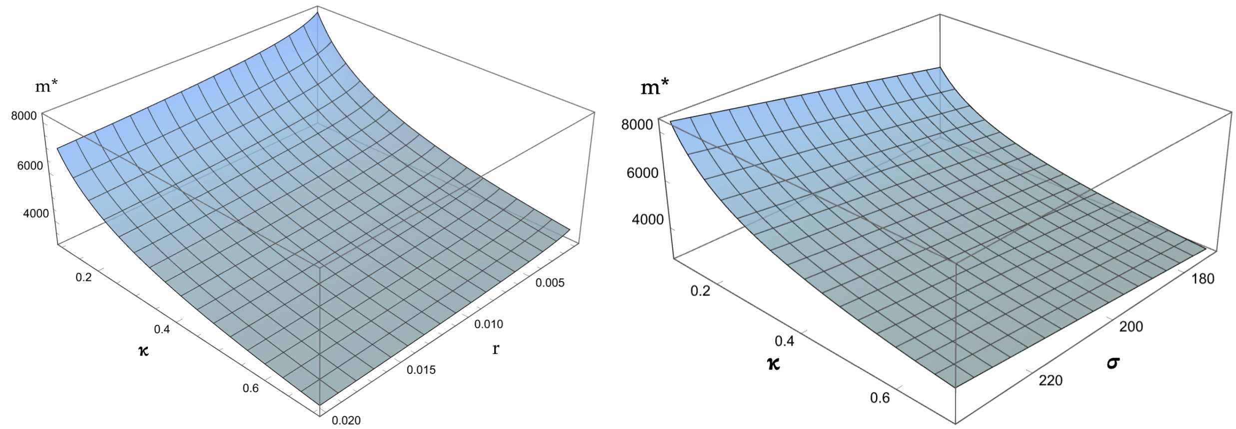
$$\begin{aligned} 2C_5 &= [r + r/\sigma^2(m^{*2} - \underline{m}^2)]\lambda^{-1}A_1^{-1} = r\lambda^{-1}A_1^{-1}, \\ -2C_6 &= r/\kappa m^* A_1 + r\lambda^{-1}A_1, \\ C_5 + C_6 &= b - r/\kappa m^*. \end{aligned}$$

Define $n = m^*\lambda = m^*\sqrt{2\kappa}/\sigma$, then

$$\frac{2b\lambda}{r} - \frac{2n}{\kappa} = \frac{\kappa - n}{\kappa}e^{-n} - \frac{\kappa + n}{\kappa}e^{n}.$$

Note that in the data, $E[m^*]$ is above \$27K, and the $50th$ percentile of balance is around \$6K, while daily consumption uncertainty is much smaller ($\approx$ \$200) and the expected $\kappa \approx 0.24$ (2.8

Figure A-1: m^* decreases with payment efficiency κ, with interaction effects from r and σ



calendar day delays), suggesting $e^{-n} \to 0$ and $n << e^n$. Taking this approximation we have:

$$\frac{2b\kappa\lambda}{r} = -ne^n \implies m^* = \frac{\sqrt{\kappa}\sigma \cdot \mathcal{W}\left(-\frac{2\sqrt{2}b\kappa\sqrt{\kappa}}{r\sigma}\right)}{\sqrt{2}\kappa},$$

where $\mathcal{W}\left(-e^{\left(\frac{2\sqrt{2}b\kappa^2}{r\sqrt{\kappa}\sigma}\right)}\right)$ gives the principal solution of the Lambert W function $-\frac{2\sqrt{2}b\kappa\sqrt{\kappa}}{r\sigma} = xe^x$.

Figure A-1 illustrates the lower target balance m^* monotonically changes with payment efficiency κ conditional on levels of rate r and consumption uncertainty σ, as in summarized in Proposition 1.

A.2. Proof of Proposition 2

To compute the expected turnover, we first compute the ergodic distribution of the account balance $m(t)$, which evolves according to a Brownian motion with volatility σ, subject to control actions at thresholds m^* and m^{**}. In the inaction region $m^* \leq m \leq m^{**}$, the process follows a standard Brownian motion without drift. Therefore, the stationary probability density function in this region is constant, denoted by f_{inaction}. In the lower action region $0 < m < m^*$, an inflow transfer is initiated when $m(t) < m^*$. The transfer succeeds with rate κ, causing $m(t)$ to jump to m^*. If $m(t)$ reaches zero before the transfer succeeds, it automatically resets to m^* without triggering a transfer. In the upper action region $m > m^{**}$, an outflow transfer is initiated when $m(t) > m^{**}$. The transfer succeeds with rate κ, causing $m(t)$ to jump to m^{**}.

In the lower action region, the Fokker-Planck equation is $0 = \frac{1}{2}\sigma^2 \frac{d^2 f(m)}{dm^2} - \kappa f(m)$. Let $\lambda = \sqrt{\frac{2\kappa}{\sigma^2}}$, then $f(m) = C_1 e^{\lambda m} + C_2 e^{-\lambda m}$. At boundary $m = 0$, the probability density must be zero due to the reset and therefore $C_2 = -C_1$. At $m = m^*$, continuity with the inaction region requires:

$$f(m^*) = C_1 \left(e^{\lambda m^*} - e^{-\lambda m^*}\right) = f_{\text{inaction}}.$$

So we have $C_1 = \frac{f_{\text{inaction}}}{e^{\lambda m^*} - e^{-\lambda m^*}}$. The ergodic distribution in the lower action region is:

$$f(m) = f_{\text{inaction}} \cdot \frac{e^{\lambda m} - e^{-\lambda m}}{e^{\lambda m^*} - e^{-\lambda m^*}}.$$

