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

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Abstract

What drives deposit demand? Are deposits sticky or active? Analyzing over 50 billion transactions from more than 1,400 U.S. banks, we find that, contrary to conventional wisdom, depositors *actively* manage their bank accounts, and surprisingly, more convenient payments make deposits less sticky. Specifically, depositors with shorter bank-to-bank transfer delays move more funds between bank accounts and maintain smaller balances. We extend the Baumol-Tobin framework by incorporating transfer delays to align with the new empirical findings and explore policy counterfactuals. Ceteris paribus, if all deposit transfers are expected to be processed the next business day, the demand for low-interest, precautionary, and transactional deposits would decrease by approximately 30%, while related deposit transfer flows would increase by 40% as depositors become more active. Our findings indicate that payment convenience significantly influences the sticky demand for deposits, which has important implications for deposit franchise value and monetary transmission.

Keywords: banking, deposits, payment, activeness, money demand.
JEL Codes: G21, E41, E42.

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1 Introduction

Deposits are a key component of monetary aggregates and serve as a primary, cost-effective, and stable funding source for banks. What drives the substantial demand for deposits? What services do banks provide that render aggregate deposit demand sticky? Understanding the origins of deposit demand is crucial for bank funding stability and monetary transmission (Hanson, Shleifer, Stein, and Vishny 2015, Drechsler, Savov, and Schnabl 2017), but it remains challenging partially due to the lack of granular data on individual behavior. This paper characterizes depositor-level money demand and demonstrates that payment convenience is essential to the demand for deposits. Contrary to conventional wisdom, we find that depositors *actively* manage their bank accounts despite stable aggregate deposit demand, shedding new light on the roles of money and deposits in the economy.

Our paper rests on the fact that payments and transfers in the U.S. banking system often incur fees and delays. Leveraging novel, transaction-level data, we empirically show that frictions and uncertainties in transfer timing prompt depositors to actively maintain large, rate-insensitive account balances to facilitate payments and provide liquidity buffers. When payment convenience is enhanced – specifically, when delays in bank-to-bank deposit transfers decrease – depositors hold smaller balances and move more funds between accounts. We develop a novel deposit account management model that incorporates delays in transfers to reproduce these empirical findings and explore counterfactual scenarios where all deposit transfers are mandated to be processed the next business day in expectation. Our analysis reveals that mandating next-day processing for all transfers significantly increases the volume of deposit transfer flows and reduces the level of account balances. These findings highlight how payment convenience impacts the sticky demand for deposits, which has important implications for monetary policy and the banking system, especially at a time when innovations and regulations are reshaping payment convenience in deposits and other means of payment.

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. Given the prevalence and significance of interbank transfers at the depositor level, we systematically track these 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.

Our transaction-by-transaction approach also allows us to 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 reveals that transfer delays have a significant effect on both deposit turnover and deposit balances: depositors with higher transfer delays are less active in interbank transfers and maintain larger balances. In the cross section, depositors with substantial balances, particularly uninsured depositors, have significantly higher deposit turnover and keep fewer funds in banks with a decrease in transfer delays. If a depositor never transferred funds across their bank accounts during the sample period, we cannot compute their transfer delays directly from transactions. For these depositors, we use state-city level average transfer delays as a proxy and find that these depositors maintain higher balances when the average transfer delays in their areas increase.

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 FedNow, which changes transfer speed to instantaneous for all bank accounts without depositors choosing the speed of transfers endogenously.

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.

In addition to examining the demand for bank deposits at the depositor level, we demonstrate that depositors actively manage their portfolio of deposits across different bank accounts. All else equal, depositors allocate more funds to deposit accounts offering higher interest rates. On average, for each depositor, a one-standard-deviation increase in the deposit rate offered by an account is associated with a 5% increase in that account's balance. However, this effect diminishes when transfer delays are longer, indicating that the incentive to seek higher interest rates is stronger with faster payments. These findings suggest that banks implementing faster transfer services may not necessarily gain more from attracting new

depositors than they lose from the reduced franchise value of their existing deposits.

Our findings on transfer delays and their impact on banks' deposit balances and deposit turnover motivate us to develop a model that reconciles these observations and further explores the counterfactual of implementing faster payments uniformly across banks. Specifically, we extend the Baumol-Tobin framework of optimal deposit account management by incorporating transfer delays. 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 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: depositors maintain smaller deposit balances and transfer more funds when transfer delays are reduced, and the impact of payment technologies depends on the levels of consumption uncertainty and interest rate dispersion.

We calibrate this model using detrended data moments from a representative sample of depositors. Specifically, we examine changes in depositor behavior related to facing consumption uncertainty in a zero-consumption-growth environment, thereby capturing only the precautionary component of deposits rather than total deposits. Empirically, we find that both consumption uncertainty and interest rate dispersion significantly influence depositors' sensitivity to transfer delays.

We examine three counterfactual scenarios: (a) reducing expected transfer delays to one business day while maintaining a 2% annualized interest rate; (b) reducing expected transfer delays to one day with a 1% interest rate; and (c) reducing expected transfer delays to one day while increasing consumption uncertainty by 26%, matching the post-pandemic rise in consumer debt levels. Under benchmark scenario (a), if in expectation, all bank deposit transfers are completed 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 savings. 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%×23%= 6.9%. The effects of faster payments are less pronounced when interest rates are lower or consumption uncertainty is higher, as external investment opportunities diminish and liquidity needs increase. Additionally, we sort depositors into quintiles based on average balances. We find that reducing transfer delays impacts high-balance depositors the most. Uninsured depositors decrease their funds held at banks the most and transfer significantly higher amounts between bank accounts.

Finally, the interaction between transfer delays and interest rates shows that payment frictions affect the deposit demand curve. We present a novel empirical estimate of the aggregate deposit demand curve that accounts for depositor heterogeneity and its nonlinear relationship with interest rates. Because depositors who face or choose higher average deposit rates are likely to have different rate sensitivities than those with lower rates, it is crucial to allow the slope of the demand curve to vary with interest rate spreads. We categorize depositors into percentile groups based on their average rate spreads to capture a detailed spectrum of depositor behavior conditional on the rate spread distribution. The aggregate demand curve estimated through this bottom-up method is smooth and robust. Building on these estimates, we demonstrate that aggregate deposit demand increases with longer transfer delays. This suggests that policymakers should consider changes in payment convenience when evaluating the transmission of monetary policy and welfare implications of inflation. Assessing these effects is left for future research.

Literature and Contribution. Our paper contributes to the extensive literature on the functions of banks and deposits (e.g., Moulton 1918, Tobin 1963, Fama 1980, Diamond and Dybvig 1983, Gorton and Pennacchi 1990). It is well established that depositors value deposits not only as a store of value but also for the various services banks provide, which enable banks to benefit from a sizable and stable markup in rate setting (e.g., Hanson, Shleifer, Stein, and Vishny 2015, Drechsler, Savov, and Schnabl 2021, Begenau and Stafford 2022, Egan, Lewellen, and Sunderam 2022, d'Avernas et al. 2023, Li, Loutskina, and Strahan 2023,

Egan, Sunderam, Hortacsu, and Kaplan 2024, DeMarzo, Krishnamurthy, and Nagel 2024, Kundu, Muir, and Zhang 2024). Our paper offers a micro-founded perspective on banks' market power in the deposit market: depositors hold substantial precautionary savings in their bank accounts to meet payment and liquidity needs when payments and transfers are slow. When payments are faster across all banks, depositors maintain smaller balances and move deposits more actively, reducing the value of deposit franchise.

Focusing on deposits and bank funding, our paper contributes to the literature on financial stability (e.g., Diamond and Dybvig 1983, Diamond and Rajan 2001, Goldstein and Pauzner 2005, Egan, Hortaçsu, and Matvos 2017, Greenwood, Stein, Hanson, and Sunderam 2017, Brunnermeier and Niepelt 2019, Hanson, Ivashina, Nicolae, Stein, Sunderam, and Tarullo 2024), particularly in light of recent changes in depositor bases (Acharya, Chauhan, Rajan, and Steffen 2023, Acharya and Rajan 2023, Blickle, Li, Lu, and Ma 2024). Additionally, an emerging literature finds that deposits at digital banks are more volatile and serve as a more convenient medium of exchange (e.g., Erel, Liebersohn, Yannelis, and Earnest 2023, Jiang, Yu, and Zhang 2023, Koont 2023, Koont, Santos, and Zingales 2023). We provide depositor-level evidence showing that enhanced payment convenience in deposits and fast payment technologies encourages depositors to move funds more actively across their accounts. The activeness of depositors has important implications for bank stability. Goldstein, Yang, and Zeng (2023) theoretically demonstrates that greater payment convenience may lead to an increase in payment volume, highlighting the impact on bank liquidity management and the risk of disintermediation (e.g., Freixas, Parigi, and Rochet 2000, Duffie 2019, Li and Li 2021, Afonso, Duffie, Rigon, and Shin 2022, Whited, Wu, and Xiao 2022, Liu, Makarov, and Schoar 2024). Additionally, illustrating the disruption of payment functions in deposits by FinTech, our paper complements existing studies on how neglected risks from innovations affect banking stability (Gennaioli, Shleifer, and Vishny 2012, 2013).

Our paper also sheds new light on the implications of payment technologies on banking and the real economy. Previous research documents how payment innovations affect financial

inclusion (e.g., Bachas, Gertler, Higgins, and Seira 2018, Higgins 2022, Dubey and Purnanandam 2023), borrowing and lending (e.g., Fuster, Plosser, Schnabl, and Vickery 2019, Berg, Burg, Gombović, and Puri 2020, Ghosh, Vallee, and Zeng 2023), payment media choices (e.g., Massoud, Saunders, and Scholnick 2006, Scholnick et al. 2008), bank competition (e.g., Sarkisyan 2023, Wang 2023), and risk-sharing for relatively low-income households (e.g., Jack and Suri 2014, Balyuk and Williams 2021). We show that faster payments enable depositors to hold fewer transactional and precautionary savings (e.g., Bewley 1983, Parker and Preston 2005, Carroll and Kimball 2006), which erodes the value of deposit franchise.

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, Akerlof 1979, Akerlof and Milbourne 1980, Alvarez and Lippi 2009, Kaplan and Violante 2014, Di Tella, Hébert, and Kurlat 2024). In particular, our measures of depositor activeness and payment frictions – deposit turnover and transfer delays – closely parallel the concepts introduced in Akerlof (1979) and Akerlof and Milbourne (1980). These foundational works emphasize that monitoring and managing account balances, along with the volume of payment flows, are essential for understanding money demand. Building on these perspectives, we present a novel extension to this longstanding theoretical framework, supported by granular empirical evidence.

Our paper adds to the expansive 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.

Finally, the aggregate money demand curve is known to bear significant welfare implications (e.g., Friedman 1956, Sargent and Wallace 1976, Lucas 2000). However, research findings on whether money demand is stable and its functional form remain inconclusive (e.g., Woodford and Walsh 2005, Benati 2023). We introduce a novel model-free approach that accounts for varying demand elasticities among depositors to provide a microfounded estimate of the aggregate demand for bank deposits, a key component of monetary aggregates. Our estimates of individual-level deposit demand seamlessly form an aggregate demand curve, with the relationship between deposit demand and interest rates significantly influenced by payment convenience. These findings highlight the importance of incorporating depositor heterogeneity in uncovering the aggregate deposit demand curve.

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 develops a two-account deposit management model with transfer delays. Section 4 empirically tests how payment frictions affect depositor activeness and deposit balances. Section 5 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, termed *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.

Following Buda, Hansen, Carvalho, Ortiz, Rodrigo, and Rodriguez Mora (2022), we focus on the active users who had ten spending, income, or transfer-related transactions each quarter across 36 quarters out of 40 quarters in sample. Even though the dataset does not contain supplementary demographic information, it provides a monthly estimate of users' current city of residence. The data processor specializes in serving the banking and fintech industries, ensuring minimal user selection bias and attrition. We report summary statistics of depositors in sample by the end of the section; the total deposit balance changes inferred from the data match the aggregate trends in Flow of Funds (Figure 9).

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 her bank accounts 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).[1]

Before introducing the construction of deposit turnover, we first present two new stylized facts that motivate the analysis on interbank transfers.

[1]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.

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 1, 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 out all transaction records across their associated bank accounts $a \in \mathcal{A}_i$. The challenge is that the dataset does not include transaction identifiers across different financial institutions, nor does it provide the identities of the banks involved, so we cannot directly identify interbank transfer transactions between a and $a' \in \mathcal{A}_i$, $a' \neq a$.

We develop an algorithm to detect interbank deposit activities by examining transaction records across multiple accounts held by depositor i. On each day t, we first check all outflow (debit) transactions D_{iat} of all depositor i's accounts $a \in \mathcal{A}_i$, including account transfers, ATM or cash withdrawals, and deposits, which constitute approximately 20% of all transactions. For each debit transaction occurring on date t, the algorithm searches for corresponding credit transactions $C_{ia't'}$ in the depositor's other accounts $a' \in \mathcal{A}_i, a' \neq a$ within a five-day window, specifically for dates t' such that $t \leq t' \leq t + 5$.

