The Making of an Alert Depositor: How Payment and Interest Drive Deposit Dynamics*

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Abstract

We introduce a new metric, *deposit turnover,* to quantify deposit flows across banks, revealing significant heterogeneity in deposit dynamics. Analyzing 50 billion transactions across 1,400 U.S. banks, we find faster payment and greater uncertainty significantly increase interbank deposit transfers. In addition, shorter payment delays further amplifies depositors' responsiveness to liability repayments and interest rate dispersion across bank accounts. Furthermore, we show that depositors' exposure to fast payment technologies through social networks causally promotes their payment technology adoption, reduces transfer frictions, and directly impacts depositor behavior and consumer spending. Our quantitative analysis finds that the impact of fast payment technologies on depositor alertness depends on the interest rate environment and the level of depositor indebtedness, and a reduction of 1-day in payment delays has to be accompanied by a $50bp$ rate cut in order not to affect depositor alertness and bank funding risk. This highlights the need to evaluate payment infrastructure upgrades, like FedNow, in tandem with monetary policy.

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1 Introduction

Deposits are a crucial, low-cost, and stable funding source for banks, and retail deposits accounting for half of the deposits at large U.S. bank holding companies. Traditionally, depositors have been considered *sleepy*, often ignoring fluctuations in the underlying fundamentals of banks. Nonetheless, the 2023 regional bank crisis highlights that not all depositors fit this passive profile: some corporate and retail depositors promptly shuffle their deposits across banks. Given the crucial importance of stable deposits to bank funding and financial stability, this raises two important questions: To what extent are depositors alert rather than sleepy? And what explains the varying levels of alertness among depositors?

Our paper provides the first detailed analysis of the economic factors driving retail depositors' depositing activities across banks. We begin by introducing a new measure of depositor alertness, *deposit turnover*, which we define as the gross amount of funds that depositors actively move between their accounts at different depository institutions. This depositor-level measure is derived from a comprehensive database covering a million retail depositors across more than a thousand national and regional banks and credit unions in the U.S., and offers a new perspective complementary to the existing literature that focuses on bank-level deposit flows. First, it highlights the intensive margin of flows across banks, crucial for understanding payment fragility and the dynamics of modern bank runs, such as in 2023 when depositors shifted funds from regional banks to systemically important banks. Second, this depositor-level measure provides a clear lens to examine the economic forces driving deposit flows between bank accounts. We find that depositor-level financial uncertainty is key to understanding deposit dynamics and has significant implications for assessing the impact of payment system upgrades in a changing interest rate environment.

Using deposit turnover as a proxy for depositor alertness, we identify two key drivers: payment delays and uncertainty in meeting financial obligations and earning interest income. First, we find that payment delays contribute to depositor alertness.Payment processing delays are usually unobservable; however, using transaction-level data linked across bank accounts, we infer these delays by tracking the number of business days between the initiation and completion of each interbank fund transfer across the accounts of the same depositor. Our findings show considerable variation in these delays, with an average of two days to complete a regular bank transfer. We provide direct evidence that such delays influence depositor behavior. When the payment technology of a bank account becomes faster in the sense that the delay between initiating a bank transfer and receiving the transfer becomes shorter, deposits become more convenient, encouraging depositors to transfer funds more actively across accounts to facilitate their transactional demand. This finding and the payment channel we uncover thus echo several recent studies showing that deposits at digital banks are typically more flighty (e.g., Erel, Liebersohn, Yannelis, and Earnest 2023, Jiang, Yu, and Zhang 2023, Koont 2023, Koont, Santos, and Zingales 2023) because deposits at digital banks tend to serve as a more convenient medium of exchange. In this sense, our paper offers microfounded evidence for these observed effects of digital disruption at the depositor level. We further document that depositors using various transfer technologies demonstrate varying levels of alertness. This finding thus helps shed light on the impact of fast payment systems on deposit behaviors and bank liquidity management (e.g., Duffie 2019, Sarkisyan 2023, Wang 2023).

Second, bank deposits provide payment convenience and interest earnings, and depositors may have varied preferences for convenience and income across bank accounts (Drechsler, Savov, and Schnabl 2017, Begenau and Stafford 2022, d'Avernas et al. 2023, Kundu, Muir, and Zhang 2024, Li, Lu, and Ma 2024). We capture the roles of bank deposits as a means of payment and a store of value by constructing depositor-level uncertainty about meeting financial obligations and earning interest income. To assess depositor-level uncertainty, we extract bank transactions related to credit card payments, personal loans (including auto loans), and mortgage repayments. Duffie and Krishnamurthy (2016) find that rate hikes correlate with greater dispersion of expected deposit rates, rendering each bank's deposits a less attractive store of value. To understand the individual-level shadow cost of money, we calculate account-level interest rates by dividing the interest income by the account balance at the end of each month, and compute the interest rate dispersion between the highest and lowest rates across accounts of a given depositor. Our analysis reveals that depositors tend to move their funds between banks more frequently in response to greater interest rate dispersion and when faced with larger uncertain liabilities.

We find that the efficiency of payment technology and the amount of funds deposited are closely linked: depositors with more efficient payment technology tend to transfer larger sums across accounts in response to rate dispersion or uncertain liabilities. In other words, depositors' sensitivity to rate changes and financial liabilities increases with faster payment. These findings has significant implications, suggesting that policy evaluations should consider both the introduction of fast payment technologies and their interaction with rate changes and aggregate indebtness of households.

Our depositor-level analysis reveals new facts about deposit dynamics that standard models cannot capture. We present an inventory model of money management between two bank accounts, extending the Baumol-Tobin approach by incorporating uncertain settlement delays. Faced with these delays, depositors maintain positive balances in their low-interest accounts to fund consumption, and make lumpy transfers when balances fall below an endogenous threshold. Higher interest rates and faster payments lead to more frequent transfers. This model not only captures these observed behaviors but also provides a framework for evaluating the combined effects of faster payment systems and monetary cycles on deposit flows. We use the model to match key data moments and find that reducing payment delays from two days to one day – such as through the adoption of FedNow – would increase total deposit turnover by 26%. However, if this upgrade is accompanied with a 50-basis point rate cut, the turnover remains unchanged compared to the two-day delay scenario. This suggests that reducing payment friction is most effective when paired with a monetary easing cycle. Additionally, the effect of payment technology on depositor behavior is particularly pronounced in an "indebted" economy. As of July 2024, aggregate consumer loans are about 26% higher than they were in January 2020, and reducing the overall payment delays by one day would significantly boost gross interbank transfer volume by 58%.