In the inaction region $m^* \leq m \leq m^{**}$, $m(t)$ evolves as a Brownian motion without drift within the interval $[m^*, m^{**}]$ by reflecting boundaries at m^* and m^{**}, with the Fokker-Planck equation $0 = \frac{1}{2}\sigma^2 \frac{d^2 f(m)}{dm^2}$. This implies that the second derivative of $f(m)$ with respect to m is zero:

$$\frac{d^2 f(m)}{dm^2} = 0.$$

In the stationary state, since there are no absorbing state within the inaction region, and no control actions are taking place, $\frac{df(m)}{dm} = 0$. Consequently, the probability density function $f(m)$ is constant in the inaction region:

$$f(m) = f_{\text{inaction}}.$$

In the upper action region, the Fokker-Planck equation is identical to lower action region with solution

$$f(m) = D_1 e^{\lambda m} + D_2 e^{-\lambda m}.$$

As $m \to \infty$, the probability density must remain finite, so $D_1 = 0$. Continuity at $m = m^{**}$

requires:

$$f(m^{**}) = D_2 e^{-\lambda m^{**}} = f_{\text{inaction}} \implies D_2 = f_{\text{inaction}} e^{\lambda m^{**}}.$$

The ergodic distribution in the upper action region is:

$$f(m) = f_{\text{inaction}} e^{\lambda(m^{**} - m)}.$$

To find f_{inaction}, we use the normalization condition:

$$\int_0^\infty f(m)\, dm = 1.$$

This integral is the sum of the integrals over the three regions:

$$\int_0^{m^*} f(m)\, dm + \int_{m^*}^{m^{**}} f_{\text{inaction}}\, dm + \int_{m^{**}}^\infty f(m)\, dm = 1.$$

For the first integral during $0 < m < m^*$:

$$I_1 = \int_0^{m^*} f(m)\, dm = f_{\text{inaction}} \cdot \frac{e^{\lambda m^*} + e^{-\lambda m^*} - 2}{\lambda(e^{\lambda m^*} - e^{-\lambda m^*})}.$$

For the integral for $m > m^{**}$:

$$I_2 = \int_{m^{**}}^\infty f(m)\, dm = \frac{f_{\text{inaction}}}{\lambda}.$$

The normalization condition becomes:

$$I_1 + f_{\text{inaction}}(m^{**} - m^*) + I_2 = 1.$$

Substituting the expressions for I_1 and I_3:

$$f_{\text{inaction}}\left(\frac{e^{\lambda m^*}+e^{-\lambda m^*}-2}{\lambda(e^{\lambda m^*}-e^{-\lambda m^*})}+(m^{**}-m^*)+\frac{1}{\lambda}\right)=1.$$

Thus,

$$f_{\text{inaction}}=\frac{1}{\dfrac{e^{\lambda m^*}+e^{-\lambda m^*}-2}{\lambda(e^{\lambda m^*}-e^{-\lambda m^*})}+(m^{**}-m^*)+\dfrac{1}{\lambda}}.$$

Now we have

$$E[m^*-m\mid m<m^*]=\frac{\int_0^{m^*}(m^*-m)f(m)\,dm}{\int_0^{m^*}f(m)\,dm}.$$

That is,

$$\int_0^{m^*}(m^*-m)f(m)\,dm=f_{\text{inaction}}\cdot\frac{1}{e^{\lambda m^*}-e^{-\lambda m^*}}\int_0^{m^*}(m^*-m)\left(e^{\lambda m}-e^{-\lambda m}\right)dm.$$

Let $u=m^*-m$, so $m=m^*-u$ and $dm=-du$. The limits change to $u=0$ when $m=m^*$ and $u=m^*$ when $m=0$. The integral becomes:

$$-f_{\text{inaction}}\cdot\frac{e^{\lambda m^*}}{e^{\lambda m^*}-e^{-\lambda m^*}}\int_0^{m^*}ue^{-\lambda u}du+f_{\text{inaction}}\cdot\frac{e^{-\lambda m^*}}{e^{\lambda m^*}-e^{-\lambda m^*}}\int_0^{m^*}ue^{\lambda u}du,$$

where $\int_0^{m^*}ue^{-\lambda u}du=\dfrac{-1+e^{-\lambda m^*}(\lambda m^*+1)}{\lambda^2}$ and $\int_0^{m^*}ue^{\lambda u}du=\dfrac{e^{\lambda m^*}(\lambda m^*-1)+1}{\lambda^2}$. By simplifying it further, we have:

$$E[m^*-m\mid m<m^*]=\frac{1}{\lambda}=\sqrt{\frac{\sigma^2}{2\kappa}}.$$

Similarly for $E[m-m^{**}\mid m>m^{**}]$, we have:

$$E[m-m^{**}\mid m>m^{**}]=\frac{\displaystyle\int_{m^{**}}^{\infty}(m-m^{**})f(m)\,dm}{\displaystyle\int_{m^{**}}^{\infty}f(m)\,dm},$$

where

$$\int_{m^{**}}^{\infty} f(m)\, dm = \frac{f_{\text{inaction}}}{\lambda},$$

and

$$\int_{m^{**}}^{\infty} (m - m^{**}) f(m)\, dm = f_{\text{inaction}} \int_{0}^{\infty} u e^{-\lambda u} du \quad (u = m - m^{**}) = \frac{f_{\text{inaction}}}{\lambda^2}.$$

Therefore, we have

$$E[m - m^{**} \mid m > m^{**}] = \frac{1}{\lambda} = \sqrt{\frac{\sigma^2}{2\kappa}}.$$

The expected value of the deviation from the S-s band is

$$\text{EV} = E[m^* - m \mid m < m^*] \cdot P(m < m^*) + E[m - m^{**} \mid m > m^{**}] \cdot P(m > m^{**}),$$

where the probability of the deviations from the inaction region is

$$P(m < m^*) = \int_{0}^{m^*} f(m)\, dm = f_{\text{inaction}} \cdot \frac{e^{\lambda m^*} + e^{-\lambda m^*} - 2}{\lambda(e^{\lambda m^*} - e^{-\lambda m^*})},$$

and

$$P(m > m^{**}) = \int_{m^{**}}^{\infty} f(m)\, dm = \frac{f_{\text{inaction}}}{\lambda}.$$