If a credit transaction is identified on the same day ($t' - t = 0$), it is considered a potential same-day transfer. We then evaluate the discrepancy in transaction amounts between the debit and credit entries. If the absolute difference satisfies $0 \leq |D_{iat} - C_{ia't'}| \leq 50$, the

transactions are likely wire transfers, intrabank movements (i.e., funds transferred between accounts of the same bank), or payments facilitated by rapid payment platforms such as Zelle or Venmo. The upper threshold of 50 is based on the maximum observed wire transfer fees.[2] If these criteria are met, the transaction pair is recorded as a bank transfer; in the case of multiple matching credit transactions, the first transaction in chronological order is selected.

If no same-day match is found, the algorithm extends the search to include up to five subsequent business days following the debit transaction ($t < t' \leq t + 5$). Transactions identified within this extended window are typically Automated Clearing House (ACH) transfers, which are predominantly fee-free, although some institutions may impose nominal flat fees up to \$10.[3] If debit transaction D_{iAt} and the corresponding credit transaction C_{iAt} meet all conditions, we record the value of D_{iAt} as an interbank transfer.

Exact same-day matches with no differences in values between credit and debit transactions, which are likely transfers between accounts in the same bank, are excluded from the turnover calculation since they are not leaving the bank (so they don't change liquidity management or total deposit size for the bank). Therefore, interbank deposit turnover for depositor i is computed as the aggregate of all deposit outflows across all their accounts within a specified 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:

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

where $\mathcal{A}_i$ represents the set of all accounts held by depositor i, and $\mathcal{T}$ denotes the transaction dates within the month.

[2] 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 II.1.

[3] 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.

During the sample period, ACH transfers account for the majority of 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 2.

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 II.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.[4]

Based on our notion of transfer delay, Figure 3 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.

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

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). 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, i.e., *Rate Dispersion*$_{it} = max_a i_{i,a,t} - min_a i_{i,a,t}$.

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.[5]

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, highlighting substantial variability in deposit turnover, with an average deposit turnover of \$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

[5]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.

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.

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.

3 A Model of Deposit Demand with Transfer Delays

The new facts highlight the importance of transfer delays in deposit demand, which standard economic order quantity models omit. In this section, we follow Alvarez and Lippi (2009) and Kaplan and Violante (2014) to extend a two-account inventory model of money management in the spirit of Baumol (1952), Tobin (1956) and Miller and Orr (1966) to examine how depositors allocate their funds between two bank accounts in the presence of

uncertain transfer delays. Our model generates testable predictions that inform our empirical analysis in Section 4. We calibrate the model in Section 5 and provide counterfactual analyses to evaluate the effects of uniformly faster deposit transfers across banks.

Time is modeled as continuous. A representative depositor with discount rate β is endowed with two bank accounts, account C and account S, which may be 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 $r > 0$. Suppose the total repayment amount is exogenous yet uncertain: let $g > 0$ denote the constant flow of consumption from bank account C. Specifically, 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 dispersion 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. 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 costs associated with payday borrowing, overdrafting, or any mental cost of lack of liquidity; in fact, the 10th percentile in the data for monthly balance is \$1,142. Why depositors leave significantly positive balance in bank accounts is an interesting question for future research; in our paper, we adjust the cost b sufficiently high so that the depositor will not have negative balance. 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.

Under this setup, the depositor chooses a sequence of voluntary deposit transfers x_j made at t_j and processed at $t_i^{'}$ 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

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

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: $0 < \underline{m} \leq m^* < m^{**} \leq \overline{m}$. 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:

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

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 $m > \overline{m}$.

The optimal solution to this system encompasses the following conditions. First, non-negativity of bank account balance implies a boundary condition from below:

$$V(0) = V(m^*) + b\,,$$

implying that the depositor has to suffer from the penalty b in order to instantaneously transfer funds from bank account S to C and avoid a potential default.

The optimality of the target balance implies the following two optimality conditions:

$$V'(m^*) = r\,,$$

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

The adjustments at the two thresholds imply two "value matching" conditions:

$$\lim_{m\to\underline{m}_-} V(m) = \lim_{m\to\underline{m}_+} V(m)\,,$$
$$\lim_{m\to\overline{m}_-} V(m) = \lim_{m\to\overline{m}_+} V(m)\,,$$

two "smooth pasting" conditions:

$$\lim_{m\to\underline{m}_-} V'(m) = \lim_{m\to\underline{m}_+} V'(m)\,,$$
$$\lim_{m\to\overline{m}_-} V'(m) = \lim_{m\to\overline{m}_+} V'(m)\,,$$

implying that the value function and its first-order derivative are both continuous at the two thresholds, and further, two "super contact" conditions:

$$\lim_{m\to\underline{m}_-} V''(m) = \lim_{m\to\underline{m}_+} V''(m)\,,$$
$$\lim_{m\to\overline{m}_-} V''(m) = \lim_{m\to\overline{m}_+} V''(m)\,,$$

implying that the value function and its second-order derivative are both continuous at the thresholds. Finally, the value function should grow at a finite rate when m goes to infinity:

$$\lim_{m\to\infty} V'(m) < +\infty\,.$$

Our setup is significantly different from existing money demand models. Because of the uncertainties in transfer delays and consumption, the characteristic equations for the HJB conditions in the action regions have two real roots; in general, the optimal deposit policy cannot be solved in closed-form.[6] We analyze a limiting case where spending has no drift ($g = 0$) and the discount rate approaches zero ($\beta \to 0$). Although this special case is also considered in Constantinides and Richard (1978), the stochastic transfer arrival in our framework leads to value functions in the action regions that are transcendental equations with two exponential terms, rather than the degenerate homogeneous solution found in their work. We derive analytical properties of the optimal policy ($\underline{m}, m^*, m^{**}$, and $\bar{m}$) as functions of (r, κ, σ, b) with the following results, where Appendix I provides detailed

[6]Without the Brownian term, Alvarez and Lippi (2009) derived a closed-form solution by introducing a random transfer cost. In an earlier draft of this work, we excluded the uncertainty in consumption 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 type of variable transfer cost.

analytical properties of m^* and m^{**} and the proofs:

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 dispersion r is higher. Moreover, depositors with greater consumption volatility σ maintain higher balances and experience a larger decrease in balances as κ increases.*

Proposition 2 (Turnover)**.** *The expected transfers between accounts increase with more efficient transfer technology (κ), and the effect is amplified when interest rate dispersion 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 into how deposit turnover is influenced by payment technology, conditional on interest rate dispersion and the depositor's consumption uncertainty. Intuitively, 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 dispersion 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.

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.

The expected transfer is also influenced by both the interest rate dispersion r and the volatility σ of the account balance. As the interest rate dispersion r increases, the opportunity cost of funds tied up during the transfer process rises because any money involved in transfers does not earn interest while pending. This higher cost incentivizes the depositor to minimize the time and amount of funds in transit to reduce interest losses, leading to a decrease in turnover as r increases. An increase in r, at the same time, amplifies the effect of payment convenience on expected transfers because more efficient payments allow for larger reduction of delay-induced costs, encouraging the depositors to be more active. On the other hand, 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 dispersion 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 dispersion 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.

Mapping the two-account model to data. In this stylized model, the depositor maintains two accounts, C and S. Transfers between these accounts represent interbank deposit turnover, while the total balance m corresponds to the balance of account C. Empirically, although we cannot observe account types in the data directly, the aggregated data behaves similarly to

checkable deposits as documented in the Flow of Funds (Figure 9), suggesting the dominating type of accounts in our dataset is checking account. In this context, the empirically measured deposit balance aligns well with the model's total balance m. Deposit turnover corresponds to the sum of transfers across multiple liquid accounts, which is different from the transfers in our simplified two-account model. Simplifying the model to two accounts is without loss of generality when examining the effects of transfer delays driven by precautionary motives: even with more complex account specialization where different accounts are designated for different consumption bundles (Appendix II.3), the impact of payment delays on the velocity of deposits can be generalized through similar precautionary incentives.

4 Transfer Delays and Depositor Behavior

This section empirically investigates how transfer delays influence depositor activity and account balances. We begin by demonstrating that depositors with slower payment technologies tend to have lower deposit turnover and maintain larger account balances. In addition, uninsured depositors are particularly sensitive to payment speeds. When transfer speeds increase, these depositors experience significant decreases in their account balances and notable increases in deposit turnover. For the depositors who never initiated interbank transfers, using the average transfer delays at the state-city level as a proxy for their payment frictions, we find that these depositors also reduce their balances when their payment frictions decrease. We also provide account-level evidence on depositors optimizing interest income conditional on transfer delays. Finally, we introduce a quasi experiment of payment technology shocks to disentangle depositors' reactions to transfer delay changes from the sorting between depositors and bank accounts with different transfer delays.

4.1 Faster transfer is associated with more deposit turnover and smaller balances

Our proxy for depositor activeness is *Deposit Turnover*$_{i,t}$, defined as total interbank transfers during a month t for depositor i. We check 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:

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

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 in 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 results in two panels in Table 4. In panel (a), we report how transfer technology drives deposit turnover and balances in dollar amounts. 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%.

4.1.1 The semi-elasticities of deposit demand with respect to transfer delays.

In the panel regression with time fixed effects above, we leverage all information across depositors to accurately estimate the local average effect of transfer delays on depositor behavior. However, in reality, depositors facing different levels of transfer delays over time adjust their deposit balances and activeness. Our model suggests that the effects of transfer technologies are amplified when a depositor faces higher interest rate dispersion and/or consumption uncertainty. This motivates us to examine the empirical factors influencing the semi-elasticity of deposit turnover and balances with respect to transfer delays.

Taking deposit turnover as an example, 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: $\log(\textit{scaled deposit turnover}_{it}) = \beta_i \times \textit{transfer delays}_{it} + \epsilon_{it}$, 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: $\beta_i = \gamma_0 + \sum_k \gamma_k X_k + \epsilon_i$, where X_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.

Depositors with higher interest rate dispersion and consumption uncertainty are more responsive to changes in transfer delays. Panel (a) in Figure 4 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 balance with respect to transfer delays is positive, and panel (b) 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.

4.1.2 Uninsured depositors.

Uninsured depositors pose a higher run risk (e.g., Diamond and Dybvig 1983, Dávila and Goldstein 2023), 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). Their coordinated flows could potentially cause increases in the demand for reserves while eroding the deposit franchise. We restrict our sample to depositors with total balances higher than $250,000 during the sample period to focus on the effect of delays on uninsured depositors.

Table 5 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 when measured in consumption units. However, in dollar amounts, they reduce their balances by 36% less (reducing balances by $1,708 compared to $2,325 for other depositors) and transfer 10% more in deposit turnover.

Depositors without access to credit. In contrast, depositors without access to credit lines through credit cards become more active and hold lower balances. Although the effects are still significant, they are of smaller magnitude: these depositors hold only 2.7% less deposits when transfer delays are one day shorter. This may be because hand-to-mouth depositors are less attentive to transfer technology, or because increased payment efficiency boosts their consumption via relaxing a binding liquidity constraint, resulting in a relatively larger transactional demand for deposits and smaller decline in deposit balances. We report the results for these depositors in Table A-3.

4.1.3 Incorporating depositors without interbank transfers.

Approximately half of the depositors in our sample exhibit zero deposit turnover throughout the sample period. This could be due to incomplete bank coverage, as our dataset includes

only 1,400 out of over 5,000 depository institutions, or because, even with complete coverage, these depositors are less active and do not engage in fund transfers across their own bank accounts. However, these depositors still use bank transfers to pay or receive payments from other individuals or businesses, making transfer delays relevant to their deposit behavior.

To understand how payment frictions affect these depositors and to assess the external validity of our sample, we proxy their transfer delays using the following approach. First, we infer the residential addresses of all depositors by analyzing location-related and physical transaction records from their bank and credit card accounts, such as utility bills and coffee shop transactions. We detail the location inference algorithm in Appendix II.2. Next, we calculate the monthly average transfer delays at the state-city level using data from depositors who have positive deposit turnover during that month. For depositors with zero deposit turnover, we assign the corresponding state-city average transfer delay as a proxy for their transfer delays in that month.

This allows us to incorporate depositors without interbank deposit turnover into our analysis, providing a more complete picture of all depositors' behavior and confirming the relevance of transfer delays for this group. In Figure A-6, we present a comparison of the distributions of deposit balances for both groups of depositors—those with positive transfer activities across their own bank accounts and those with zero deposit turnover. The differences between the distributions of these two groups are insignificant, suggesting that our proxying method is appropriate.

Additionally, we run a series of covariate balance tests between depositors with and without interbank transfers. We regress the normalized depositor-level characteristics on a binary indicator variable that equals 1 for depositors who had positive deposit turnover during the sample period. Specifically, we estimate:

$$X_{i,t} = \beta I(\sum_{i} Deposit\ Turnover_{i,t} > 0) + \epsilon_{i,t},$$

where $X_{i,t}$ is a characteristic variable of depositor i in month t. The characteristics include deposit balance, salary, digital payment ratio, consumption uncertainty, and intrabank transfer

volume – that is, the amount of money transferred across accounts within the same bank.[7] We find no significant differences between the two groups of depositors along all these dimensions. This further supports the validity of including depositors without interbank transfers in our analysis of transfer delays.