We further exploit technology diffusion through social network to examine the causal impact of payment technologies on depositors' responsiveness. Depositors and banks might select each other based on their payment needs, leading to endogeneity in the matching process between depositors and payment technologies. To address these identification issues, we leverage the introduction of fast payment platforms including Zelle, PayPal, Venmo, and Cash App. These platforms provide an exogenous shock to the payment technologies available to depositors. By tracking the initial receipt of funds through these platforms for each depositor, we observe that depositors with no prior experience with these services begin to actively use them for payments following their first inbound transaction. Since the timing and amount of these initial receipts are independent of the depositors' existing transfer delays, they serve as a natural exogenous shock to payment technology adoption. Our empirical analysis shows that adopting these payment technologies significantly reduces transfer delays, indicating a causal relationship between the use of fast payment methods and changes in depositor behavior. Using the introduction of these faster payment platforms to instrument transfer delays, we find that faster payment technology increases deposit turnover and notably boosts depositors' consumption, while having no significant effect on overall interest income. This result aligns with the large literature on the benefits of efficient payment technologies for consumer consumption (Jack and Suri 2014), investment (Higgins 2022), borrowing and lending (Ghosh, Vallee, and Zeng 2023), and risk-sharing within families and social networks (Balyuk and Williams 2021).

Literature. Fractional-reserve banking relies heavily on stable funding to support liquidity transformation, as highlighted by Gorton (1988), Hanson, Shleifer, Stein, and Vishny (2015), Drechsler, Savov, and Schnabl (2018, 2021) and Egan, Lewellen, and Sunderam (2022). Acharya, Schnabl, and Suarez (2013), Krishnamurthy, Nagel, and Orlov (2014) provide detailed analyses of funding risk in the wholesale market, but the risk associated with deposits has remained largely unexplored, with measures of funding risk in Brunnermeier, Gorton, and Krishnamurthy (2013), Bai, Krishnamurthy, and Weymuller (2018) assess bank funding risk under most severe adverse scenarios. Recently, the collapse of Silicon Valley Bank has spurred research into the causes of coordinated depositor withdrawals. Interest rate risk, particularly for uninsured depositors, has been identified as a significant factor driving deposit outflows at the bank level (e.g., Benmelech, Yang, and Zator 2023, Drechsler, Savov, Schnabl, and Wang 2023, Jiang, Matvos, Piskorski, and Seru 2023, Haddad, Hartman-Glaser, and Muir 2023). Related studies, such as Acharya and Rajan (2023), Acharya, Chauhan, Rajan, and Steffen (2023) and Hanson, Ivashina, Nicolae, Stein, Sunderam, and Tarullo (2024), suggest that post-crisis regulations and quantitative easing policies have inadvertently led to an influx of uninsured deposits and increasingly unstable bank liquidity transformation, raising concerns about financial stability. Besides uninsured deposits, Cipriani, Eisenbach, and Kovner (2024) find that even insured depositors flock to large banks during the 2023 regional banking crisis, indicating that factors beyond concerns about full deposit recovery contributed to the withdrawals. In fact, while most bank runs in history have been driven by deteriorating bank fundamentals that leads to concerns about deposit safety (Correia, Luck, and Verner 2023), non-systematic runs triggered by sudden deposit outflows also impact output and financial stability (Jamilov, König, Müller, and Saidi 2024). Our paper unpacks deposit shuffling across banks at the depositor level, and provides causes of deposit flows across banks with micro-founded evidence unrelated to bank fundamentals. We show that these economic forces driving depositor alertness persist among FDIC-insured depositors.

Our findings suggest payment plays an important role in depositor alertness, contributing to a growing literature in macro-finance that demonstrates the significant impact of payment risks on macroeconomic outcomes and optimal policy design (e.g., Lagos and Wright 2005, Piazzesi, Rogers, and Schneider 2021, Piazzesi and Schneider 2021, Bianchi and Bigio 2022). However, as the demand for payment convenience becomes higher relative to that for storage convenience, banks face a more challenging liquidity management problem (e.g., Freixas, Parigi, and Rochet 2000, Li and Li 2021, Afonso, Duffie, Rigon, and Shin 2022, Li, Li, and Sun 2022, Acharya and Rajan 2023, Acharya, Chauhan, Rajan, and Steffen 2023, Lopez-Salido and Vissing-Jorgensen 2023), resulting in potentially less efficient lending or higher financial stability risks. Our research traces the origins of such bank-level risks to household balance sheets. The demand by depositors for bank deposits, especially valuing deposits more as a medium of exchange than as a store of value, can fundamentally drive dis-intermediation and financial stability risks at the bank level.

A growing line of research, such as Drechsler, Savov, and Schnabl (2021) and Li, Loutskina, and Strahan (2023), analyzes deposit beta at the bank level, underscoring the roles of interest rate risk, the value of deposit franchises, rate-setting strategies, and deposit market power. More recently, Greenwald, Schulhofer-Wohl, and Younger (2023) highlights the dynamic nature of deposit betas. And closely related to our paper, d'Avernas, Eisfeldt, Huang, Stanton, and Wallace (2023) and Kundu, Muir, and Zhang (2024) find evidence that depositors substitute between liquidity services and deposit rates at a bank level. Our research contributes with an essential layer of granularity by analyzing data at the depositor level, suggesting depositor-level financial risks and transactional demands of money play an important role in the stickiness of banks' deposit base.

The rest of the paper is organized as follows. Section 2 describes the data and the construction of key variables, including the notion of deposit turnover and transfer delay. Section 3 presents a straightforward model to reconcile the new stylized facts and generate new testable hypotheses regarding the channels. Section 4 empirically tests the predictions of the channels. Section 5 establishes causal evidence by introducing a payment technology shock to causally examine the effect of payment speed on depositor behaviors. Section 7 concludes.

2 Deposit Alertness and Delays

In this section, we outline the dataset and detail the construction of key variables, including a novel metric for depositor alertness, termed *deposit turnover* and a measure of payment friction at the depositor level called *transfer delay*, along with a range of household balance sheet variables. We also present a series of novel stylized facts about 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 June 2010 until October 2022. To maintain consistency and mitigate concerns about changes in the population, our analysis focuses on data from 2013 onward. 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.

Following Buda, Hansen, Carvalho, Ortiz, Rodrigo, and Rodriguez Mora (2022), we focus on 0.4 million active users who had ten spending, income, or transfer related transactions each quarter across 36 quarters out of 40 quarters in sample.[1] 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 fin-tech industries, ensuring minimal user selection bias and attrition. We report summary statistics of the users in sample by

[1]There are 1.26million active users in the sample period. However, not all of them have balance data available; to analyze the effects of payment and interest jointly, we restrict the sample to those with balance data available. Note that the empirical results are robust to the sample selection; with the full sample without rate, we also obtain same results for the payment channel.

the end of the section.

2.2 Deposit Turnover

We introduce a new metric, *deposit turnover*, to assess how alert retail depositors are. It measures the total dollar amount of deposits that a depositor transfers across her bank accounts within a given period. The larger the deposit turnover is, the more alert the corresponding depositor is, and the higher the risk it poses to the banks in question. Conceptually, it is consistent with the idea developed in Bolton, Li, Wang, and Yang (2023) and Jermann and Xiang (2023) that deposits represent a debt contract with random maturity, and a larger amount of debt maturing in a given period poses a higher risk on the bank. The deposit turnover metric thus provides a more accurate representation of depositors' activities than looking at the net sum of deposits and withdrawals at the bank level. It helps fill the existing gap in measuring the alertness of retail depositors by leveraging upon more granular data.