Therefore,

$$\begin{aligned} \text{EV} &= \left(\frac{1}{\lambda}\right) \cdot \left(f_{\text{inaction}} \cdot \frac{e^{\lambda m^*} + e^{-\lambda m^*} - 2}{\lambda(e^{\lambda m^*} - e^{-\lambda m^*})}\right) + \left(\frac{1}{\lambda}\right) \cdot \left(\frac{f_{\text{inaction}}}{\lambda}\right) \\ &= f_{\text{inaction}} \cdot \left(\frac{(e^{\lambda m^*} + e^{-\lambda m^*} - 2)}{\lambda^2(e^{\lambda m^*} - e^{-\lambda m^*})} + \frac{1}{\lambda^2}\right). \end{aligned}$$

Thus,

$$\text{EV} = \frac{\dfrac{(e^{\lambda m^*} + e^{-\lambda m^*} - 2)}{\lambda^2(e^{\lambda m^*} - e^{-\lambda m^*})} + \dfrac{1}{\lambda^2}}{\dfrac{e^{\lambda m^*} + e^{-\lambda m^*} - 2}{\lambda(e^{\lambda m^*} - e^{-\lambda m^*})} + (m^{**} - m^*) + \dfrac{1}{\lambda}}.$$

For large λm^*, the exponentials dominate, and the expression simplifies. Assuming $e^{\lambda m^*} \gg 1$ and $e^{-\lambda m^*} \approx 0$, we have:

$$e^{\lambda m^*} - e^{-\lambda m^*} \approx e^{\lambda m^*}, \quad e^{\lambda m^*} + e^{-\lambda m^*} - 2 \approx e^{\lambda m^*}.$$

Then, the expression for EV simplifies to:

$$\text{EV} \approx \frac{\frac{1}{\lambda^2} + \frac{1}{\lambda^2}}{\frac{1}{\lambda} + (m^{**} - m^*) + \frac{1}{\lambda}} = \frac{\frac{2}{\lambda^2}}{\frac{2}{\lambda} + (m^{**} - m^*)}.$$

Therefore,

$$\text{EV} = \frac{2}{\lambda \left(2 + \lambda(m^{**} - m^*)\right)}.$$

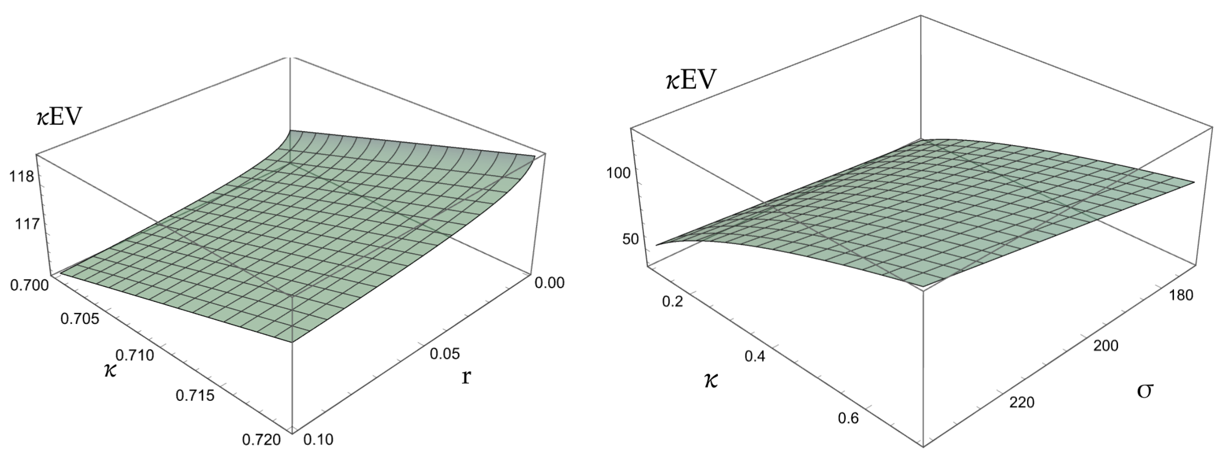
For any given point in time, the expected transfer is $\kappa \times EV$ which is given by

$$\kappa \text{EV} = \frac{\sigma\sqrt{\kappa}}{\sqrt{2} + \frac{\sqrt{\kappa}}{\sigma}(m^{**} - m^*)}.$$

The thresholds m^* and m^{**} are both functions of κ, σ, and r. Specifically, m^* and m^{**} increase with σ. They decrease with κ because a higher transfer success rate allows for tighter thresholds. They also decrease with r: transfers are costly in both direction, as interest accrued in the transfer process is always lost. Given that we have an analytical solution for m^{**} and m^* from above, we illustrate the interactive effects between κ, σ and r in Figure A-2.

Note that the effect of r is relatively small and monotonic but difficult to visualize over a broad range of κ. Therefore, we focus on a small interval of κ to highlight these effects. The second derivative $\frac{\partial^2(\kappa \text{EV})}{\partial\kappa\partial r}$ is weakly decreasing because the effect of r on m^* and m^{**} is less significant compared to the effect of κ. In contrast, $\frac{\partial^2(\kappa \text{EV})}{\partial\kappa\partial\sigma}$ is significantly increasing. σ having a strong impact on the thresholds, and κEV increase at a higher rate with respect to larger κ.