In Table 6, we present the results of deposit balance changes in response to the average transfer delays for these depositors. Using the location-based transfer delay proxies, we find that these depositors also increase their balances when transfers become slower. Averaging transfer delays across depositors within a locale reduces idiosyncratic noise in the measurement, thereby mitigating attenuation bias due to measurement error. Consequently, we observe larger coefficient estimates in dollar values, with magnitudes in consumption units comparable to those in our benchmark model in Section 4.1.

However, it is important to consider other potential sources of bias. While averaging at the locale level reduces idiosyncratic noise, it may introduce biases if unobserved factors at the state-city level are correlated with both transfer delays and deposit balances. For example, regional economic conditions or local banking practices could affect both the speed of transfers and depositor behavior, leading to omitted variable bias.

Despite potential biases, our findings suggest that transfer delays have a consistent impact on depositor behavior across different subsamples and groups of depositors. The consistency of the results with those from the benchmark model supports the robustness of our findings on the correlation between transfer delays and depositor behavior.

4.2 Identifying the impact of fast payments on depositor behavior

To further establish a causal relationship between transfer delays and depositor behavior, we must address potential endogeneity concerns arising from depositor self-selection into accounts with shorter transfer delays. We exploit a natural experiment that leverages

[7] Recall that in the deposit turnover measure, we excluded matched debit and credit transfers occurring on the same day with exactly matching values, as these are most likely transfers between accounts within the same bank.

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 II.1), empirically, Figure 6 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 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 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 7 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 8 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-7.

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

$$\textit{Transfer Delay}_{i,t} = \gamma_0 + \gamma_1 I(\textit{Post } \widehat{\textit{First Inflow}})_{i,t} + X_{i,t} + \delta_t + \varepsilon_{i,t},$$

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

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 $I(\textit{Post } \widehat{\textit{First Inflow}})_{i,t}$ 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. $\textit{Transfer Delay}_{i,t}$ 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 $X_{i,t}$ 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:

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

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

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

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. $X_{i,t}$ 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 $I(\textit{Post } \widehat{\textit{First}} \textit{ Outflow})_{i,t}$ 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 7 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-4.

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 3, 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-4).

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 II.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.

4.3 Estimating the demand elasticity of deposits across bank accounts

Before introducing the counterfactuals on the uniformly faster deposit transfers, we first examine depositors' account-switching behavior across different banks. In the absence of a regulatory mandate for all banks, an individual bank can compete for new depositors by offering faster transfer services, as the infrastructure is already in place (Duffie 2020). Although the interest rates offered by these transactional accounts are relatively low (with a mean annualized rate of 15 basis points), the cross-sectional flows of deposits across banks provide valuable information into deposit elasticity among transactional accounts. This elasticity is crucial for understanding banks' cross-sectional funding costs and competitive dynamics. In this section, we empirically document the price and delay elasticities of deposit demand across various deposit accounts.

Specifically, we examine how interest rates and transfer delays influence the allocation of deposits across different bank accounts a for a given depositor i at time t:

$$\begin{aligned}\%\Delta Deposit_{i,a,t} = \beta_0 + \beta_1 \times Interest\ Rate_{i,a,t} + \beta_2 \times Transfer\ Delay_{i,a,t} \\ + \beta_3 \times (Interest\ Rate_{i,a,t} \times Transfer\ Delay_{i,a,t}) + \Gamma \times \mathbf{X}_{i,a,t} + \delta_{i,t} + \epsilon_{i,a,t},\end{aligned}$$

where $\%\Delta Deposit_{i,a,t}$ is the change in the balance of account a for depositor i over total deposits held by i across all deposit accounts at time t. $Interest\ Rate_{i,a,t}$ is the standardized average interest rate over the past 12 months of account a for depositor i in month t, and $Transfer\ Delay_{i,a,t}$ 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 $Interest\ Rate_{i,a,t} \times Transfer\ Delay_{i,a,t}$ 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,[8] 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 $\delta_{i,t}$ absorbs time-depositor level variations.

Results in Table 8 suggest that interest rates have significant impact on depositors' fund allocation across bank accounts. Columns (1)-(2) use the full sample, while columns (3)-(6) focus on active depositors with available account-level transfer delay estimates. Column (6) controls for all account-level observables and the interacted time-depositor fixed effects, and find that a one standard deviation increase in the deposit rate attracts an additional 5% more deposits in that account. Given the standard deviation offered in these accounts during the sample period is about 13.7bp, this suggest that the price elasticity of deposits across accounts is about 3.6.[9] This effect is significantly dampened when transfers are slow: with higher transfer delays, depositors are less likely to shop for interest rates, and with a one standard deviation higher transfer delay (roughly one business day), the sensitivity of deposits to interest rates is reduced to 3.7%.

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

[9]When interest rates are low, its level approximates a change in the discount factor, which is, conceptually, the price of money.

5 Payment Convenience and the Aggregate Deposit Demand

Our reduced-form analysis demonstrates that transfer delays, as a form of payment "inconvenience," significantly influence depositor behavior in the cross section. In this section, we first show how payment convenience affects aggregate deposit demand by estimating an aggregate demand curve through a novel empirical approach that accounts for depositor heterogeneity and non-linearity in demand elasticities. We then explore a counterfactual scenario in which payment convenience is enhanced across the banking sector. Specifically, we evaluate how mandating next-day processing for all bank deposit transfers affects depositor behavior.

5.1 The aggregate deposit demand curve and payment convenience

Before introducing the counterfactuals, we empirically estimate the aggregate deposit demand curve using individual deposit holdings to underscore the role of payment convenience in shaping deposit demand, a crucial component of monetary aggregates with significant implications for monetary transmission and bank funding.

To set the stage, Figure 9 confirms that the depositors in our sample are representative of the total deposit market. Taking advantage of the large and balanced panel of individual depositors' holdings, we estimate the empirical aggregate money demand curve in multiple steps to account for depositor heterogeneity and the non-linear relationship between deposit demand and interest rates. First, we compute each depositor's average deposit demand M_i, measured by their average balance scaled by the 12-month moving average of spending, and the average price of deposits they face, represented by the annualized spread s_i between the Effective Federal Funds Rate and the maximum interest rate offered at their banks. The average rate spreads reflect the opportunity cost of holding deposits and are known to vary significantly across depositors due to reasons such as local market power, services, search costs, or attention (e.g. Drechsler, Savov, and Schnabl 2017, d'Avernas et al. 2023, Egan, Sunderam, Hortacsu, and Kaplan 2024, Yankov 2024). We assume that depositors adjust their

demand for deposits in response to prevailing rate spreads, rather than rate spreads adapting to the demands of individual depositors. This assumption is grounded in the observation that retail depositors have predominantly idiosyncratic deposit demands and are too small to exert influence on banks' deposit rate setting.

Second, we obtain individual-specific estimates of how their demand responds to changes in the rate spread, captured by the coefficient α_i from a regression of demand on rate spread for each depositor. Since the demand-price relationship of money is known to be non-linear (Friedman 1956, Meltzer 1963, Lucas 2000, Benati 2023), and given the heterogeneity among depositors, we group depositors into 100 bins based on their average rate spreads (results are robust to using quantile-based bins and the number of bins).

Within each bin, we then compute the weighted average slope of the individual demand functions. The slope α_i for each depositor i is weighted by their average scaled money demand M_i to reflect their economic significance:

$$\alpha_b = \frac{\sum_{i \in b}(M_i \cdot \alpha_i)}{\sum_{i \in b} M_i}.$$

α_b represents the average sensitivity of deposit demand to spread changes for depositors in bin b.

It is important and useful to allow the slope of demand curve to vary with the average rate spreads depositors face. Intuitively, depositors with an average of 2% interest rate spread between Fed Funds Rate and his deposit rates are likely to be much less sensitive to rate spread than someone with 0% rate spread – otherwise he would have moved to a bank with higher rate. As we will show, in fact, the slopes of these rate-spread based bins are quite smooth in adjacent bins.

We calculate the average demand $M_b = \sum_{i \in b} M_i/|b|$ and average spread $s_b = \sum_{i \in b} s_i/|b|$ for each bin b, where $|b|$ is the number of depositors in the bin. Then, using the weighted average slope and the average demand and price in each bin, we estimate the intercept of the demand function for that bin: $c_b = M_b - \alpha_b \cdot s_b$, which yields a linear demand function for each bin.

Finally, we piece together these locally linear demand functions across all bins. Ordering the bins by increasing average price, we calculate the cumulative demand changes implied by the slopes and price differences between bins. Specifically, starting from the first bin, we incrementally compute the demand at each subsequent bin using:

$$M_b = M_{b-1} + \alpha_b(s_b - s_{b-1}),$$

where b indexes the bins in order of increasing spread and α_b is the slope for bin b.

Our estimation of deposit demand captures a comprehensive range of depositor behavior conditioned on the rate spread distribution, accommodating heterogeneity and non-linearity in the money demand relationship. This indicates that the previously observed instability in aggregate money demand may stem from not accounting for depositor heterogeneity. We plot the cumulative demand against the spread as the aggregate money demand curve in panel (a) of Figure 10, which fits best with a semi-log functional form (Figure A-8).

To demonstrate the role of payment convenience in the money demand curve, we build upon the previously estimated aggregate deposit curve by incorporating transfer delays alongside interest rates, following the same estimation procedure. First, we obtain individual-specific estimates of how deposit demand responds to interest rates (coefficient α_i') and transfer delays (β_i) using individual-level multivariate regressions. Next, we apply the quintile-based method described earlier to determine the aggregate money demand's sensitivity to transfer delays (β_b) for each depositor bin b. In Panel (b) of Figure 10, we plot aggregate deposit demand against transfer delays to illustrate that the aggregate deposit demand monotonically increases as transfer times become slower. These findings align with the predictions of our model and highlight the importance of payment convenience.

To summarize, the monotonic relationship between aggregate deposit demand and transfer delays, along with their interaction with interest rates, indicates that changes in transfer delays will both shift and rotate the deposit demand curve. In the next two sections, we quantify the impact of payment convenience on aggregate money demand through model calibration.

5.2 Mandating next-day processing for all transfers: changing rates and consumption uncertainty

We calibrate the benchmark model outlined in Section 3 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 economic growth. To focus on deposit balance and turnover dynamics without long-term growth trends, we detrend the data moments using a 12-month moving average during calibration. Researchers often use detrending to examine business cycle sources (Kydland and Prescott 1982); in our case, since we calibrate the model at a daily frequency, growth effects are likely small and negligible. After detrending, the average depositor has a daily consumption uncertainty of $E(\sigma)/28 = \$4,822/28 \approx \$172.21$, an average deposit balance of $E(m) = \$5,766$, a deposit turnover of $E\left(\sum|X|\right) = \$1,426$, and makes about 7.84 fund transfer transactions per month.

We first consider the behavior of this average depositor using the 2-business-day average transfer delay (i.e., $\kappa \approx 0.24$) and a 2% annualized interest rate dispersion. The cost of hitting a zero balance represents not only the expectation of overdraft fees but also the foregone emergency consumption. Since it is difficult to measure empirically, we keep it constant throughout the exercises.

Panel (a) in Figure 11 shows how the depositor's balance evolves over a month, with a 2% interest rate, a 2-business-day transfer delay, and daily consumption uncertainty of approximately \$172.21, based on 10,000 simulations. The results indicate that the average deposit balance is \$5,715, the average deposit turnover is \$1,613, and the average number of fund transfer transactions is 6.59. These findings indicate that the model aligns with

empirical estimates of deposits held for precautionary savings under the specified parameters.

Next, we examine the impact of faster transfer technology. Panel (b) in Figure 11 illustrates the scenario where the depositor is able to complete all fund transfers into account C with a 1-business-day transfer delay (i.e., $\kappa \approx 0.5$). Under this condition, the average precautionary and transactional deposit balance in account C drops by 30% to \$4,019, indicating an outflow of deposits from account C. Meanwhile, the volume of deposit turnover increases by 57% to \$2,527. The substantial increase in deposit turnover imply large and 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).

Comparison 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 4. 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 7.

Interaction with interest rates. The decrease in deposit balances is dampened if the introduction of faster payments coincides with lower interest rates or higher consumption uncertainty. Panel (c) in Figure 11 shows that the effect of shorter transfer delays is mildly dampened when the interest rate is lower. Intuitively, with a 1% lower rate, depositors hold slightly more money in bank account C because the outside opportunity is less attractive. Deposit turnover remains roughly the same, as the accrued interest loss during the transfer process is negligible.

Interaction with consumption volatility. Panel (d) in Figure 11 demonstrates that increased consumption uncertainty significantly dampens the impact of introducing faster payments

on total deposit balances. With the same transfer technology, depositors facing higher transactional demand (i.e., greater consumption uncertainty) hold more deposits in bank accounts. Although these depositors reduce their total deposits when payments become more efficient, they still maintain higher balances to fund their large, uncertain spending.