To elucidate the concept of deposit turnover and its construction from data, let's consider an example involving two clients at Bank Sanders: Tigger and Winnie. Both Tigger and Winnie had a net inflow of \$500 into their accounts last month, which makes it seem like their deposit activities are analogous. However, when we apply the deposit turnover metric, we uncover a different picture. To determine Tigger's deposit turnover, we examine all his debit and credit transactions exceeding \$50. Suppose Tigger transferred \$100 from his account in Bank Adventures (a debit transaction) to another in Bank Chestnuts (a credit transaction) 10 times. We label these pairs of debit-credit transactions as paired deposit transactions and sum up all such transactions to compute his deposit turnover, which is \$100 $\times$ 10 = \$1,000. On the other hand, Winnie did not transfer any money across his accounts. He did spend \$100 at Piglet's Diner, and the next day he deposited \$30 into his account from selling honey. However, given the monetary difference between the credit (\$30) and debit (\$100) transactions is large, we do not consider them as a paired deposit transaction. Thus, Winnie's deposit turnover is \$0. By employing the deposit turnover metric, the difference in deposit behaviors between Tigger and Winnie becomes evident.

Deposit turnover emerges as a pivotal metric for understanding the alert levels of depositors. To deduce this metric from our data, which is de-identified and lacks bank identifiers or personally identifiable information, we adopt a specific algorithm informed by regulatory frameworks governing transfers. The cornerstone of this approach is the Expedited Funds Availability Act, known as Reg CC. According to Reg CC, for wire transfers between banks, the obligation is 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 times and fees.

In the data, we target transactions related to deposits and transfers to filter out the wire transfers and ACH transfers across banks, based on the processing times and fee differences. For each outgoing and incoming bank transfer deemed deposits/savings/transfers by banks, we record the dollar value of each transaction C (for credit transaction) and D (for debit transaction). A transaction is designated as a *paired deposit transaction*, represented as (C, D), subject to the following conditions:

1. Account distinction: C and D are from *different* accounts of the same depositor.
2. Value threshold: Both the values of C and D are larger than 50, to make sure we are not capturing small fees/refunds across accounts.
3. Small monetary difference: The absolute difference between D and C, $|D - C|$ is smaller than \$50 if D occurs on the same day or next business day after C, and smaller than \$10 if the time between D and C is bigger than one business day (but no more than than five business days).[2]

[2]While ACH transfers generally incur minimal fees, bank wire transfers can be expensive. An analysis of the costs associated with wire and ACH transfers across leading U.S. banks informed these thresholds. For details of wire

4. Temporal constraint: The temporal difference between the two transactions does not exceed five business days, with the incoming (C) transaction occurring after the outgoing (D) transaction. In cases where several outgoing transactions correspond to a single incoming transaction, the one with the shortest time interval is selected.[3]

After extracting all paired deposit transactions indexed by k, we aggregate the transactions by depositor and month. The deposit turnover for depositor i in month t is defined as

$$Deposit\ Turnover_{i,t} = \Sigma_k C^k_{i,t}.$$

While our deposit turnover metric offers valuable insights into the alertness of depositors, it does have some limitations. For instance, it does not capture other kinds of financial activities like investments in money market funds, and it may be influenced by individual depositor's preferences such as financial prudence and risk aversion, although these factors may be partly addressed through depositor-level fixed effects.

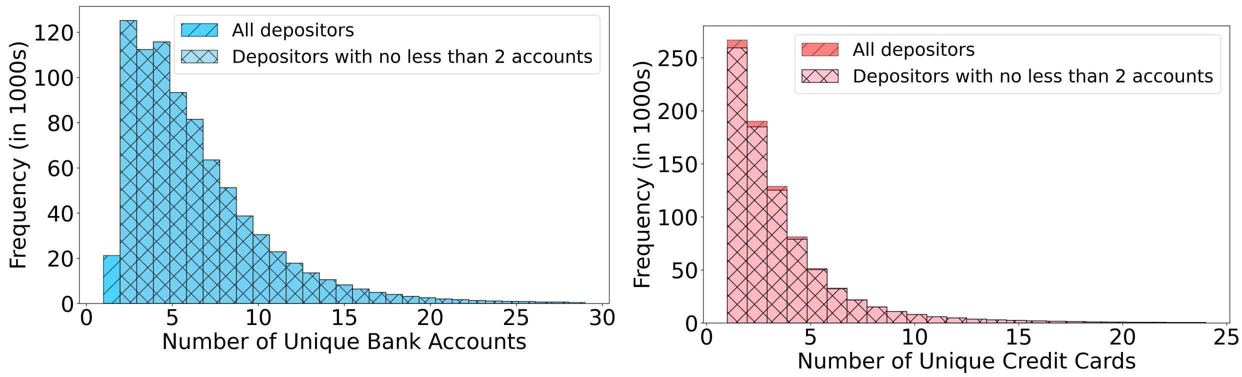
Note that the notion of interbank deposit transfers is only well-defined if depositors possess multiple bank accounts. Although the information about the number of bank accounts per American is limited, a 2019 survey by the Mercator Advisory Group indicated that the average number of bank accounts is 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.

Types of Deposit Turnover. Using the meta information and transfer delays for paired deposit transactions, we further distinguish deposit turnover based on the method of transfer used. Our study primarily concentrates on bank-to-bank transfers due to their crucial impact on the stabil-

transfer charges, please refer to Appendix A.

[3]This approach is designed to minimize the possibility of counting duplicate transactions. For example, if Tigger holds another account at Pooh Bank, he could transfer $100 to Pooh Bank before moving it to Bank Chestnuts. These steps would result in three separate records: (1) from Bank Adventures to Pooh Bank, (2) from Pooh Bank to Bank Chestnuts, and (3) directly from Bank Adventures to Bank Chestnuts. The rule of choosing the transaction with the smallest temporal gap helps to avoid such duplication when all movements occur within a similar timeframe.