Figure A-2: Expected deposit turnover increases with payment efficiency κ, with interaction effects from r and σ



B. Empirical Appendix

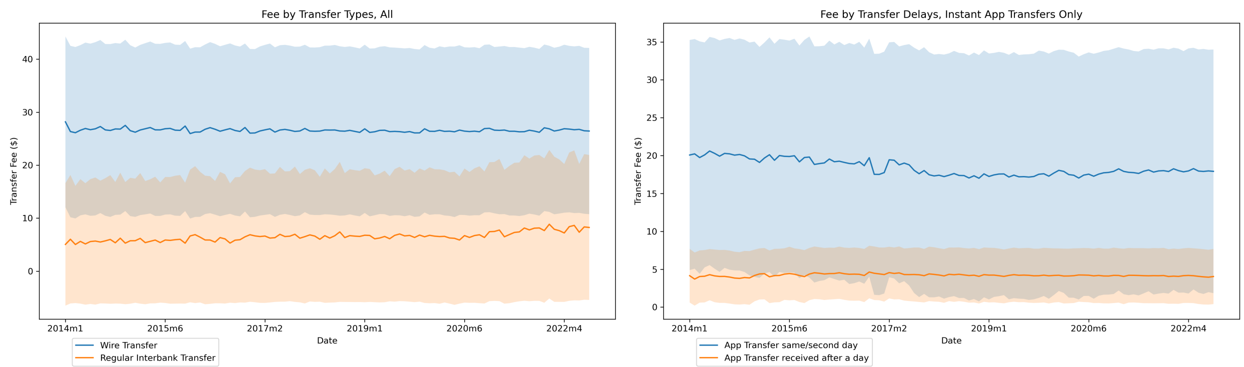
B.1. Fees and limits for bank wire transfers and fast payment technologies

To determine the suitable threshold for deposit turnover imputation, we collect information on wire transfers for a sample of U.S. banks. Note the fees are variable for some banks; in those cases, we record the maximum and arrive at the threshold of $50 for wire transfer identification in the transaction data.

Table A-1: Summary of Wire Transfer Fees

Bank Name	Incoming Domestic	Outgoing Domestic	Incoming International	Outgoing International
Ally Bank	$0	$20	$0	$0
Bank of America	$15	$30	$15	$45
Chase	$15	$35	$15	$50
Wells Fargo	$15	$25	$16	N/A
Capital One 360	$0	$30	$0	$50
Charles Schwab Bank	$0	$25	$0	$25
Discover	$0	$30	$0	$30
PNC Bank	$15	$25	$15	$40
Axos Bank	$0	$35	$0	$45
BMO Bank	$0	$30	$0	$50
Comerica Bank	$12	$27	$15	$48
KeyBank	$20	$25	$20	$45
TD Bank	$15	$30	$15	$50
U.S. Bank	$20	$30	$25	$50

Figure A-3: Distribution of Fees by Transfer Type



These two histograms present the average of inferred fees paid for different types of interbank transfers in our sample from 2014 to 2022. We infer the payment fees from the differences in transaction amount between each debit and credit transaction pair. Plot on the left shows the average inferred fees paid for same/next-day wire transfers and regular ACH transfers. Plot on the right zooms into the transactions associated with fast payment technologies only and report the average fees associated with those transactions. Shaded areas are standard deviations.

Table A-2: Fast Payment Technologies: Fees and Limits

i. PayPal

Account Type	**Transaction Type**	**Fee**	**Limits**
Bank Account	Standard	Free	—
	Instant	1.75% (> $0.25, < $25)	Max $25,000 per transaction
Cards	Standard	No fee	—
	Instant	1.75% (> $0.25, < $25)	Max $5,000 per transaction/day/week Max $15,000 per month
Checks	Mailed	$1.50[9]	—

ii. Venmo

Transfer Type	**Limit**	**Fees**	**Transfer Speed**
Standard	Up to $19,999.99 per week; $5,000 per transfer	Free	1-3 business days
Instant	Up to $5,000 per transfer	0.5% - 1.75% (min $0.25)	Instant

iii. Cash App

Transfer Type	**Limit**	**Fees**	**Transfer Speed**
Standard	$1,000 in 30-day for unverified and	Free	1-3 business days
Instant	Undisclosed higher limits for verified accounts	0.5% - 1.75% (min $0.25)	< 30min

See the next page for information sources and limits for Zelle.

Table A-2: Fast Payment Technologies: Fees and Limits (Cont.)

iv. Zelle Transfer Limits for Major Partner Banks

Bank	Daily Send Limit		Monthly Send Limit
Non-partner bank			$500 per week ($5,000 in the app)
Ally Bank	Instant: $2,000	Scheduled: $5,000	$10,000
Bank of America	$3,500		$20,000
Capital One	$2,500		Not disclosed
Chase	$500-$10,000 per transaction (determined by Chase)		Not disclosed
Citibank (accounts >30 days old)	$2,500		$15,000
Discover Bank	$600		Not disclosed
Quontic Bank	Per transaction: $500	Per day: $1,000	Not disclosed
TD Bank	Instant: $1,000	Scheduled: $2,500	Instant: $5,000Scheduled: $10,000
Truist Bank	$2,000		$10,000
USAA Federal Savings Bank	$1,000		$10,000
Wells Fargo	$3,500		$20,000

Sources: https://www.bankrate.com/banking/zelle-limits-at-top-banks/#transfer-limits;
https://cash.app/help/3073-withdrawal-transfer-speed-options;
https://help.venmo.com/hc/en-us/articles/209690048-Personal-Profile-Bank-Transfer-Limits#:~:text=If%20you’ve%20confirmed%20your,to%20transfer%20more%20than%20%245%2C000;
https://venmo.com/send-receive/manage-balance/#:~:text=Move%20money%20ASAP.&text=A%201.75%25%20fee%20(minimum%20\protect\T1\textdollar0.25),removed%20from%20your%20Venmo%20account;
https://www.paypal.com/us/webapps/mpp/paypal-fees;
https://www.chase.com/personal/zelle;
https://www.bankrate.com/banking/zelle-limits-at-top-banks/;
https://www.gobankingrates.com/banking/mobile/zelle-limits/.
Last retrieved October 2024.