To illustrate this, we consider the scenario where aggregate consumer debt in 2024 has grown by 26% from the pre-pandemic level, implying higher consumption uncertainty. We simulate the introduction of faster payments with a 26% increase in consumption uncertainty compared to the benchmark in Figure (a). We find that higher consumption uncertainty significantly increases the deposits held in banks to $5,114, dampening the negative impact on balances from faster payments compared to Figure (b). At the same time, the effect of faster payments on deposit activity is amplified, as depositors with more transactional demand transfer even more when transaction friction is lower.

In summary, the mandate for all bank deposits to be cleared the next business day leads to significant decreases in deposit balances and increases in deposit turnover. These effects are influenced by prevailing interest rates, and high-balance depositors with substantial consumption uncertainty have the largest changes in both balances and turnover. These findings suggest that the impact of introducing fast payment technologies on bank funding costs depends on both the interest rate environment and the level of uncertainty in aggregate demand within the economy.

5.3 Mandating next-day processing for all transfers: the cross section of depositors

We divide depositors into quintiles based on their average deposit balance during the sample period; the first quintile comprises depositors with the lowest balances, while the fifth quintile includes those with the highest balances. Additionally, we report an "uninsured" subsample consisting of depositors who, at any time during the sample period, held balances exceeding $250,000 in any bank account. The data moments are detrended using 12-month moving averages, and the model moments are computed from 10,000 simulations.

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 in each subsample. The *transfer delay* is measured in business days; specifically, a delay of 2 (or 1) business days corresponds to 2.8 (or 1.4) calendar days, and we set $\kappa = 0.24$ (or $\kappa = 0.5$) accordingly. We use a 2% annualized interest rate dispersion, denoted as $r = 2\%/365$.

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 and report the average and volatility. The benchmark calibration (shown in columns (2), (5), and (8) of Table 9) closely matches the empirical mean and variance of deposit balances, as well as the average deposit turnover, for each subsample in the data (columns (1), (4), and (7) of Table 9). Columns (3), (6), and (9) present a scenario with a one business-day transfer delay, effectively representing a situation where depositors face minimal transfer delays (e.g., when all bank transfers are cleared the next business day). Under this scenario, total precautionary and transactional deposit balances decrease by about 30%, while the average monthly related deposit turnover per depositor increases by approximately 40%.

These results highlight two key effects of a faster deposit transfer mandate. First, increased payment efficiency per dollar of deposits reduces the need for depositors to maintain large balances in low-interest accounts to support the same level of spending. Second, reduced (temporal) transfer frictions lead to higher deposit turnover, resulting in gross deposit flows increasing relative to the total amount held in banks. Depositors with high balances, particularly uninsured depositors, experience the largest changes in balances and turnover in dollar terms. Besides directly eroding deposit franchise, the more volatile deposit flows potentially impact banks' demand for reserves (Lopez-Salido and Vissing-Jorgensen 2024).

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 rates in an account leading to an increase of deposits allocated to that account, 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 establish that the adoption of faster payment technologies causally 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, it could reduce aggregate deposits held for precautionary and transactional savings by approximately 30% and increase related deposit transfer flows by over 40%. These effects depend on factors such as interest rates and consumption uncertainty, highlighting the interplay between payment technologies and economic conditions.

These findings have important implications for banks and policymakers. For banks, universally faster payments could erode the stable source of markups that deposits traditionally provide, potentially impacting 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.

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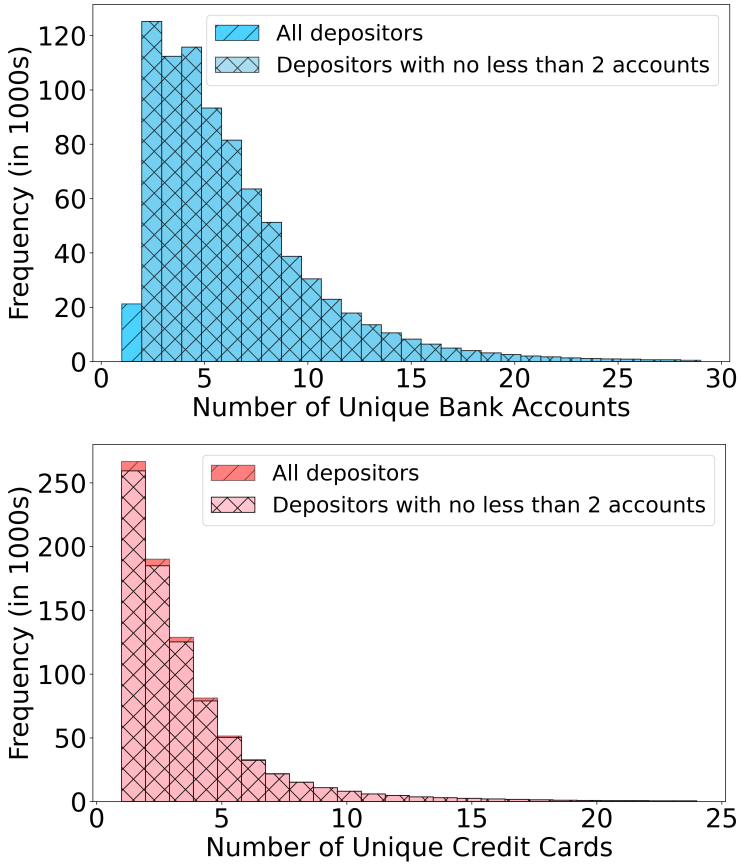
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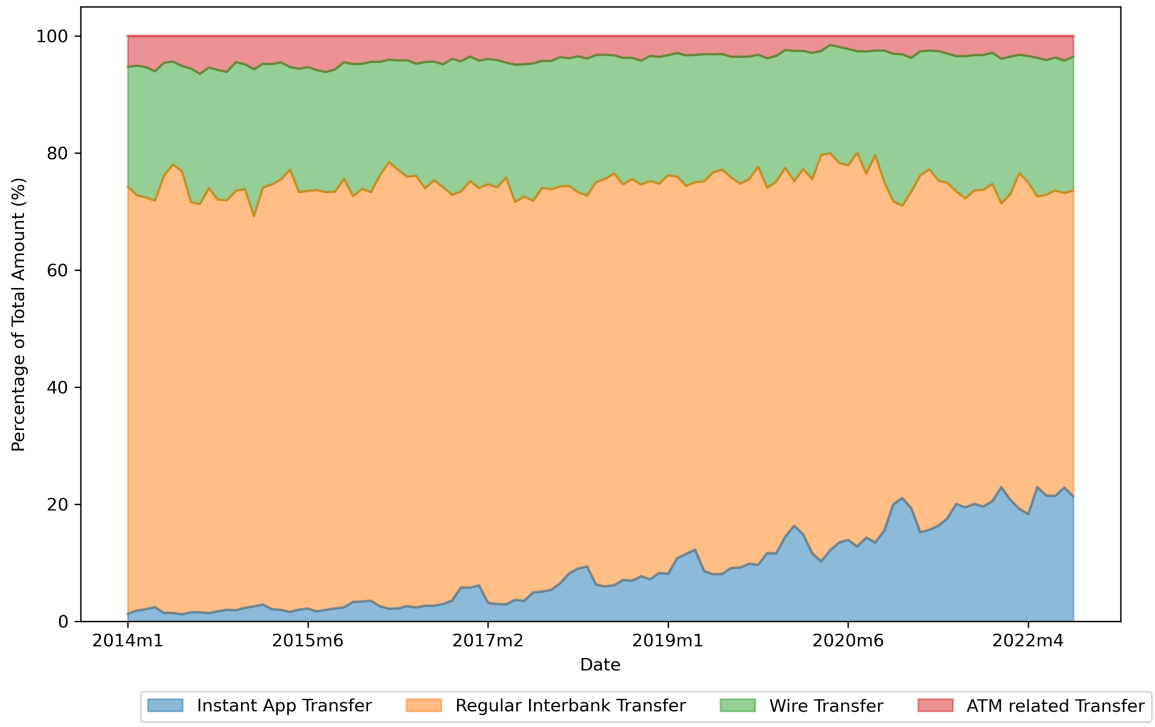
Figures and Tables

Figure 1: Bank Accounts and Credit Cards per Depositor



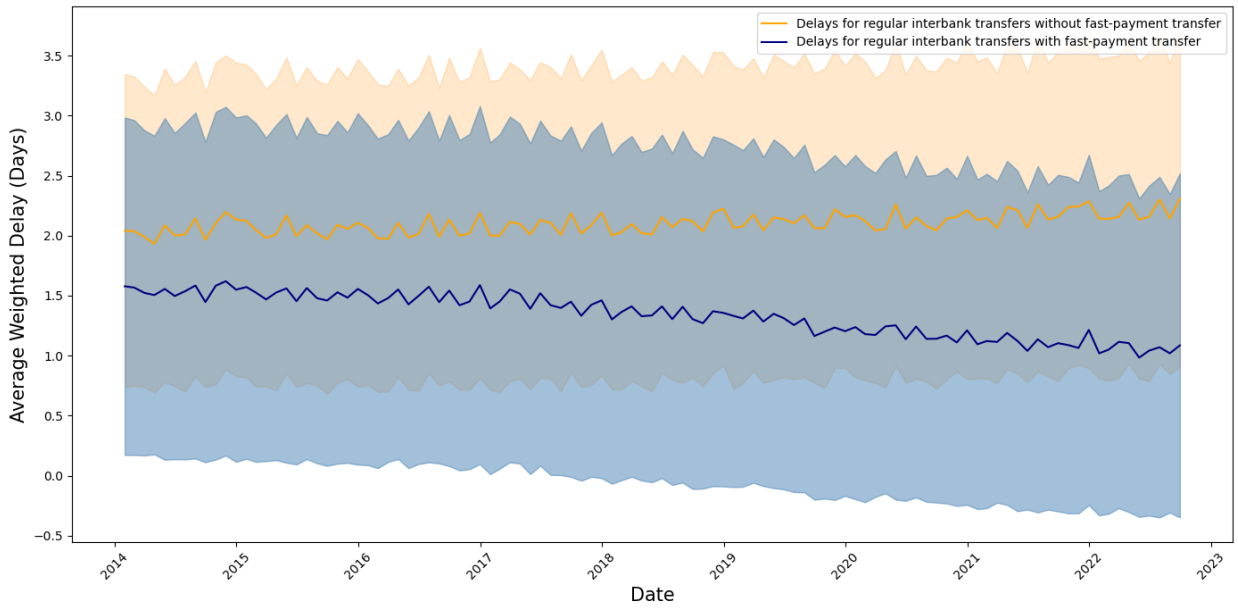
These two plots present the distributions of the average numbers of bank accounts (including checking and savings accounts; histogram on the left) and credit cards (histogram on the right) for depositors in our sample from 2013 to 2022. More than 95% of the depositors in our sample have at least two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

Figure 2: Types of interbank turnover



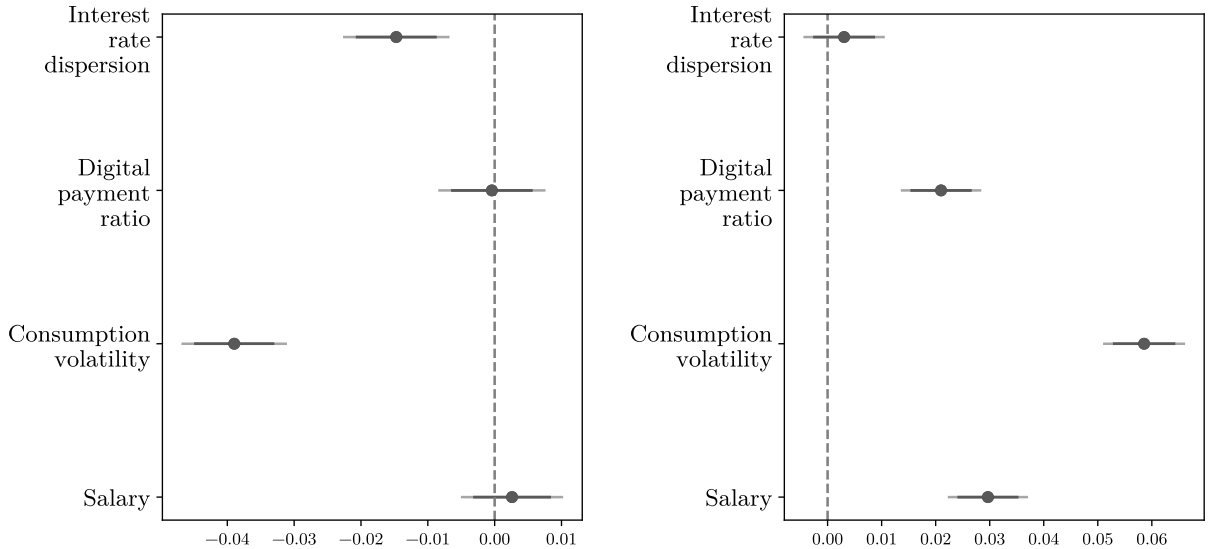
This graph delineates multiple types of interbank transfers in our sample between 2015 and 2022. Depositors have the option to reallocate deposits between accounts held at the same financial institution or to transfer assets to an alternate bank. Transactions marked with fast payment services (such as 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 3: 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.