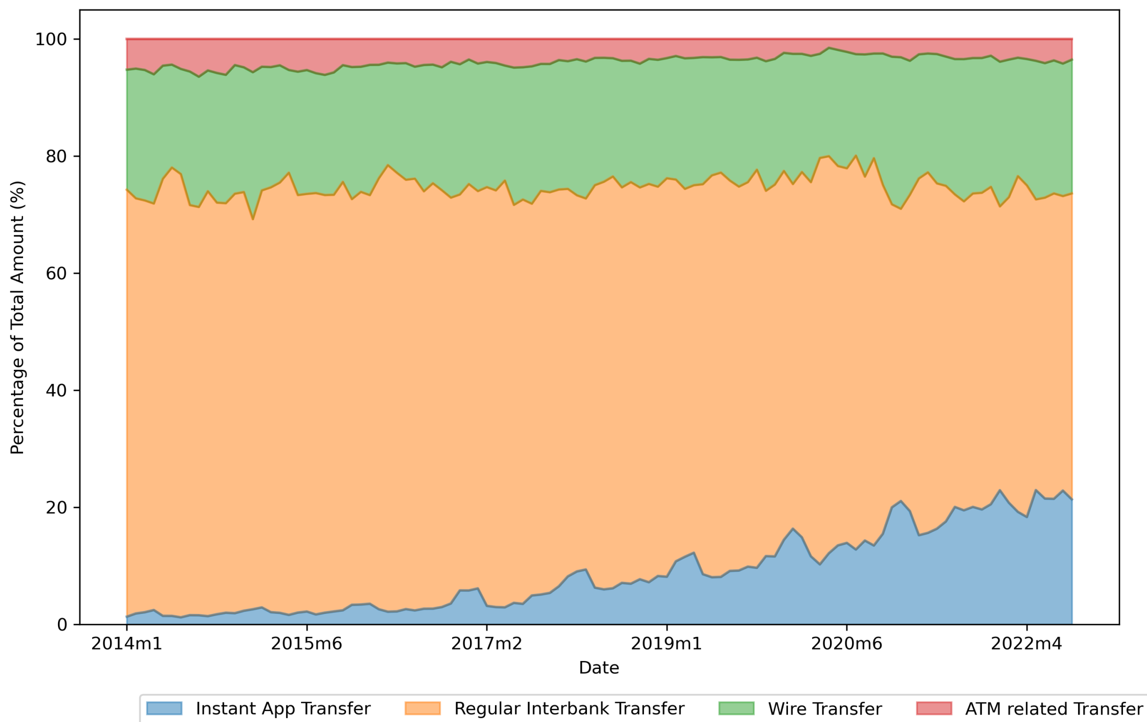
Figure 1: Bank Accounts and Credit Cards per Depositor



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.

ity of the banking sector. Consequently, in the following analysis, we do not consider intrabank transfers that are initiated and settled within the same bank; instead, analysis below focus on interbank transfers with delays, and those initiated by fast payment services such as Zelle, Cash App, and Venmo, along with a limited selection of transactions identified with ATM-related details, as illustrated 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 self deposit tranfers with a non-zero transaction delay that do not fall into the categories of ATM-related, instant payment app 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. Nevertheless, in Appendix A, we report evidence of fee differences for different payment methods of interbank transfers.

Figure 2: Types of interbank turnover

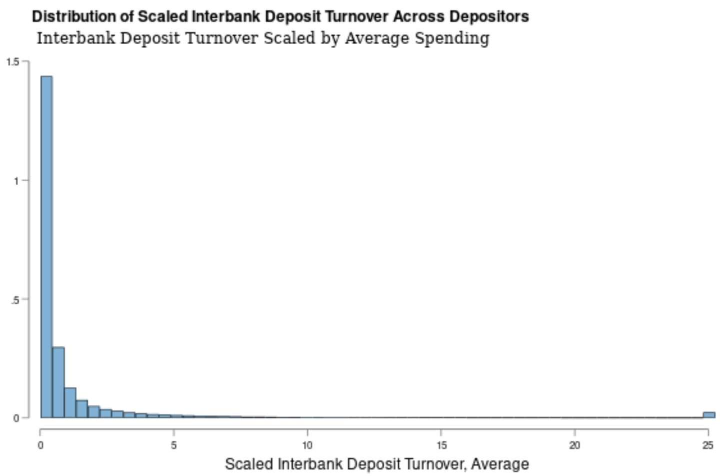


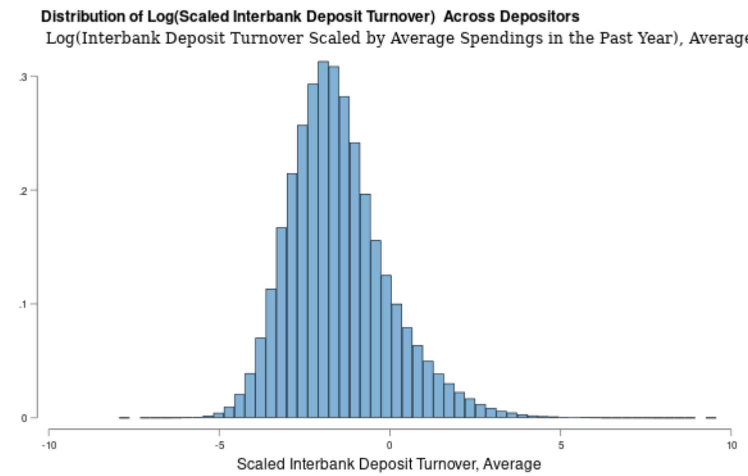
This graph delineates multiple types of interbank transfers in our sample between 2015 and 2022. Depositors have the option to reallocate deposits between accounts held at the same financial institution or to transfer assets to an alternate bank. Transactions marked with fast payment services (such as Zelle, PayPal, Cash App, and Venmo) are classified as "Instant App Transfer" (blue at the bottom). Transactions that settle 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 settled 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.

Scaled Interbank Deposit Turnover. To put this novel metric into context, we plot the distribution of average monthly depositor turnover, scaled by average monthly spendings in the preceding year following the suggestions in Attanasio and Pistaferri (2016), to assess how "active" depositors are in the cross section. Plot (a) in Figure 3 reveals that for most depositors, the average interbank deposit turnover ranges from 0% to 50% of their average spendings. Plot (b) in Figure 3 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.

Cross Validating Interbank Deposit Turnover using Fedwire Volumes. To further validate our interbank deposit turnover measure, we compare the percentage changes in monthly interbank deposit turnover (green) to the percentage changes in Fedwire volume (blue) for a sample period between 2014 and 2022. Figure 4 illustrates this comparison. The comparison shows a significantly positive correlation between the two time series, indicating that the changes in our interbank deposit turnover measure are likely driven by economic fundamentals and payment needs, which at the same time influence total interbank transfers settled in the Fedwire system. It is important to note that we use changes in Fedwire volumes to cross-validate changes in our constructed measure, rather than implying causation between the two measures. Understanding the economic relationship between interbank deposit turnover and Fedwire volumes, and identifying the common drivers behind them remains an interesting question we leave for future research.