B.2. Inferring location from transactions

To assign a primary location to each depositor for each month, we utilized their physical debit transaction records from both card and bank panels spanning from January 2013 to December 2022. We focused on transactions most indicative of a depositor's residence. Specifically, we selected transactions that met the following criteria: they were non-duplicate, successfully processed, conducted in U.S. dollars, and categorized as physical debit transactions. We excluded travel-related expenses and miscellaneous transactions without clear descriptions, as these do not reliably indicate a depositor's residence. Transactions without city information or with city fields starting with digits (which might indicate an address rather than a city name) were also excluded.

We matched these transactions with a standardized locations table to ensure consistency in city and state names, overriding any discrepancies in the original data. For each depositor and each state-city pair within a given month, we calculated the number of distinct days on which eligible transactions occurred, providing a measure of transaction frequency in each location.

To determine the primary location for each depositor in each month, we employed a geometric median approach. We calculated the weighted average Euclidean distance between each pair of cities where the depositor had transactions, weighting by the number of transaction days in each city. The city that minimized this weighted average distance was selected as the depositor's primary location. If a single city accounted for more than half of the depositor's total transaction days in that month, we automatically assigned that city as the primary location to ensure accuracy in cases where one location was predominant.

This allows us to robustly infer the residential addresses of depositors based on their transaction behavior.

B.3. Bank account specialization

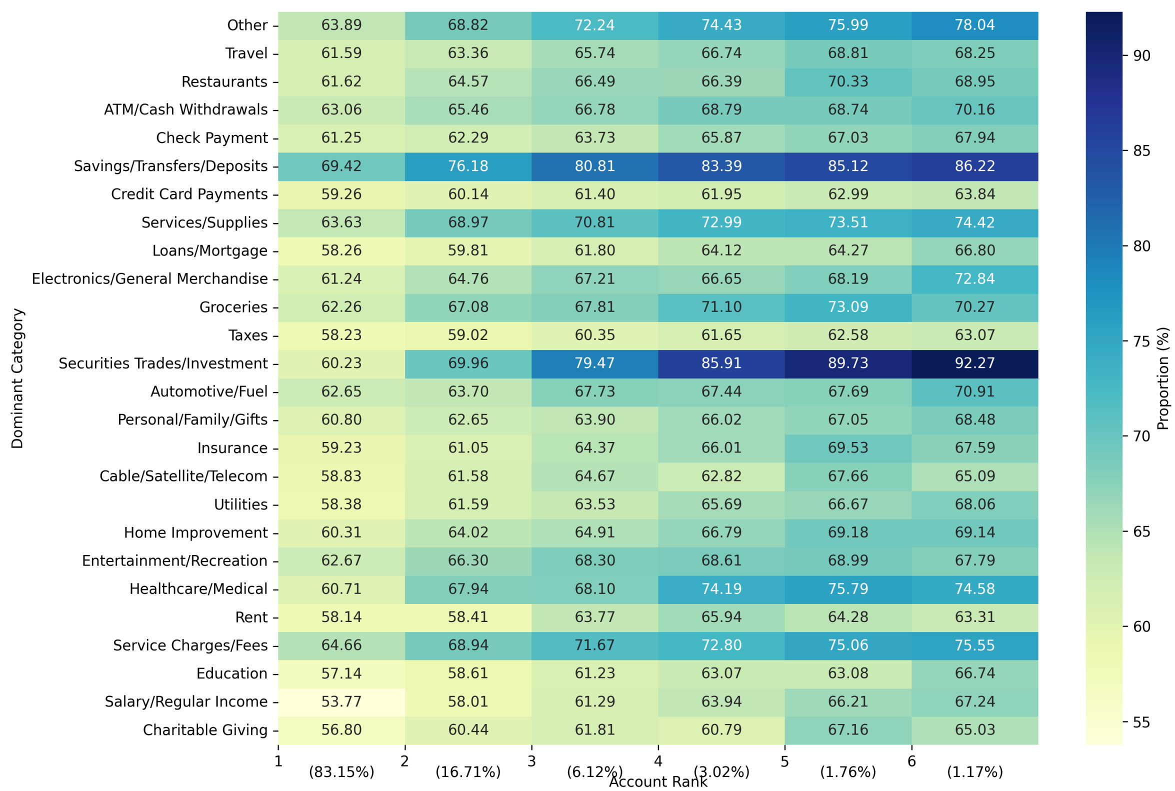
Most bank accounts predominantly serve a specific purpose, with 57% of all accounts being utilized mainly for one distinct function. This trend suggests that the high deposit turnover might stem from the specialized use of accounts for unique purposes.

Figure A-4 illustrates the transaction distribution patterns among depositors who maintain at least two bank accounts. Each account's primary usage is identified by its dominant category, defined as the category that accounts for more than 50% of the total transaction volume in dollars. Impressively, over 90% of the depositors in the dataset have at least one account with such a dominant category. On the horizontal axis of the heatmap, accounts are ranked based on their significance determined by dollar usage, where a rank of "1" signifies the most frequently used account in monetary terms, and higher numbers indicate progressively less used accounts, assuming a depositor has up to six accounts.

The intensity of the color within each cell of the heatmap represents the degree of dominance of a particular transaction category within an account. Darker shades indicate a stronger alignment to that category, meaning that a dark cell in a specific column suggests that many users primarily utilize that account for transactions within that domain. Accompanying these visual cues are percentage annotations adjacent to the account ranks, which display the proportion of the total transaction volume attributed to each account relative to the user's entire transaction history. These percentages provide additional insight into the relative importance of each account in a user's financial activities.

Interestingly, the specialization of an account for a single purpose does not appear to correlate with the account's popularity or rank. The dominance of a transaction type within an account is independent of its rank, indicating that an account's primary function is not related to how frequently it is used by the depositor. This observation suggests that users prioritize the functional specialization of their accounts over the prominence or visibility of the account within their portfolio. Such behavior likely contributes to more efficient financial management, allowing users to allocate their resources according to specific needs and preferences rather than relying on the most frequently used or visible accounts.