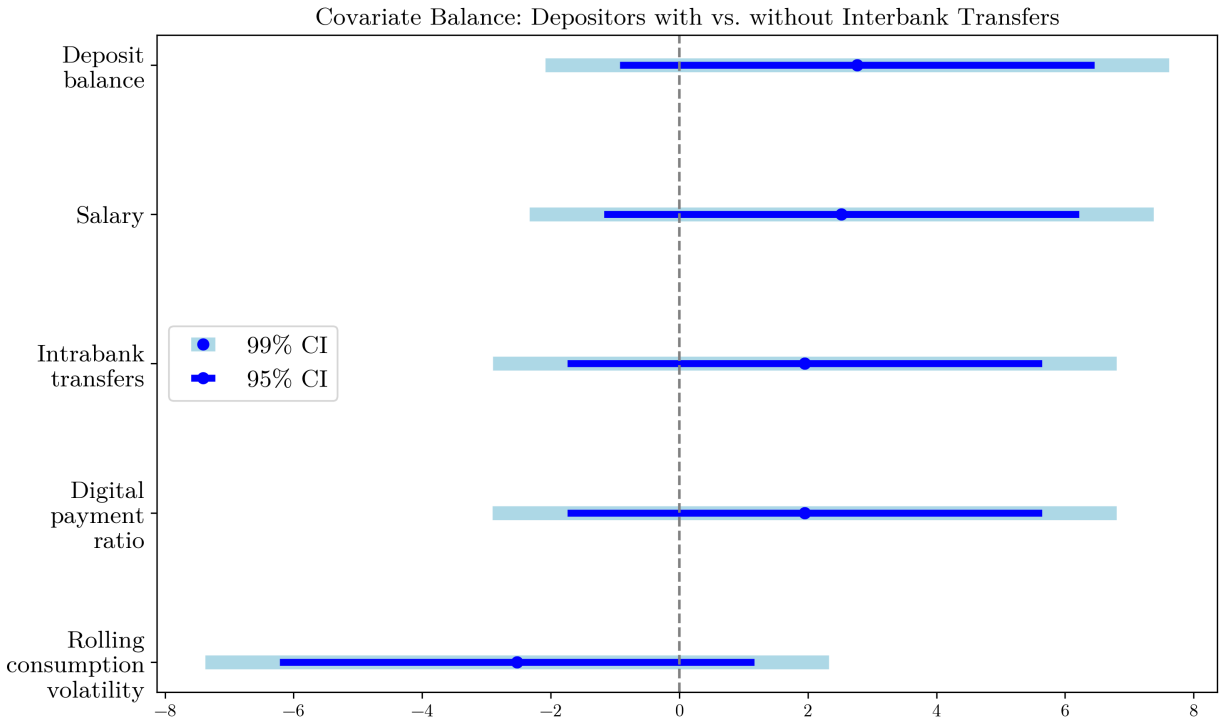
Figure 4: Factors affecting semi-elasticity of deposits to transfer delays



(a) Turnover semielasticity (b) Balance semielasticity

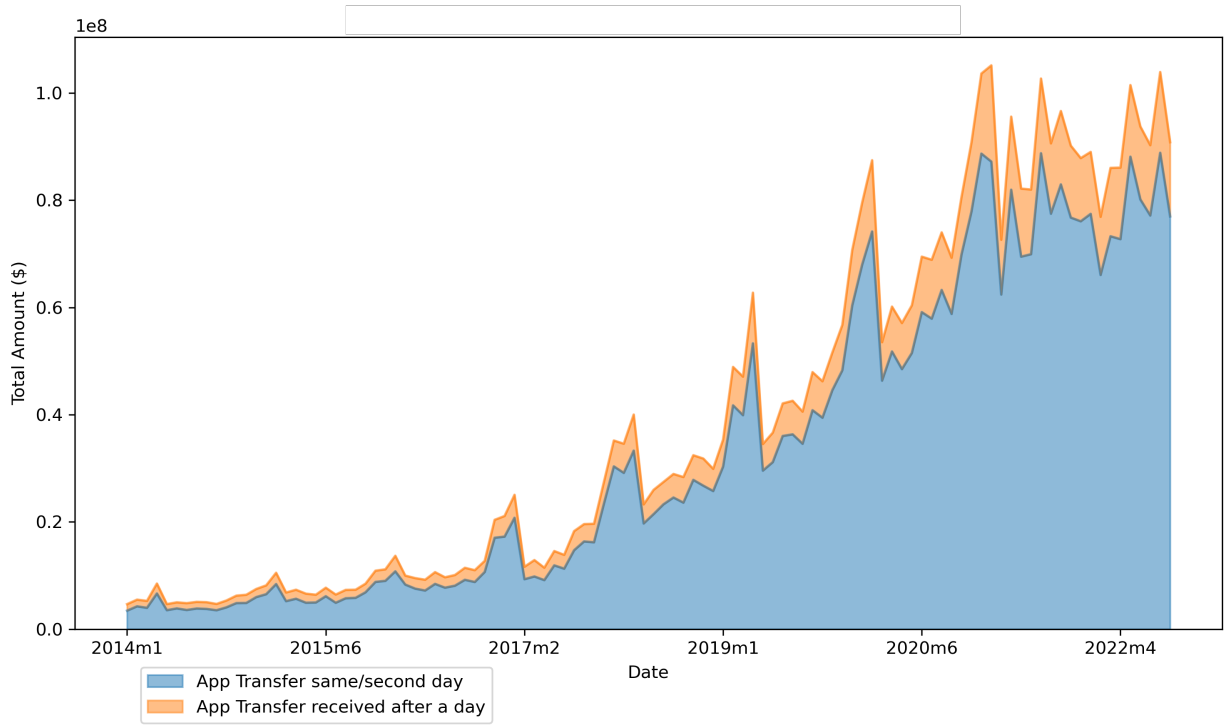
Panel (a) plots the regression coefficients of: $\beta_i = \gamma_0 + \sum_k \gamma_k X_k + \epsilon_i$, where X_k include standardized variables such as salary, consumption uncertainty, digital payment ratio, and interest rate dispersion, and β_i represents the semi-elasticity of deposit turnover with respect to transfer delays from individual regressions for each depositor by regressing their log(*scaled deposit turnover*) on transfer delays: $\log(\textit{scaled deposit turnover}_{it}) = \beta_i \times \textit{transfer delays}_{it} + \epsilon_{it}$. Panel (b) plots the regression coefficients of: $\beta_i' = \gamma_0 + \sum_k \gamma_k X_k + \epsilon_i$, where X_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 balance*) on transfer delays: $\textit{log(scaled deposit balance}_{it}) = \beta_i \times \textit{transfer delays}_{it} + \epsilon_{it}$, 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 5: Covariate Balance between Depositors with and without Interbank Transfers



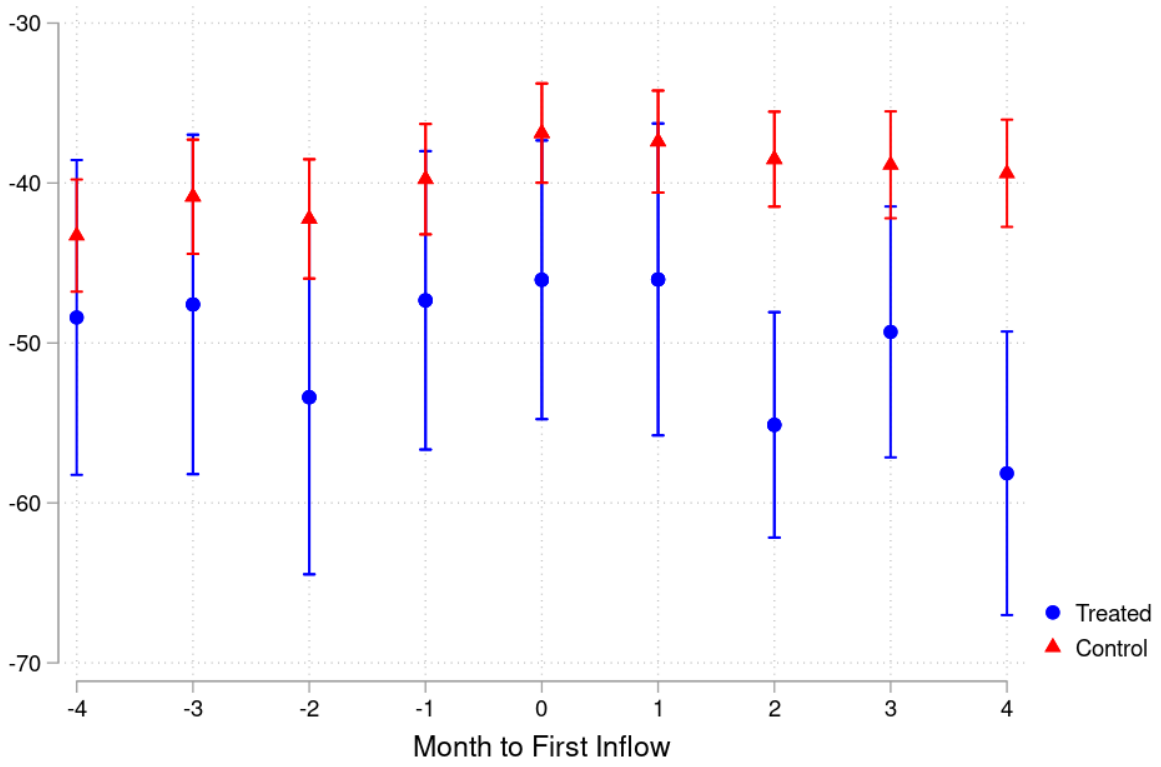
This figure plots the coefficients and 95% (in dark bands) and 99% (in light bands) confidence intervals of individually estimated and normalized regressions of: $X_{i,t} = \beta I(\sum_i Deposit\ Turnover_{i,t}) > 0)$. All variables are normalized to have mean zero and standard deviation of one.

Figure 6: Transfer delays and fast payment applications



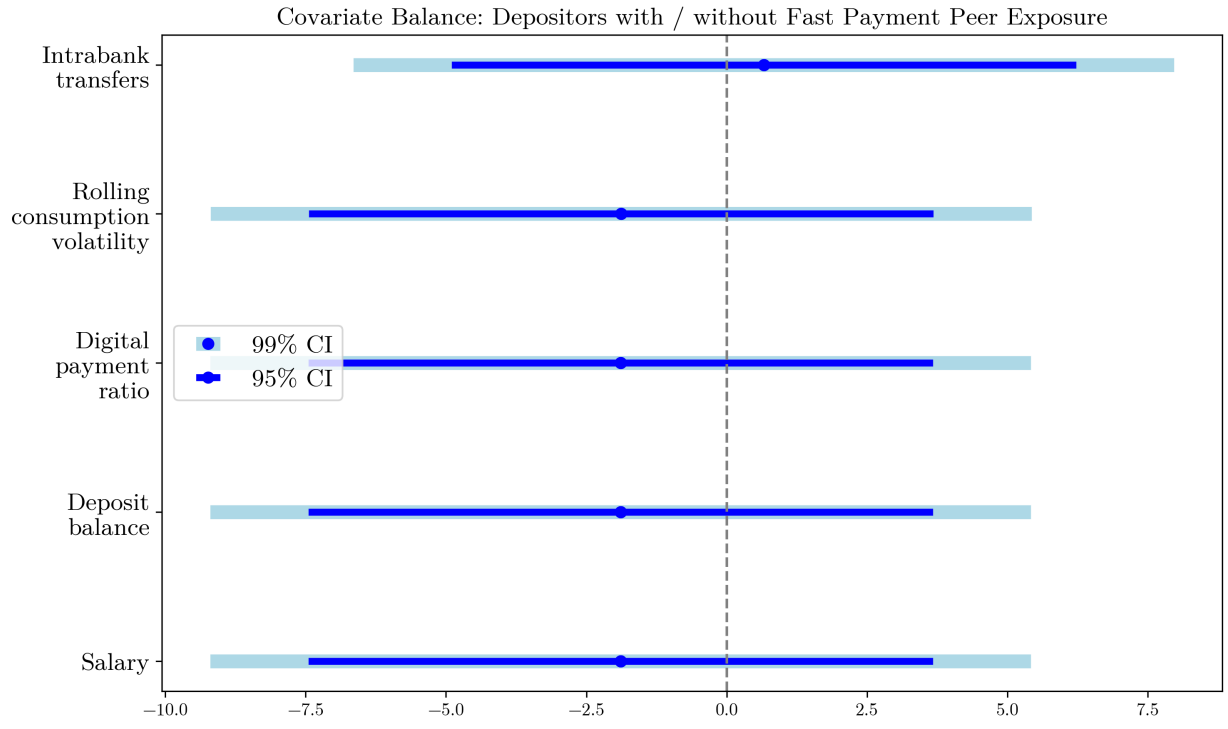
This graph highlights that a significant proportion of interbank transfers leveraging fast payment applications are completed within the same or the next business day, spanning the sample period from 2014 to 2022.

Figure 7: Depositors in treated and control groups have similar trends.