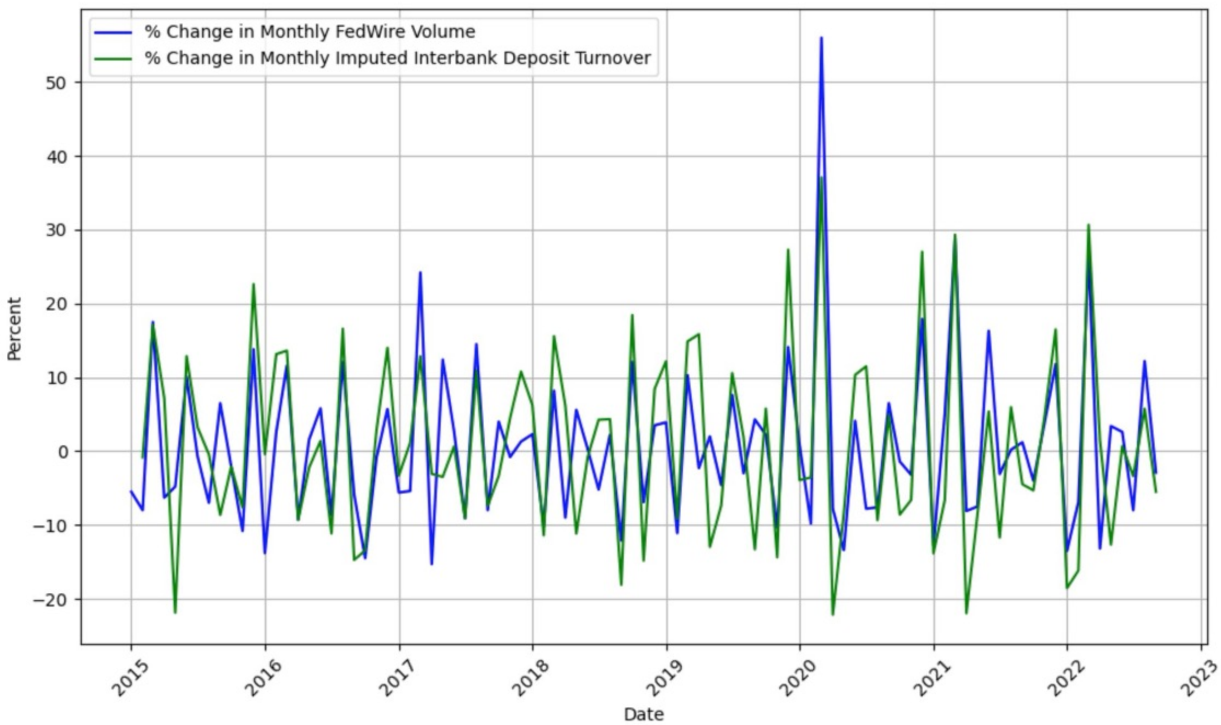
Figure 3: Distribution of Scaled Interbank Deposit Turnover





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 timepoint 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.

Figure 4: Interbank deposit turnover v.s. Fedwire volumes



This graph compares the percentage changes in monthly interbank deposit turnover (green) to the percentage changes in the volume of Fedwire (blue) in a sample between 2014 and 2022. Aggregate data for monthly Fedwire volume is obtained from the Federal Reserve Bank of New York.

2.3 Payment Frictions

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,

$$Delay_k = Date(C_k) - Date(D_k), \tag{1}$$

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.

To ensure accuracy, we 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,

$$AvgDelay_{a,t} = \frac{\Sigma_k Delay_k \cdot \mathbf{I}(D_k \text{ is originated from account } a)}{\Sigma_k \mathbf{I}(D_k \text{ is originated from account } a)}. \tag{2}$$

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

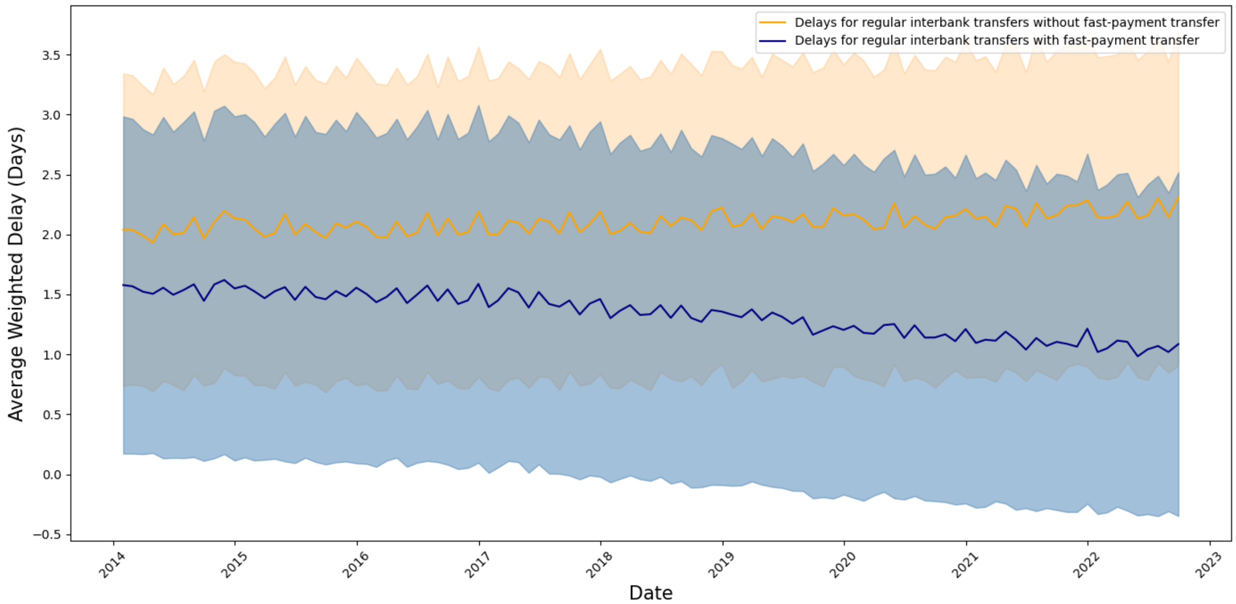
$$PaymentDelay_{Depositor,t} = \frac{\Sigma_a D_{a,t} \times AvgDelay_{a,t}}{\Sigma_a D_{a,t}}. \tag{3}$$

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

[4] It's worth noting that we assume the delay in a given account's payment processing is independent of the transaction's value.

Figure 5: Transfer Delays Over Time



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

over time.

Table 1 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. Intriguingly, this table suggests a trend where larger deposit transfers tend to coincide with shorter delays, suggesting a potential endogenous efficiency in processing higher-value transactions.

Table 1: Average Amount by Transfer Delay

Delay (in days)	Mean ($)	SD ($)	Median ($)	P10 ($)	P90 ($)	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.

2.4 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, and manually filtered 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*$_{it} = max_a i_{i,a,t} - min_a i_{i,a,t}$.

Financial Obligations. To measure uncertainty in financial obligations for individual depositors, we analyze bank transactions associated with credit card payments, personal loans, and mortgage repayments. In the sample, the median credit card payment amounts to \$3,498, while the median payments for loans and mortgages are \$870.

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 act 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. In the data, about 26% of depositors incurred overdraft fee during the sample period, and about 3% of depositors opted in overdraft protection services.

Labor Income. We construct salary income from credit transactions that are either categorized under 'Salary/Regular Income' or contain payroll-related terms in their description. We excluded 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-validated the aggregate trend with labor income dynamics of depositors in our dataset to those in the Panel Study of Income Dynamics.

Consumption Stability and Financial Indicators. Analyzing depositor behavior requires a look at how people adjust their consumption, especially when they face unpredictable income shocks. Depositors frequently experience changes in income may change their spending patterns more often. As a result, these depositors are likely to be more alert to changes in interest rates. We introduce a *consumption smoothing efficiency* (CSE) metric to capture each depositor's relative steadiness of consumption at any given time. CSE is computed 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. CSE provides a standardized measure, allowing for a comparative analysis of consumption behaviors. 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.

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 adoption 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 comfort with online payment. Digital adoption ratio highlights a depositor's trust in technology, accessibility to digital platforms, and preference for transactional convenience.