Figure A-4: Dominant Transaction Categories for Multi-Account Depositors

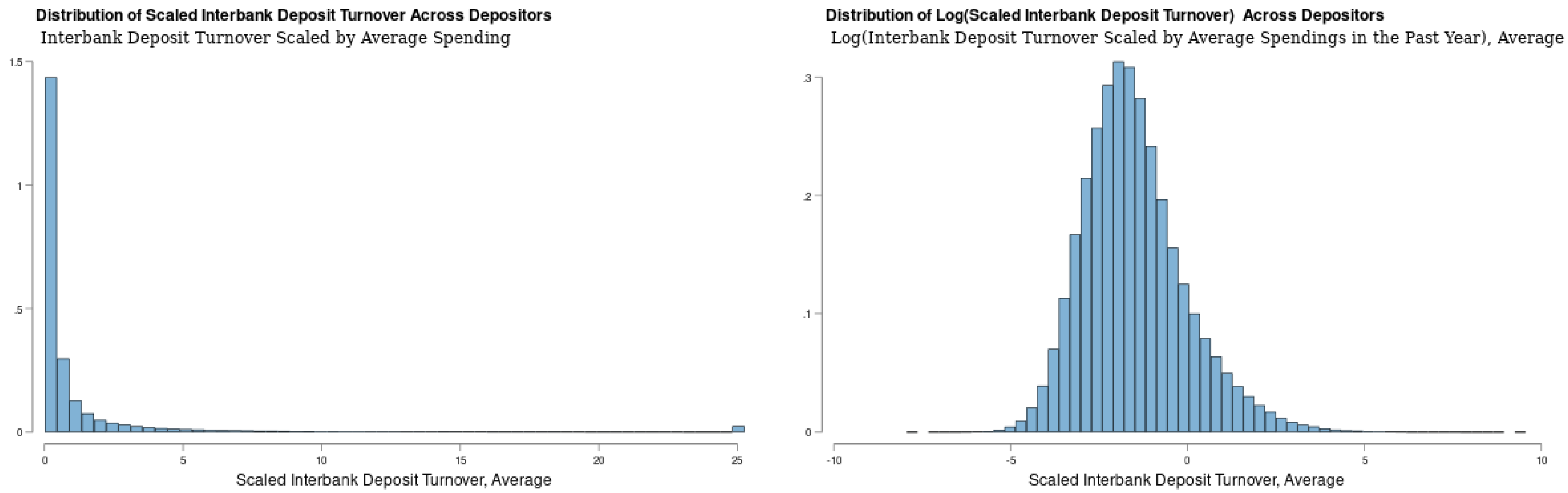


This figure summarizes the transaction category distribution among depositors with at least two bank accounts. Each account is categorized by its dominant transaction type, which constitutes over 50% of its total dollar volume. Notably, more than 90% of depositors have at least one such specialized account. The heatmap ranks accounts from left to right based on their dollar usage, with rank "1" being the most utilized. Color intensity indicates the strength of dominance for each transaction category within an account, where darker shades signify higher specialization. Additionally, percentage annotations next to each rank illustrate the account's contribution to the user's overall transaction volume, highlighting the relative importance of each account in their financial activities.

B.4. Distributions of deposit turnover and scaled deposit turnover

Figure A-5 plot the distribution of average monthly deposit turnover, scaled by average monthly spending in the preceding year following Attanasio and Pistaferri (2016), to compare how "active" depositors are in the cross section. Plot (a) in Figure A-5 reveals that for most depositors, the average interbank deposit turnover ranges from 0% to 50% of their average spending. Plot (b) in Figure A-5 presents the logarithm of the deposit turnover measure. It is important to note that a well-defined logarithm of the deposit turnover measure exists only for months in which a depositor has a non-zero interbank deposit transfer. This can be interpreted as the intensive deposit turnover, in the sense that, conditional on the months when a depositor initiates deposit turnover, the total scaled value is predominantly negative, suggesting that interbank deposit turnover is by and large smaller than monthly spending.

Figure A-5: Distribution of Scaled Interbank Deposit Turnover



These two histograms present the distributions of interbank deposit turnover for depositors in our sample from 2014 to 2022. Plot on the left shows the density of average monthly interbank deposit turnover, scaled by average spending in the past year at any given time point across depositors. Plot on the right shows the density of the logarithm of the scaled interbank deposit turnover; the logarithm is only defined for the months when depositors have positive interbank deposit transfers.

B.5. Uninsured depositors and depositors without credit cards

To further explore the drivers of deposit activity and its relationship with payment speed, we repeat our baseline empirical analysis in Section 3.1 on two specific depositor subgroups: large-sized uninsured depositors and depositors without credit cards.

Uninsured depositors. As well understood in the literature, uninsured depositors pose a higher run risk (e.g., Diamond and Dybvig 1983, Dávila and Goldstein 2023, Chen, Goldstein, Huang, and Vashishtha 2024), which was particularly pronounced during the 2023 regional bank crisis (e.g., Chang, Cheng, and Hong 2023, Drechsler, Savov, Schnabl, and Wang 2023, Jiang, Matvos, Piskorski, and Seru 2023). We restrict our sample to depositors with balances higher than $250,000 during the sample period to focus on the effect of payment speed on uninsured depositors.

Table A-3 summarizes the results. As transfer delays are reduced by one business day, uninsured depositors exhibit similar reductions in deposit balances and increases in deposit turnover compared to insured deposits. Thus, within our sample period, we do not find evidence that run risk plays a particularly significant role for uninsured depositors in balancing consumption uncertainty and savings. However, this result should be interpreted with caution, as it is specific to our sample period. This finding aligns with the message in Drechsler, Savov, Schnabl, and Wang (2023), which suggests that uninsured deposits exhibit a higher propensity to run when interest rates rise sufficiently.