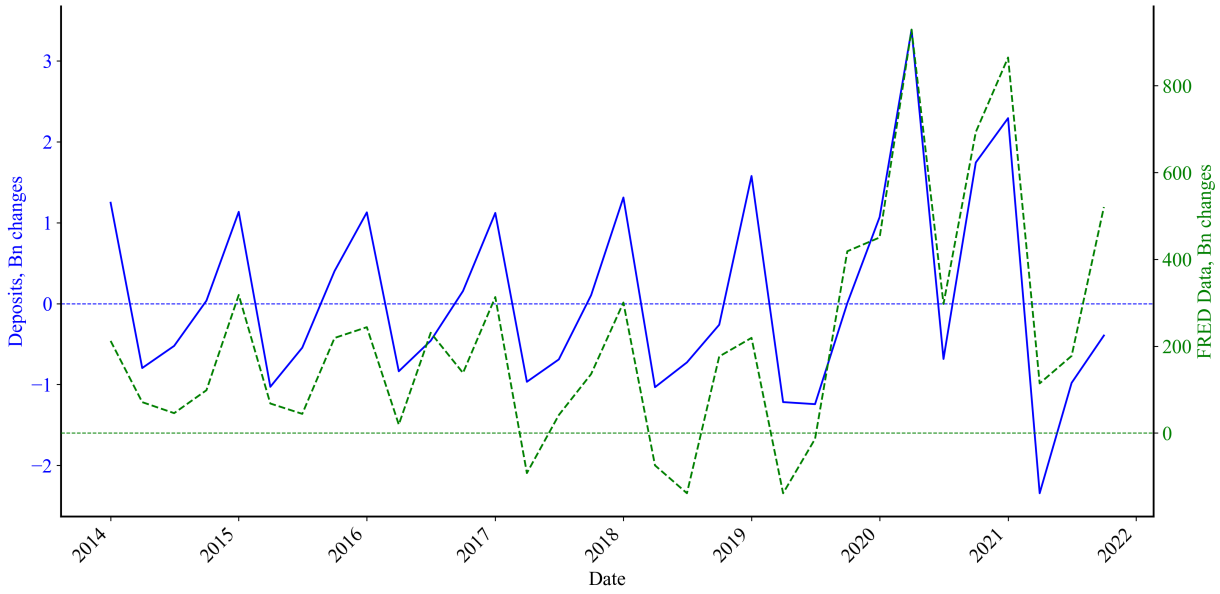
This figure displays the coefficients of *Transfer Delays* from regressions of *Deposit Turnover* on *Transfer Delays*. The regressions include time-varying depositor-level controls such as salary, consumption uncertainty, interest rate dispersion, digital payment ratio, and fixed effects for calendar 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 8: Covariate balance between depositors who accessed fast payments via network exposure and depositors who used fast payments before they receive the first inflow funds.



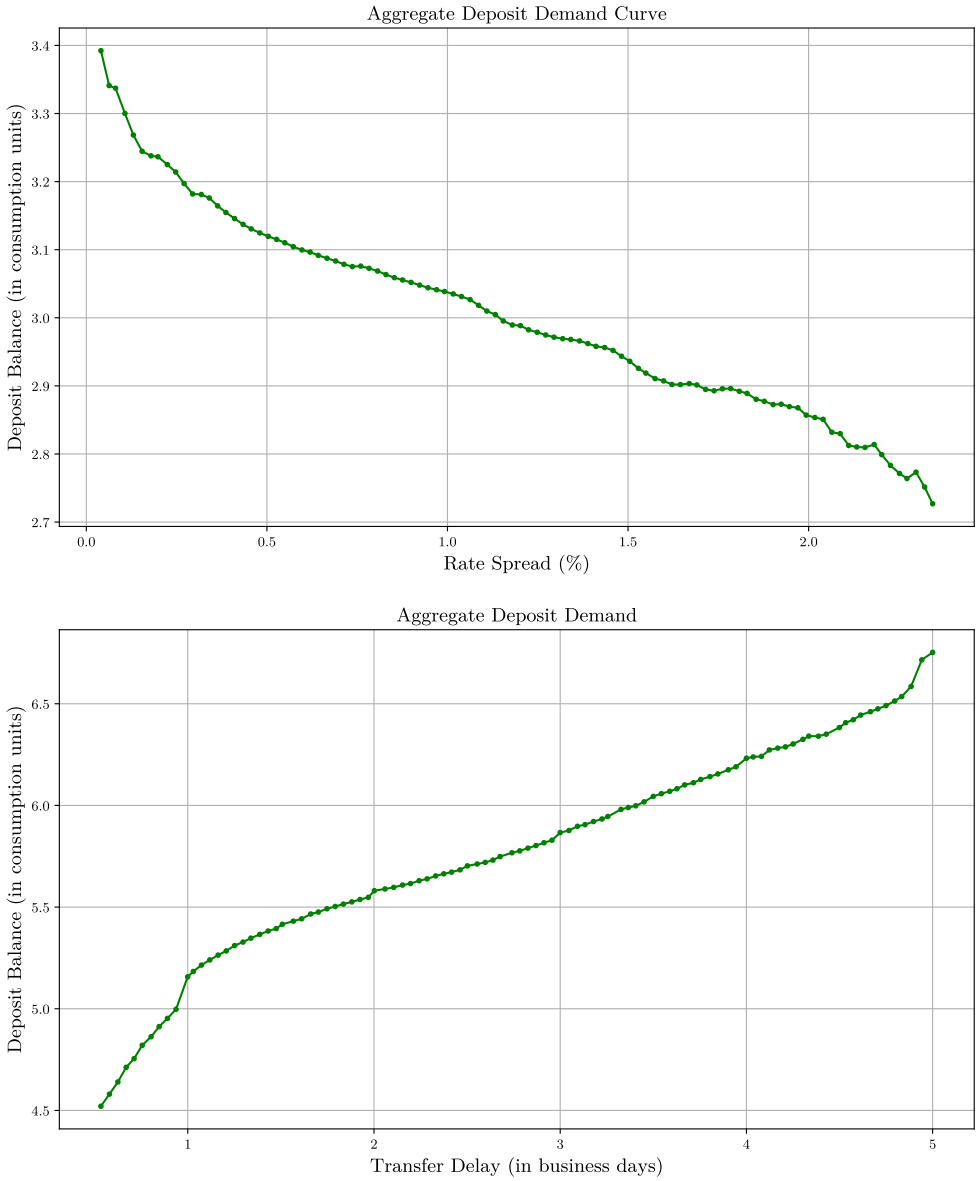
This figure plots the coefficients and 95% (in dark bands) and 99% (in light bands) confidence intervals of individually estimated and normalized regressions of: $X_{i,t} = \beta I(Treated_{i,t})$. $I(Treated_{i,t})$ equals one if depositor i who had no transactions related to fast payment technologies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

Figure 9: The aggregate deposit in sample and in Flow of Funds



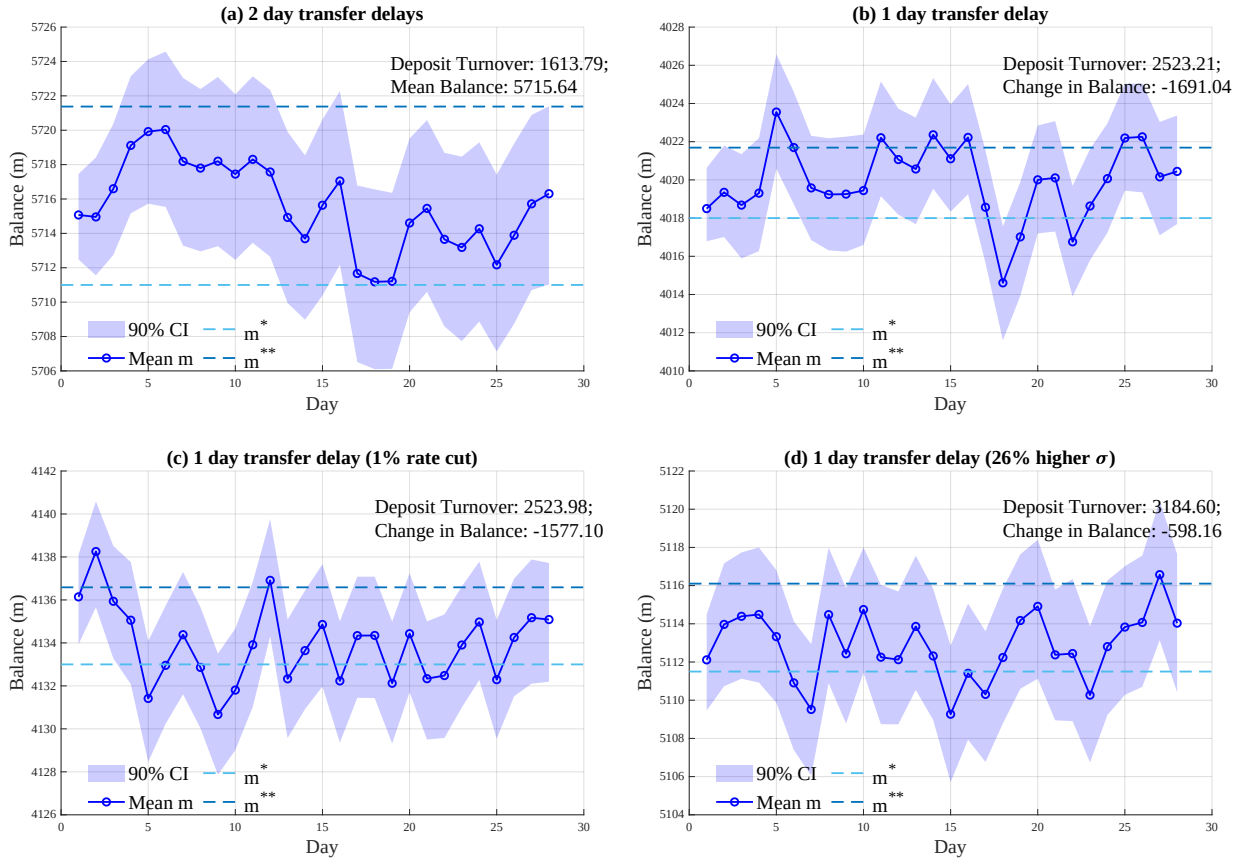
This plot compares total deposits from our sample with aggregate deposit data from FRED. The left axis displays changes in deposit balances from our data, while the right axis shows changes in household checkable deposits and currency total transactions from FRED.

Figure 10: The deposit demand curve



These graphs plot the empirical aggregate money demand curve, Panel (a) plots the cumulative demand against the spread through the following steps: 1) for each depositor, we calculate the average deposit demand M_i (their average balance scaled by the 12-month moving average of spending) and the average deposit price s_i (the annualized spread between the Effective Federal Funds Rate and the maximum interest rate offered by their banks, in percentages); 2) we compute each depositor's demand responsiveness to price changes by regressing deposit demand on the spread, obtaining the coefficient α_i. We group depositors into 100 bins based on their average rate spreads (results are robust to using quantile-based bins). Within each bin b, we compute the weighted average slope: $\alpha_b = \frac{\sum_{i \in b} M_i \cdot \alpha_i}{\sum_{i \in b} M_i}$ and the average demand $M_b = \frac{\sum_{i \in b} M_i}{|b|}$ and spread $s_b = \frac{\sum_{i \in b} s_i}{|b|}$; 3) we estimate the intercept $c_b = M_b - \alpha_b \cdot s_b$, resulting in a linear demand function for each bin; 4) we aggregate these locally linear demand functions by ordering the bins by increasing spread and calculating cumulative demand: $M_k = M_{k-1} + \alpha_b(s_k - s_{k-1})$, where k indexes the bins. Panel (b) plot aggregate deposit demand against transfer delays, where in step 2 we calculate each depositor's demand sensitivity to transfer delays controlling for the rate spread. Each marker represents an average depositor in the corresponding depositor bin.

Figure 11: 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 I. 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 2% annualized interest rate dispersion ($r = 2\%/365$); 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 (c), we change interest rate dispersion r to $r = 1\%/365$; In Figure (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., $1st$ 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:

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

where the dependent variables are $\textit{Deposit Turnover}_{i,t}$—the total interbank transfers during month t for depositor i—and $Bal_{i,t}$, the deposit balance at the end of month t. $\textit{Transfer Delay}_{i,t}$, 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 5: 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:

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

where the dependent variables are $\textit{Deposit Turnover}_{i,t}$—the total interbank transfers during month t for depositor i—and $Bal_{i,t}$, the deposit balance at the end of month t. $\textit{Transfer Delay}_{i,t}$, 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 6: Transfer delays and balance: Depositors without interbank transfers

	(a) In dollars		(b) Scaled by spending	
	(1)	(2)	(3)	(4)
Transfer Delay	9991.9***	8631.6***	0.0428***	0.0455***
	(426.1)	(354.0)	(0.00266)	(0.00255)
Depositor FE	N	Y	N	Y
Time FE	Y	Y	Y	Y
N	30333324	30305802	29695639	17053524
Adj. R^2	0.00924	0.0676	0.00783	0.0383

This table examines how transfer delays affect depositor activeness and deposit balances using the following empirical model for the depositors with zero deposit turnover throught the sample period:

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

where the dependent variables $Bal_{i,t}$ is the deposit balance at the end of month t. $\textit{Transfer Delay}_{c,t}$, is the dollar-weighted average rolling transfer delays in city c where depositor i resides in month t. 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). Note since we are not restricting to only the periods with positive interbank transfers, this panel has significantly higher number of observations.
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 7: 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: $I(\text{Post First Outflow})i,t = \zeta_0 + \zeta_1 I(\text{Post First Inflow})i,t + X_{i,t} + \delta_t + v_{i,t}$, $\text{Transfer Delay}i,t = \gamma_0 + \gamma_1 I(\text{Post } \widehat{\text{First Outflow}})i,t + X_{i,t} + \delta_t + \varepsilon_{i,t}$, $Y_{i,t} = \beta_0 + \beta_1 \widehat{\text{Transfer Delay}}i,t + Xi,t + \delta_t + \epsilon_{i,t}$.