Table 2 provides summary statistics for the variables, highlighting substantial volatility in deposit turnover (the average deposit turnover is \$7229.3, with a standard deviation of \$25441) and dollar-weighted delays (2.1 days on average with 1-day standard deviation). It's important to note that calculations for deposit turnover and transfer delays in the table are based solely on interbank self-deposit transactions, as intrabank transfers are instantaneous and present minimal payment risk for banks.A contributing factor to the observed high 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 are 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 transfer delays over time. Another factor contributing to the high rate of deposit turnover is account specialization. Figure 1 in Internet Appendix B shows depositors utilize different bank accounts for specific purposes, which suggests a need to frequently transfer deposits between one's own accounts to meet various liquidity requirements. A digital adoption ratio of 0.49 indicates moderate technological engagement. Additionally, the percentage of depositors using fast payment applications stands at 37%, suggesting a notable but not predominant use fast payment platforms.

Table 2: Summary Statistics

	mean	sd	p50	p10	p90	count
Transfer Fees	4.40	4.35	3.42	0.00	10.00	418,697
Transfer Delay	2.01	0.94	1.85	1.00	3.25	256,322
Salary	4759.14	3827.81	3900.24	817.13	9527.33	289,181
Rate Dispersion (%)	0.18	0.30	0.07	0.01	0.48	418,697
Payment Advance Ratio	0.32	0.27	0.29	0.10	0.60	417,930
Mean Interest Rate (%)	0.09	0.15	0.04	0.01	0.20	418,697
Financial Obligations	4490.12	3816.07	3498.19	778.24	9412.09	404,434
Deposit Turnover	2155.86	1695.39	1612.68	405.75	5032.22	418,697
Consumption Smoothing Efficiency	2.72	1.44	2.55	1.06	4.59	418,663
Account Balance	25471.91	55998.65	6671.17	1470.72	62834.91	418,697
% Depositors with Overdraft Protection	5%					418,697
% Depositors with Outflows from Fast Payment Apps	61%					418,697
% Depositors Used Fast Payment Apps	66%					418,697
% Depositors Overdrafted	18%					418,697

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. Financial Obligations sums up all payments to credit card, personal loans and mortgages for each depositor and is reported in dollar amount. 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 Adoption 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 Adoption Ratio, Consumption Smoothing Efficiency, and Account Balance.

3 A Model of Deposit Demand with Payment Delays

The depositor level data reveals new facts about deposit dynamics that standard economic order quantity models cannot explain. In particular, we find that deposit transfers are lumpy, and that depositing activities are sensitive to transfer delays. To capture these dynamics, we develop an inventory model of depositor money management between two bank accounts, aimed at funding consumption and earning interest in the spirit of Baumol (1952) and Tobin (1956). The contribution of our model is to extend the Baumol-Tobin framework by incorporating uncertain settlement delays between accounts and analyzing how these delays influence deposit behavior, compared to notable studies in the modern literature that focus on transaction costs (e.g., Alvarez and Lippi 2009, Kaplan and Violante 2014). The model enables us to evaluate the effects of faster payment systems and monetary cycles on deposit flows jointly, and we calibrate the model to assess the impact of delayed payments, viewing them through the lens of interest rate fluctuations.

Time is modeled as continuous. A representative depositor 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 to repay her interest-bearing liabilities, such as mortgage and auto loan repayments, while deposits in bank account S are interest-bearing with an exogenous interest rate of $r > 0$. Specifically, suppose the total repayment amount is constant: let $cr > 0$ denote the constant flow of interest repayments from bank account C. 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 in this sense, we also refer to r as the interest rate dispersion in this simple two-bank 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 settled only after a delay, modeled by an independent Poisson arrival rate κ. Importantly, these deposits in transfer can neither earn interest earnings nor be used for interest repayments. This captures the potential losses due to delays in deposit transfers. Additionally, we assume that when $m = 0$, meaning bank account C has a zero balance, a deposit transfer from bank account S to account C incurs no delays but does involve a penalty $b > 0$, irrespective of the transfer size. This penalty can be interpreted as the 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 \$1,470. 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_i made at t_i and settled 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_j are made at t_j, when the balance in account C hits 0:

$$V(m) = \min_{x_i, t_i} E_0 \left[r \int_0^{\infty} m(t) e^{-rt} dt + r \sum_i E_{t_i} \left[\int_{t_i}^{t_i'} |x_i| e^{-rt} dt \right] + b \sum_j e^{-rt_j} \right] ,$$

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 between the two accounts, where the expectation is taken with respect to the Poisson process that governs payment delays, and the third term captures expected penalties. Accordingly, the law of motion for m is given by

$$dm(t) = -cdt + \sum_i \left(1_{x_i>0} x_i \delta_{t_i'} + 1_{x_i<0} x_i \delta_{t_i} \right) + \sum_j y_t \delta_{t_j} \,,$$

where an incoming transfer into account C incurs a delay before being settled 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 an optimal target for m: $0 < \underline{m} < m^* < \overline{m}$. 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 Bellman equations:

$$rV(m) = \begin{cases} rm - crV'(m) + \kappa(V(m^*) - V(m)) + r(m^* - m)\,, & 0 \le m \le \underline{m}\,, \\ rm - crV'(m)\,, & \underline{m} \le m \le \overline{m}\,, \\ rm - crV'(m) + \kappa(V(m^*) - V(m))\,, & m \ge \overline{m}\,, \end{cases}$$

where the first term rm gives the carry cost of balance in account C, the second term $-crV'(m)$ 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, the third term gives the expected change in the value function conditional on a timely transfer, while the last term given the expected change in the value function conditional on a delay.

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 panelty 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 "smooth pasting" condition:

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

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

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

and

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

as well as two "super contact" conditions:

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

and

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

implying that the value function and its first-order derivative are both continuous at the two thresholds.

We solve for the optimal policy and derive the following results:

Proposition 1. *The size of the inaction region $\overline{m} - \underline{m}$ in the optimal transfer policy decreases in κ, r, and c. This implies that deposit turnover increases when the payment technology is more efficient, when the interest rate dispersion between banks is higher, and when interest repayments* *are higher.*

Proposition 1 offers new insights into how deposit turnover is influenced by payment technology, interest rate dispersion, and the depositor's interest repayment burden. These insights point to the two fundamental roles of deposits as a means of payment and a store of value, respectively.

First, depositors more actively shift their deposits between the two bank accounts when the payment technology linked to their accounts is more efficient. We refer to this as the payment channel, which captures the role of deposits as a means of payment. Intuitively, when the time required to settle a deposit transfer between banks is reduced, the depositor incurs lower opportunity costs during the transfer process. This encourages more transfers to capitalize on potential gains. This channel emphasizes the significant role of deposits in household portfolios as a means of payment. As payment technology improves and delays in deposit transfers shorten, deposits become more convenient for transactions, prompting depositors to transfer funds more actively across accounts to meet their transactional needs.