Depositors without access to credit. We also analyze depositors without access to credit lines through credit cards. The results, presented in Table A-4, show that these depositors exhibit higher deposit activity. While the effects of payment speed remain significant, they are of smaller magnitude: these depositors hold only 2.7% less in deposits when transfer delays are reduced by one day. These findings align with the idea that hand-to-mouth depositors face greater consumption and liquidity uncertainties, leading to a relatively higher transactional demand for deposits, increased deposit activity, and a smaller decline in deposit balances when payments become faster.

Table A-3: Transfer delays and depositor behavior: Uninsured depositors

	(a) In dollars				(b) Scaled by the moving average of spending			
	(i) Deposit Turnover		(ii) Deposit Balance		(iii) Deposit Turnover		(iv) Deposit Balance	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Transfer Delay	-53.51***	-51.02***	1887.1***	2325.1***	-0.143***	-0.132***	0.0372***	0.0367***
	(1.068)	(1.065)	(477.1)	(468.1)	(0.0115)	(0.0107)	(0.00318)	(0.00317)
Depositor Controls	N	Y	N	Y	N	Y	N	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
N	2276841	2275366	2276841	2275366	422409	422336	2219764	2218417
Adj. R^2	0.00793	0.0163	0.0684	0.0861	0.0294	0.0681	0.0830	0.0864

This table examines how transfer delays affect depositor activeness and deposit balances using the following empirical model for the uninsured depositor subsample:

$$Y_{i,t+1} = \beta_0 + \beta_1 \times \textit{Transfer Delay}_{i,t} + \Gamma \times \mathbf{X}_{i,t} + \delta_t + \epsilon_{i,t+1},$$

where the dependent variables are $\textit{Deposit Turnover}_{i,t+1}$—the total interbank transfers during month $t+1$ for depositor i—and $Bal_{i,t+1}$, the deposit balance at the end of month $t+1$. $\textit{Transfer Delay}_{i,t}$, is the dollar-weighted average duration in days it takes for depositor i to complete a transfer, calculated as a 12-month rolling average. The vector $\mathbf{X}_{i,t}$ includes depositor-specific covariates such as rolling consumption uncertainty, interest rate dispersion (capturing potential interest income), salary, and digital payment ratio (the ratio of non-physical to total consumption, reflecting a depositor's inclination towards newer, faster technologies).

Panel (a) reports how transfer delays impact deposit turnover and balances in dollar amounts. Panel (b) scales each depositor's measures by their average spending over the past year and applies a logarithmic transformation to the dependent variable, allowing coefficients to be interpreted as semi-elasticities. Standard errors are two way clustered at date and depositor levels. and are reported in parentheses. *, **, and *** indicate statistical significance level at 10%, 5%, and 1%.

Table A-4: Transfer delays and depositor behavior: depositors without access to credits

	(a) In dollars				(b) Scaled by the moving average of spending			
	(i) Deposit Turnover		(ii) Deposit Balance		(iii) Deposit Turnover		(iv) Deposit Balance	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Transfer Delay	-42.61***	-41.08***	39.59	419.5***	-0.0496***	-0.0499***	0.0257***	0.0270***
	(1.557)	(1.436)	(154.4)	(147.6)	(0.00898)	(0.00892)	(0.00285)	(0.00268)
Depositor Controls	N	Y	N	Y	N	Y	N	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
N	1961964	1957821	1961964	1957821	403856	403097	1932089	1925345
Adj. R^2	0.0111	0.0179	0.00389	0.0652	0.0213	0.0669	0.00630	0.0539

This table examines how transfer delays affect depositor activeness and deposit balances using the following empirical model for the subset of depositors without spending from credit cards:

$$Y_{i,t+1} = \beta_0 + \beta_1 \times \textit{Transfer Delay}_{i,t} + \Gamma \times \mathbf{X}_{i,t} + \delta_t + \epsilon_{i,t+1},$$

where the dependent variables are $\textit{Deposit Turnover}_{i,t+1}$—the total interbank transfers during month $t+1$ for depositor i—and $Bal_{i,t+1}$, the deposit balance at the end of month $t+1$. $\textit{Transfer Delay}_{i,t}$, is the dollar-weighted average duration in days it takes for depositor i to complete a transfer, calculated as a 12-month rolling average. The vector $\mathbf{X}_{i,t}$ includes depositor-specific covariates such as rolling consumption uncertainty, interest rate dispersion (capturing potential interest income), salary, and digital payment ratio (the ratio of non-physical to total consumption, reflecting a depositor's inclination towards newer, faster technologies).

Panel (a) reports how transfer delays impact deposit turnover and balances in dollar amounts. Panel (b) scales each depositor's measures by their average spending over the past year and applies a logarithmic transformation to the dependent variable, allowing coefficients to be interpreted as semi-elasticities. Standard errors are two way clustered at date and depositor levels. and are reported in parentheses. *, **, and *** indicate statistical significance level at 10%, 5%, and 1%.

B.6. Balance and turnover after transfer technology adoption

Figure A-6: Histograms of depositors by average balances, with/without fast payment technologies