$Y_{i,t}$ 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 ($X_{i,t}$) 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 8: Interest, delays, and deposit allocation across accounts

	%ΔDeposit					
	Full		Active Depositors			
	(1)	(2)	(3)	(4)	(5)	(6)
Interest Rate	0.0112***	0.0112***	0.0167***	0.0189***	0.0189***	0.0497***
	(0.000119)	(0.000118)	(0.000381)	(0.000407)	(0.000407)	(0.00180)
Interest Rate				-0.00484***	-0.00484***	-0.0128***
× Transfer Delay				(0.000217)	(0.000217)	(0.000704)
Transfer Delay				-0.000855***	-0.000855***	-0.000675
				(0.000190)	(0.000190)	(0.000639)
Account Controls	Y	Y	Y	Y	Y	Y
Depositor FE	Y	Y	Y	Y	Y	N
Time FE	Y	Y	Y	Y	Y	N
Depositor-Time FE	N	N	N	N	N	Y
N	23732579	23732579	2565945	2565945	2565945	1547430
Adj. R^2	0.0328	0.0328	0.0349	0.0352	0.0352	-0.0152

%ΔDeposit denotes the change in a depositor's account balance relative to their total deposits across all accounts. A value of 0.01 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 ($Interest\ Rate_{i,a,t}$) and transfer delays ($Transfer\ Delay_{i,a,t}$), 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 1-2 present results for the full depositor sample, while Columns 3-6 focus on active depositors with account-level transfer delay estimates. 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 9: 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	738.15	521.41	2324	2616.14	1496.49	887.77	822.94	1204.8	*676*
2nd Quint.	1403	1429.04	1007.4	2562	2907.07	1658.69	993.21	913.55	1349.3	*1276*
3rd Quint.	2521	2619.65	1844.78	2866	3253.92	1854.65	1034.77	1026.71	1521.3	*2282*
4th Quint.	5089	5142.21	3618.63	3284	3728.55	2126.47	1052.87	1179.41	1751.6	*4359*
5th Quint.	17943	15554.76	10938.28	3973	4511.22	2574.25	1088.62	1430.36	2129.1	*14625*
Uninsured	21101	21764.63	15302.06	4679	5308.19	3030.92	1812	1685.34	2508.5	*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 2% annualized interest rate dispersion ($r = 2\%/365$); 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 I. We then simulate the evolution of m for a year and report the average and the volatility.

Appendix for

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

Xu Lu and Yang Song and Yao Zeng

I Theory Appendix

I.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

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 $0 \leq \delta_1 \leq m^*$, $\delta_1^{ii} < 0$, 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

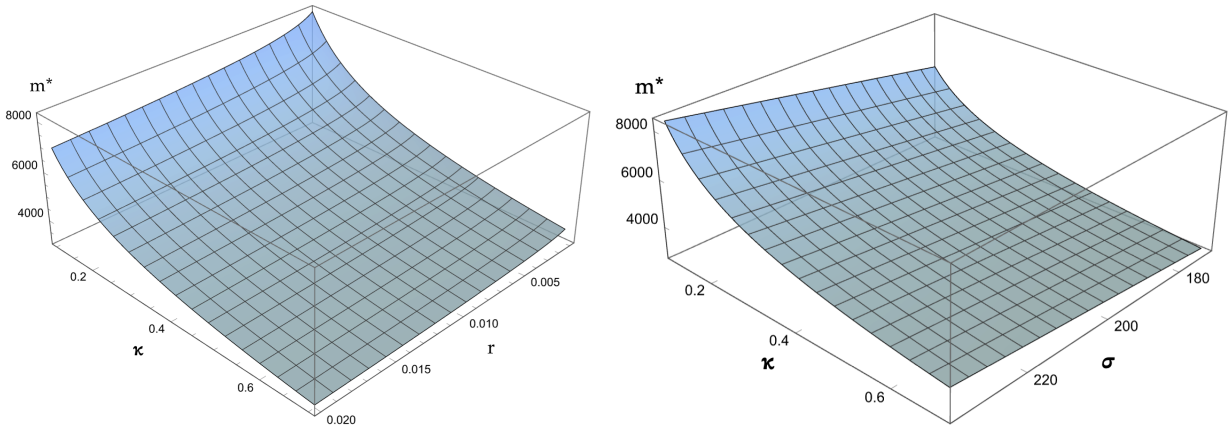
$$\begin{aligned} 2C_5 &= [r + r/\sigma^2(m^{*2} - \underline{m}^2)]\lambda^{-1}A_1^{-1} = r\lambda^{-1}A_1^{-1}, \\ -2C_6 &= r/\kappa m^* A_1 + r\lambda^{-1}A_1, \\ C_5 + C_6 &= b - r/\kappa m^*. \end{aligned}$$

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.

I.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,

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

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:

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

where $\int_0^{m^*} u e^{-\lambda u} du = \frac{-1 + e^{-\lambda m^*}(\lambda m^* + 1)}{\lambda^2}$ and $\int_0^{m^*} u e^{\lambda u} du = \frac{e^{\lambda m^*}(\lambda m^* - 1) + 1}{\lambda^2}$. 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:

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

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,

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

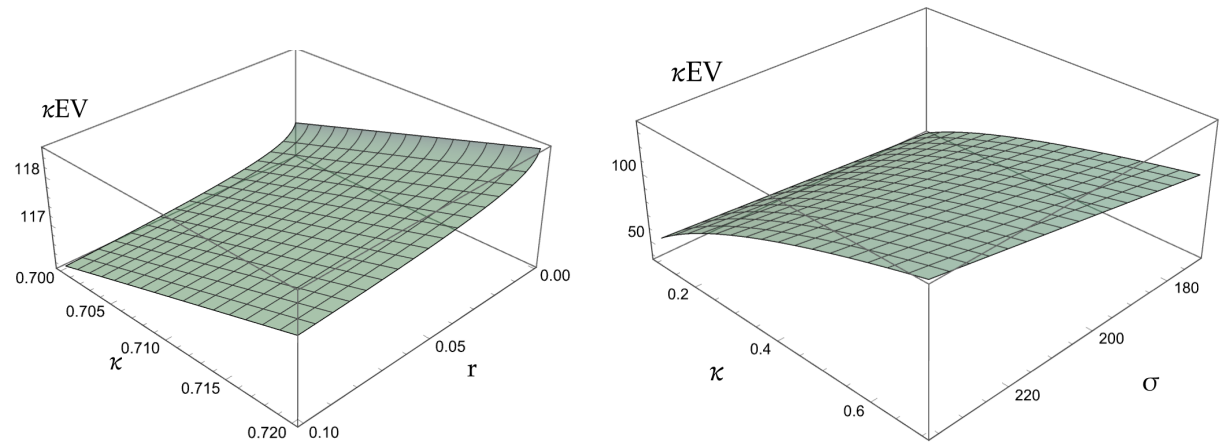
For any given point in time, the expected transfer is $\kappa \times EV$ which is given by

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

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 $\dfrac{\partial^2(\kappa\text{EV})}{\partial\kappa\partial r}$ is weakly decreasing because the effect of r on m^* and m^{**} is less significant compared to the effect of κ. In contrast, $\dfrac{\partial^2(\kappa\text{EV})}{\partial\kappa\partial\sigma}$ 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



II Empirical Appendix

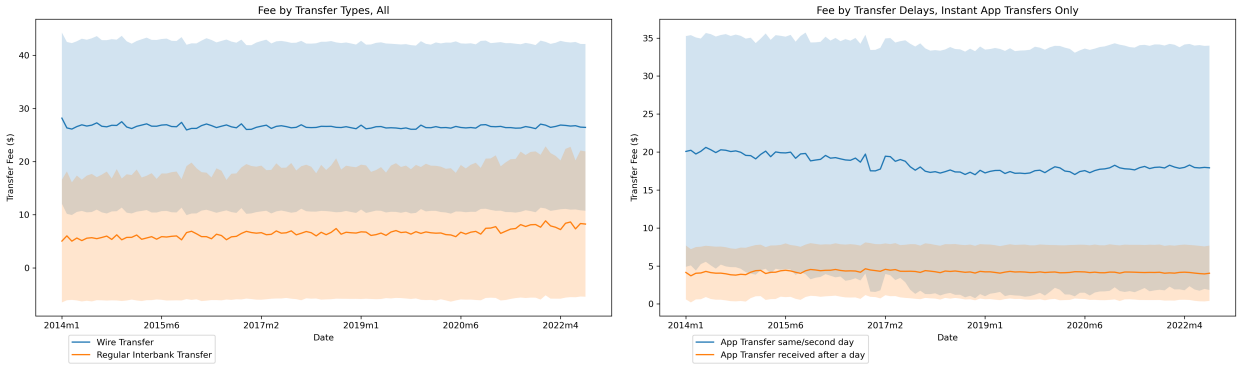
II.1 Fees and Limits for Bank Wire Transfers and Fast Payment Technologies

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[10]	—

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-3: 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.

II.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.

II.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.

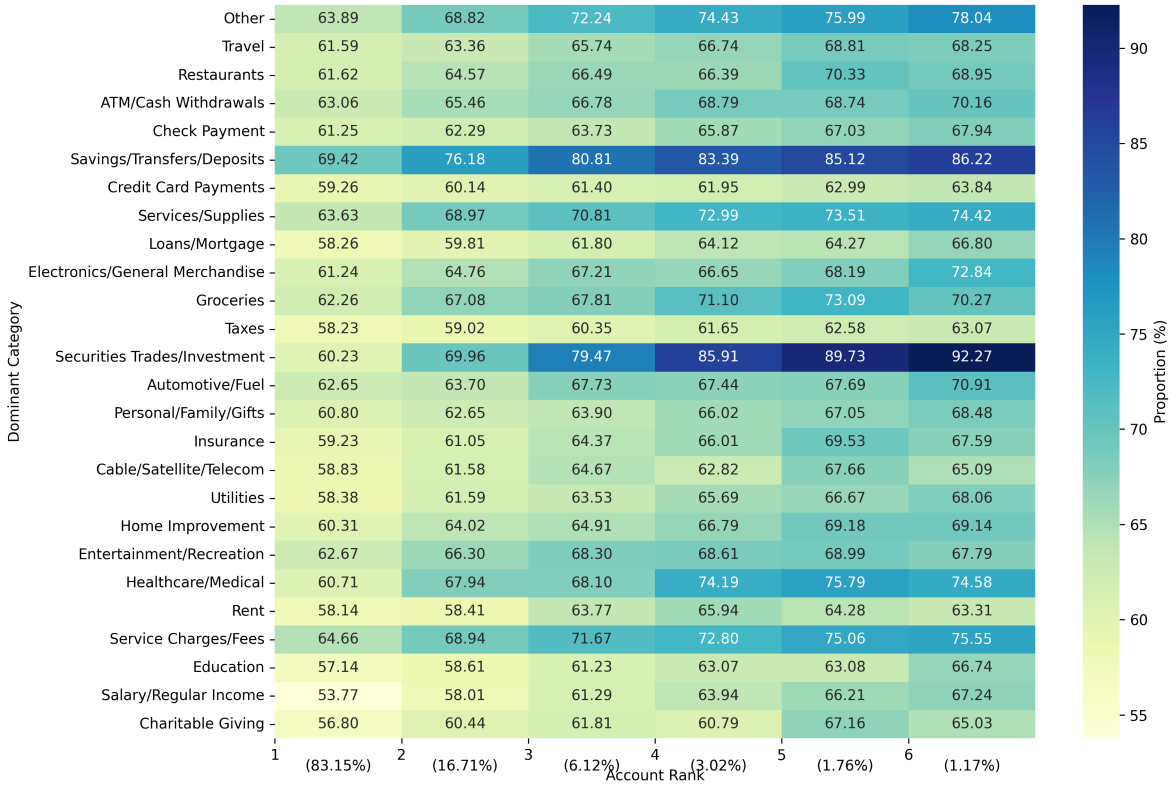
Figure A-4 illustrates the transaction distribution patterns among depositors who maintain at least two bank accounts. Each account's primary usage is identified by its dominant category, defined as the category that accounts for more than 50% of the total transaction volume in dollars. Impressively, 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