Second, depositors are more likely to shift their deposits between accounts when the interest rate dispersion between them is greater or when the interest repayment burden is higher. We call this the interest channel, which captures the role of deposits as a store of value. Importantly, the interest channel not only reflects potential gains from higher interest earnings by shifting deposits but also the savings achieved by avoiding interest-repayment-related costs, as discussed in Kaplan and Violante (2014), which might arise from delayed transfers between accounts. Specifically, a higher interest rate dispersion makes deposits in bank account S a relatively better store of value, while a higher interest repayment burden makes deposits in bank account C more valuable. In both cases, the depositor optimally transfers deposits between these two accounts to maximize the role of deposits as a store of value.

The intuition behind the deposit turnover problem can be further understood from two complementary perspectives, which we will discuss in order.

First, given our focus on payment technology and transfer delays, it is particularly helpful to analyze the model at the two limiting cases of $\kappa \to 0$ and $\kappa \to 1$, representing infinite delays and instant payments, respectively. When $\kappa \to 0$, any transfer between the two bank accounts would incur an infinite cost of delay, offering no benefits at all. In this scenario, the inaction region becomes infinitely wide, effectively resulting in no deposit turnover. Conversely, when $\kappa \to 1$, transfers between the two accounts can occur instantaneously. In this case, the model simplifies to a special case of the Alvarez and Lippi (2009) model, where the transfer fee is zero and the opportunity for free transfers is constant.

Additionally, it is 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 payment 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.

4 What Drives Deposit Alertness: Testing the Channels

In this section, we empirically test the predictions in Section 3. First, we show that depositors with slower payment technology move less funds across bank accounts. Second, we demonstrate that uncertainty in financial obligations and rate dispersion across bank accounts increase deposit alertness, but the effects are dampened when depositors face high transfer delays. We further show that the depositor alertness driven by payment and interests are not affected by FDIC deposit insurance limits; insured depositors remain more alert when payment frictions are high and interest dispersion across accounts is large. Finally, we show that the intrabank deposit turnover – that is, funds transfers across bank accounts within the same bank – is not affected by payment frictions nor interests, suggesting the payment and interest dynamics only affect deposit alertness via activities across banks, which can pose payment risk to banks in the cross section.

4.1 Payment Speed and Deposit Turnover

We investigate the effects of transfer frictions, in the form of transfer delays in interbank deposit transfers, on depositor alertness using the following empirical model:

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

$\textit{Deposit Turnover}_{i,t+1}$ represents the deposit movements across different banks for depositor i within the month $t+1$. $\textit{Transfer Delay}_{i,t}$ represents 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. We incorporate time-fixed effects δ_t to highlight differences in deposit activity across various depositors.

We also include a set of depositor-specific covariates in $\mathbf{X}_{i,t}$ to address other characteristics across depositors that can affect deposit alertness in addition to transfer delays. First, we control for uncertainty in each depositor's balance sheets - including their financial obligations (personal loans, mortgage, and credit card debt), and potential interest income captured by rate dispersion across their savings and checking accounts defined in Section 2. Second, we take into considerations financial constraints, including salary and consumption smoothness. Third, we also consider the digital adoption ratio, which compares non-physical to total consumption and reflects a depositor's inclination towards newer, faster technologies.

We report results in two panels in Table 3. First, we report how payment technology and interest drive the raw deposit turnover in dollar amount. Second, we present logged scaled deposit turnover adjusted by the depositor's average spending over the preceding year to facilitate comparisons across depositors. Columns 1–3 present baseline estimates that confirm the hypotheses of the payment channel in Section 3. The data indicate that, when accounting for both time fixed effects and depositor-specific variables, each additional day of delay in interbank transfers reduces deposit turnover by approximately \$160 (Column 3), a significant and consistent result across various models. This supports the *payment channel*: faster payment is associated with higher deposit turnovers. This pattern implies that depositors are highly responsive to the efficiency of payment technologies, proactively managing their deposits across different accounts to minimize transaction delays.

4.2 Financial Uncertainty and Deposit Turnover

We extend our analysis to explore how transfer frictions influence depositor responsiveness conditional on interest rate exposure:

$$\begin{aligned}\textit{Deposit Turnover}_{i,t+1} = \beta_0 + \beta_1 \cdot \textit{Transfer Delay}_{i,t} + \beta_2 \cdot \textit{Rate Dispersion}_{i,t} + \\ \beta_3 \cdot \textit{Transfer Delay}_{i,t} \cdot \textit{Rate Dispersion}_{i,t} + \beta_4 \cdot \textit{Debt Repayment}_{i,t} + \\ \beta_5 \cdot \textit{Transfer Delay}_{i,t} \cdot \textit{Debt Repayment}_{i,t} + \Gamma \cdot \mathbf{X}_{i,t} + \delta_t + \epsilon_{i,t}.\end{aligned}$$

As above, $\textit{Deposit Turnover}_{i,t+1}$ quantifies monthly deposit activity for depositor i. $\textit{Transfer Delay}_{i,t}$

Table 3: Deposit Turnover & Transfer Delays

	(a) Interbank Deposit Turnover			(b) Log(Scaled Interbank Deposit Turnover)		
	(1)	(2)	(3)	(4)	(5)	(6)
Transfer Delay	-172.0***	-161.8***	-160.6***	-0.128***	-0.114***	-0.111***
	(3.404)	(3.077)	(2.998)	(0.00833)	(0.00693)	(0.00668)
Month fixed effect	Y	Y	Y	Y	Y	Y
Interest rate controls	Y	Y	Y	Y	Y	Y
Budget constraint controls	N	Y	Y	N	Y	Y
Liquidity & sophistication controls	N	N	Y	N	N	Y
N	1121834	1121834	1121834	432418	432418	432418
Adj. R^2	0.0118	0.0303	0.0320	0.0969	0.164	0.172

This table presents the relation between each depositor's transfer delays at time t and deposit turnover$_{i,t+1}$, which gauges the alertness with which a depositor i transfers deposits between accounts in month $t+1$, focusing on the cross-section of depositors. Deposit turnover is derived from interbank deposit transactions. Interbank deposit transactions include transfers between different banks that have any transfer delay, and immediate transfers facilitated by services such as Zelle, Cash App, and Venmo, along with a limited selection of transactions identified with ATM-related details. Transfer delays are measured in days. Focusing on the heterogeneity of depositors, we introduce three relevant groups of depositor-level controls: 1) Budget constraint controls, including a) debt repayment (\$), the payment to the amount of debt outstanding for depositor i at month t, b) Salary is the total monthly labor income of depositor i at month t; in panel b, all three variables are scaled by the rolling average of spending for the preceding year between months $t-11$ and t for depositor i to facilitate inter-person comparisons. 2) Liquidity and Sophistication constraint controls, including a) Consumption smoothing efficiency, defined as the ratio of the rolling mean to the rolling standard deviation of consumption using monthly data from the previous 12 months for each depositor i at month t, b) Digital adoption ratio which is the ratio between non-physical and total consumption for each depositor at month t; 3) Interest rate difference across accounts for depositor i at time t, defined as $max_{i,t}r_{i,a,t} - min_{i,t}r_{i,a,t}$. The dependent variable is Deposit Turnover$_{i,t+1}$, that is, the dollar amount moved among each bank account for depositor i at month $t+1$.