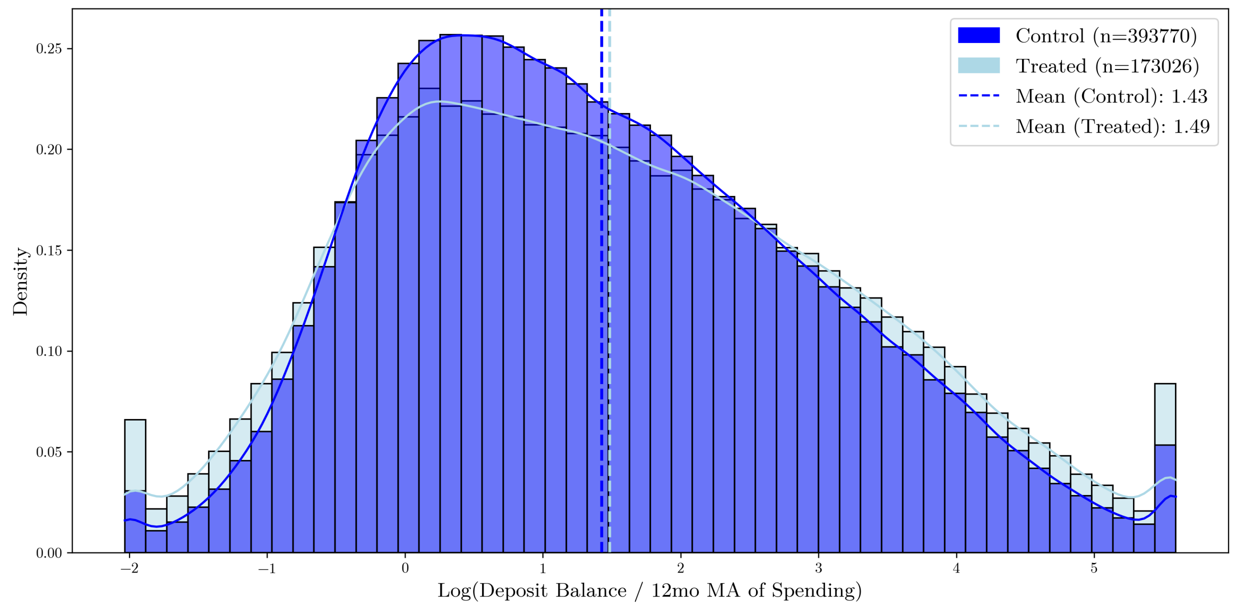


Table A-5: Balance and turnover after transfer technology adoption

	(a) Deposit Balance						(b) Deposit Turnover					
	(i) All			(ii) Post-2019			(iii) All			(iv) Post-2019		
	OLS	2SLS	3SLS	OLS	2SLS	3SLS	OLS	2SLS	3SLS	OLS	2SLS	3SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Transfer Delay	1467.5***	322.0***	1403.0***	2297.0***	2297.4***	2242.9***	-29.04***	-26.71***	-29.19***	-31.32***	-31.31***	-31.29***
	(100.3)	(75.38)	(91.63)	(477.9)	(504.0)	(503.8)	(0.449)	(0.354)	(0.410)	(2.215)	(2.492)	(2.492)
Depositor Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	3175844	4310554	3175753	3046606	3956125	3046516						

This table summarizes the impact of transfer delays on deposit balances and deposit turnover in dollar amount. Columns 1 to 6 report results where the dependent variable is the depositor's scaled balance, while columns 7 to 12 present results for scaled deposit turnover. For Deposit Balance, column 1 presents OLS estimates of the effect of transfer delays on deposit balances. Column 2 reports the last stage from 2SLS, and Column 3 shows the last stage of the 3SLS. Columns 4 to 6 reproduces the results using the subsample of treated depositors between 2019 to 2022. For Deposit Turnover, column 7 presents OLS estimates of the effect of transfer delays on deposit balances. Column 8 reports the last stage from 2SLS, and Column 9 shows the last stage of the 3SLS. Columns 10 to 12 reproduces the results using the subsample of treated depositors between 2019 to 2022.

The OLS and 2SLS estimates are straightforward. For the 3SLS, in the first stage, we estimate whether receiving funds via fast payment platforms ($I(\text{Post First Inflow})_{i,t}$) influences a depositor's likelihood of initiating outgoing transfers using the same platforms ($I(\text{Post First Outflow})_{i,t}$). We then use the predicted values of $I(\text{Post First Outflow})_{i,t}$ to understand how it affects *Transfer Delay*, and subsequently how *Transfer Delay* affects the dependent variable.

We estimate the following equations:

$$I(\text{Post First Outflow})_{i,t} = \zeta_0 + \zeta_1 I(\text{Post First Inflow})_{i,t} + \zeta_2 \mathbf{X}_{i,t} + \delta_t + v_{i,t},$$

$$\text{Transfer Delay}_{i,t} = \gamma_0 + \gamma_1 I(\text{Post } \widehat{\text{First Outflow}})_{i,t} + \gamma_2 \mathbf{X}_{i,t} + \delta_t + \varepsilon_{i,t},$$

$$Y_{i,t+1} = \beta_0 + \beta_1 \widehat{\text{Transfer Delay}}_{i,t} + \beta_2 \mathbf{X}_{i,t} + \delta_t + \epsilon_{i,t+1}.$$

In these equations, $Y_{i,t}$ is the dependent variable (deposit balances or deposit turnover), $I(\text{Post First Inflow})_{i,t}$ is a dummy variable equal to one if depositor i has received funds via fast payment platforms by time t, and zero otherwise. $I(\text{Post First Outflow})_{i,t}$ is a dummy variable equal to one if depositor i has initiated an outgoing transfer via fast payment platforms by time t, and zero otherwise.

For each depositor, we identify their first incoming fund transaction facilitated by Zelle, PayPal, Venmo, or Cash App, and record the month of that transaction as τ_i. The indicator $I(\text{Post First Inflow})_{i,t}$ equals one for month t if $t \geq \tau_i$ and depositor i has not initiated any outflow via fast payment applications prior to month τ_i. $\text{Transfer Delay}_{i,t}$ is measured as the dollar-weighted transfer delays for depositor i using a 12-month moving average for each month t.

We include time-fixed effects (δ_t) and depositor-level controls ($\mathbf{X}_{i,t}$) in all stages to focus on the cross-sectional heterogeneity of depositors. The controls include salary, consumption uncertainty, interest rate dispersion, digital payment ratio, and the amount first received via fast payment platforms.

All standard errors are clustered by date and are reported in parentheses. *, **, and *** indicate statistical significance level at 10%, 5%, and 1%.