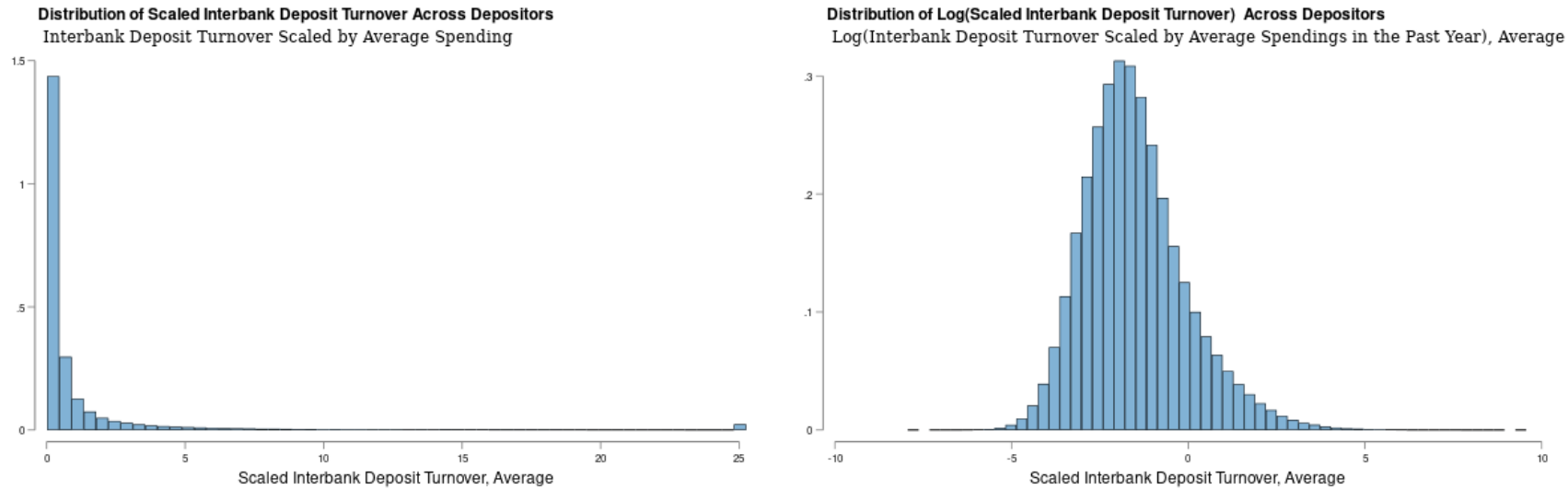
This figure summarizes the transaction category distribution among depositors with at least two bank accounts. Each account is categorized by its dominant transaction type, which constitutes over 50% of its total dollar volume. Notably, more than 90% of depositors have at least one such specialized account. 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.

II.4 Additional Summary Statistics and Robustness Checks

II.4.1 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.

II.4.2 Transfer Delays and Depositor behavior: Depositors without Access to Credits

Table A-3: 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:

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

where the dependent variables are *Deposit Turnover*$_{i,t}$—the total interbank transfers during month t for depositor i—and $Bal_{i,t}$, the deposit balance at the end of month t. *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%.

II.4.3 Balance and Turnover after Transfer Technology Adoption

Table A-4: 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(Post First Inflow)i,t) influences a depositor's likelihood of initiating outgoing transfers using the same platforms (I(Post First Outflow)i,t). We then use the predicted values of I(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:

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

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

$$Y_{i,t} = \beta_0 + \beta_1 \widehat{\text{Transfer Delay}}i,t + Xi,t + \delta_t + \epsilon_{i,t}.$$

In these equations, $Y_{i,t}$ is the dependent variable (deposit balances or deposit turnover), I(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(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(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.

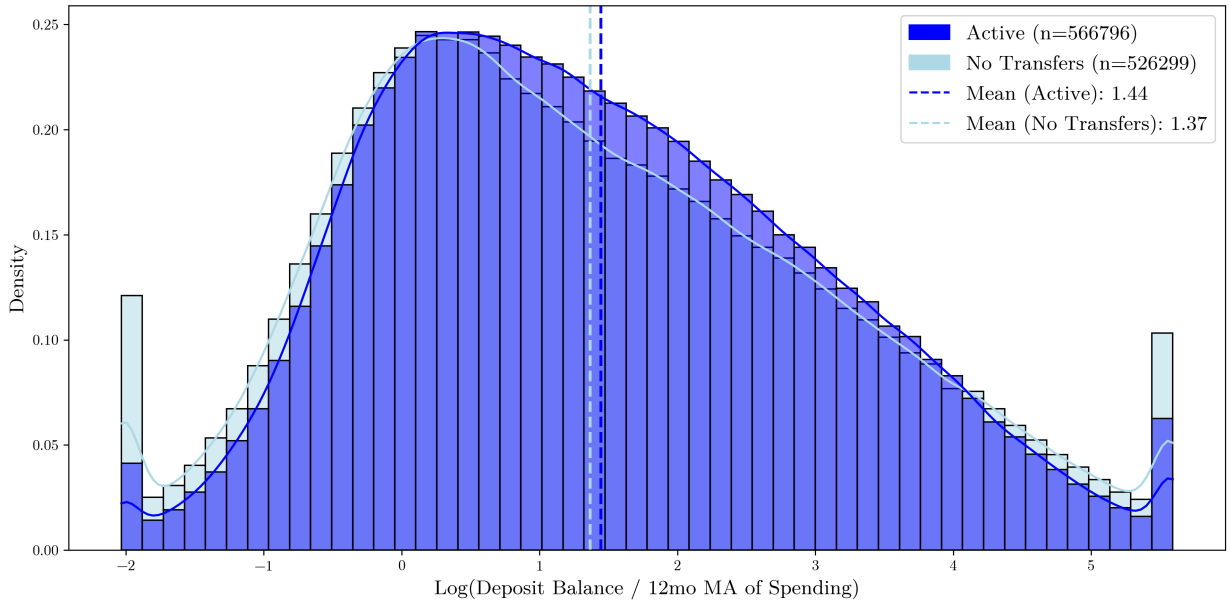
Transfer Delayi,t is measured as the dollar-weighted transfer delays for depositor i using a 12-month moving average for each month t.

We include time-fixed effects (δ_t) and depositor-level controls ($X_{i,t}$) 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%.

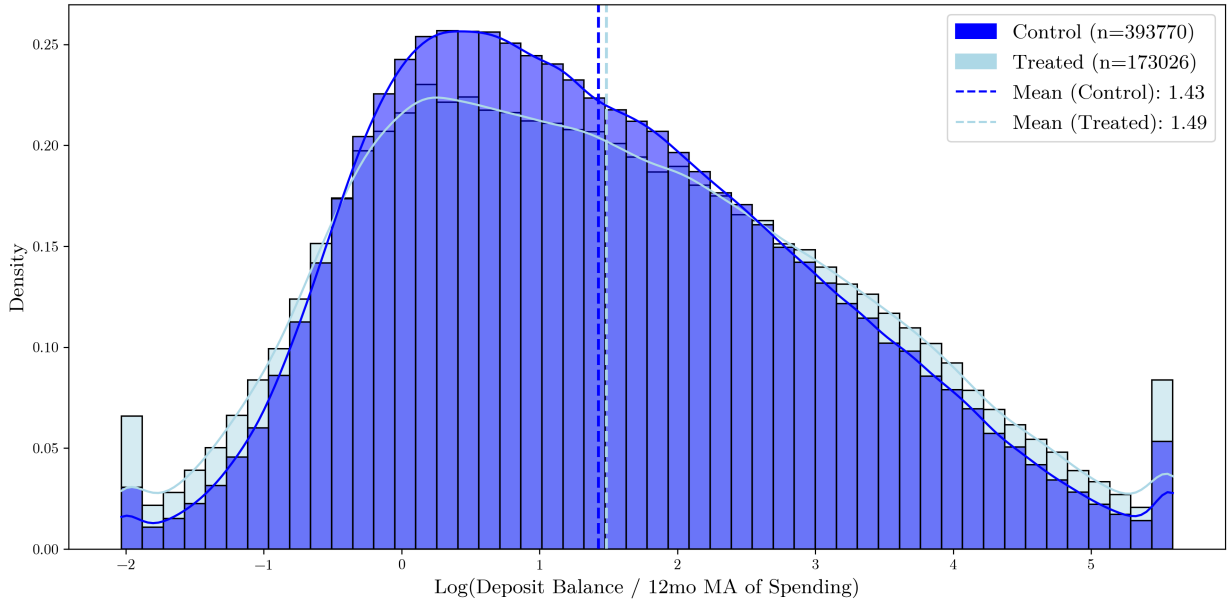
II.4.4 Distribution of depositors by average balances, with/without interbank transfers

Figure A-6: Histograms of depositors by average balances, with/without interbank transfers



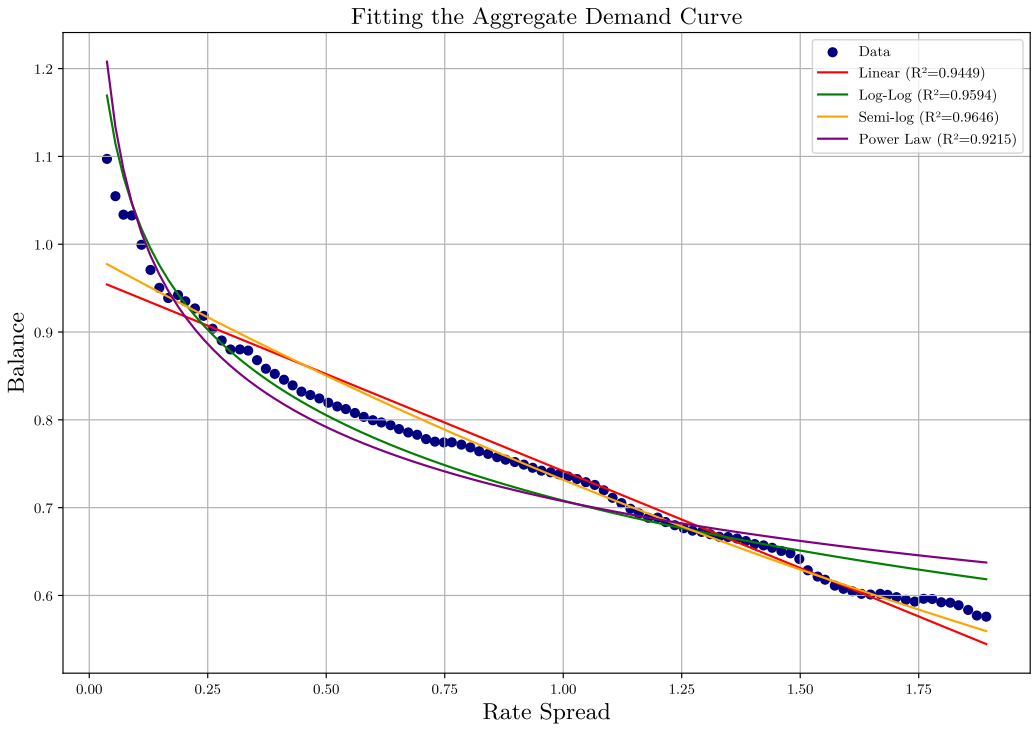
II.4.5 Distribution of depositors by average balances, with/without fast payment technologies

Figure A-7: Histograms of depositors by average balances, with/without fast payment technologies



II.4.6 The functional form of the deposit demand curve

Figure A-8: Fitting the aggregate deposit demand curve



This figure shows the empirical aggregate money demand curve through the following steps: 1) for each depositor, we calculate the average deposit demand M_i (their average balance scaled by the 12-month moving average of spending) and the average deposit price s_i (the annualized spread between the Effective Federal Funds Rate and the maximum interest rate offered by their banks); 2) we compute each depositor's responsiveness to price changes by regressing deposit demand on the spread, obtaining the coefficient α_i. We group depositors into 100 bins based on their average rate spreads (results are robust to using quantile-based bins). Within each bin b, we compute the weighted average slope: $\alpha_b = \frac{\sum_{i \in b} M_i \cdot \alpha_i}{\sum_{i \in b} M_i}$ and the average demand $M_b = \frac{\sum_{i \in b} M_i}{|b|}$ and spread $s_b = \frac{\sum_{i \in b} s_i}{|b|}$; 3) we estimate the intercept $c_b = M_b - \alpha_b \cdot s_b$, resulting in a linear demand function for each bin; 4) we aggregate these locally linear demand functions by ordering the bins by increasing spread and calculating cumulative demand: $M_k = M_{k-1} + \alpha_b(s_k - s_{k-1})$, where k indexes the bins. Fitting model definitions: *Linear:* Deposit Balance $= a \cdot$ Rate Spread $+ b$; *Semi-log:*Deposit Balance $= a \cdot e^{b \cdot \text{Rate Spread}}$; *Power Law:* Deposit Balance $= a \cdot$ Rate Spread^b ; *Log-Log:* $\ln$(Deposit Balance) $= a \cdot \ln$(Rate Spread) $+ b$.