In Panel (b), to enable cross-individual comparisons, we present logged scaled deposit turnover adjusted by the depositor's average spending over the preceding year ($t-11$ to t). All depositor-level variables are scaled by the rolling average spending as well. This ensures that the analysis reflects relative percentage changes and differences in depositors' behavior, taking into account their consumption patterns, which provides a normalized basis for comparing the financial activities across a diverse set of depositors. All 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%.

denotes the average time taken for transactions, rolling over prevailing 12 months to accommodate sporadic transfer activities. We capture interest rate exposure in two forms: first, debt repayment ($), the payment to the amount of debt outstanding for depositor i at month t, second, interest rate dispersion (percentage point) across accounts for depositor i at time t, defined as $max_{i,t}r_{i,a,t} - min_{i,t}r_{i,a,t}$. The dependent variable is Deposit Turnover$_{i,t+1}$, that is, the dollar amount moved among each bank account for depositor i at month $t + 1$. , with δ_t capturing time fixed effects to focus on cross-sectional differences among depositors. As above, we introduce depositor-level controls including salary is the total monthly labor income of depositor i at month t, consumption smoothing efficiency, defined as the ratio of the rolling mean to the rolling standard deviation of consumption using monthly data from the previous 12 months for each depositor i at month t, digital adoption ratio which is the ratio between non-physical and total consumption for each depositor at month t.

Table 4 summarize estimates aligning with the interest risk channel outlined in Section 3. When considering the interaction between transfer delays and interest rate dispersion, there's an additional, negative effect on deposit turnover. Specifically, the data show that with all variables controlled, each additional day of transfer delay combined with a one-perecntage-point increase in interest rate dispersion leads to a decrease of $66 in deposit turnover, as noted in Column 3, suggesting that depositors with higher payment frictions are less likely to move funds across accounts to shop for interest rates.

From the perspective of aggregate financial stability, the emphasis is placed on the average dollar rather than the average behavior of a depositor, hence deposit turnover, measured as dollar volume, is a useful metric. However, given the significant cross-sectional variation among depositors shown in Figure 3, we also present turnover figures normalized by average spending in the prevailing year for each depositor. This standardized metric enables more meaningful cross-sectional comparisons and demonstrates the robustness of our findings across various measures.

Table 4: Deposit Turnover, Transfer Delays and Interest Exposures

	(a) Interbank Deposit Turnover			(b) Log(Scaled Interbank Deposit Turnover)		
	(1)	(2)	(3)	(4)	(5)	(6)
Transfer Delay	-153.0***	-143.1***	-137.4***	-0.115***	-0.120***	-0.108***
	(3.016)	(3.657)	(3.473)	(0.00820)	(0.00801)	(0.00669)
Rate Dispersion	539.6***	533.4***	505.2***	0.105***	0.0944***	0.0803***
	(19.45)	(19.36)	(18.88)	(0.00367)	(0.00338)	(0.00298)
Transfer Delay × Rate Dispersion	-68.24***	-67.84***	-66.36***	-0.0210***	-0.0187***	-0.0169***
	(5.970)	(5.958)	(5.885)	(0.00318)	(0.00297)	(0.00273)
Financial Obligations		0.0211***	0.0187***		0.438***	0.296***
		(0.00131)	(0.00130)		(0.00819)	(0.00755)
Transfer Delay × Financial Obligations		-0.00176***	-0.00190***		-0.00311	-0.00148
		(0.000419)	(0.000413)		(0.00525)	(0.00466)
Month fixed effect	Y	Y	Y	Y	Y	Y
Depositor controls	Y	Y	Y	Y	Y	Y
N	1121834	1121834	1121834	432418	432418	432418
Adj. R^2	0.0219	0.0243	0.0322	0.0461	0.106	0.172

This table presents the relation between each depositor's transfer delays and rate exposures at time t and deposit turnover$_{i,t+1}$, which gauges the alertness with which a depositor i transfers deposits between accounts in month $t+1$, focusing on the cross-section of depositors, for the subset of depositors insured by FDIC. Deposit turnover is derived from interbank deposit transactions. Interbank deposit transactions include transfers between different banks that have any transfer delay, and immediate transfers facilitated by services such as Zelle, Cash App, and Venmo, along with a limited selection of transactions identified with ATM-related details. Transfer delays are measured in days. We capture interest rate exposures via two measures: on the asset side, we use the difference between the highest and lowest rate offered by bank accounts to capture potential shopping for rate incentives; on the liability side, we proxy rate exposure using monthly mortgage and personal loan repayment. Focusing on the heterogeneity of depositors, we introduce depositor-level controls including salary is the total monthly labor income of depositor i at month t, consumption smoothing efficiency, defined as the ratio of the rolling mean to the rolling standard deviation of consumption using monthly data from the previous 12 months for each depositor i at month t, digital adoption ratio which is the ratio between non-physical and total consumption for each depositor at month t. The dependent variable is Deposit Turnover$_{i,t+1}$, that is, the dollar amount moved among each bank account for depositor i at month $t+1$.

In Panel (b), to enable cross-individual comparisons, we present logged scaled deposit turnover adjusted by the depositor's average spending over the preceding year ($t-11$ to t). All depositor-level variables are scaled by the rolling average spending to reflect relative percentage changes and differences in depositors' behavior, taking into account their consumption patterns. All 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%.

Columns 4–6 in Table 3 and Table 4 report results from the standardized variables. Specifically, in panel (b) of Table 3 and Table 4, we scale the depositor-level variables by the average spending for depositor i in the preceding year (i.e., the moving average from month $t-11$ to month t, excluding the current month $t+1$ to avoid mechanical correlation), and additionally standardize transfer delays; i.e., a one unit increase is equivalent to a one-standard-deviation increase in *Transfer Delay*$_{i,t}$. Column 6 in Table 4 suggests that without interest rate dispersion across accounts, one-standard-deviation increase in transfer delays decreases scaled interbank turnover by 11% while an additional one-percentage-point increase in interest rate dispersion leads to another 1.7% decrease in scaled interbank turnover. Having interest exposure on the liability side, such as repayment to mortgages and personal loans, leads to more alertness as depositors transfer more funds across accounts, but is not conditional on payment delays, which is likely that most debt repayments are not subject to rate fluctuations and can be planned with sufficient time that overcomes payment frictions.

4.3 Do Uninsured Deposits Drive Depositor Alertness?

It is well-known that bank run risk is driven by uninsured deposits (e.g., Diamond and Dybvig 1983, Dávila and Goldstein 2023), which has been particularly pronounced during the 2023 regional bank crisis (e.g., Chang, Cheng, and Hong 2023, Drechsler, Savov, Schnabl, and Wang 2023). As we discuss before, our notion of deposito alertness is conceptually different from bank run risks because it is directly related to the roles of deposits as means of payment and store of value, rather than directly related to bank run risk. To make sure our notion of deposit alertness and it sensitivity to payment and interests are not driven by concerns related to FDIC insurance, we restrict our sample to depositors with total balances lower than $\$250,000$ throughout the sample period. Table 5 shows that the subsample with only insured depositors yield similar results as the full sample, suggesting our notion of depositor alertness is not driven by uninsured deposits.

Table 5: Deposit Turnover for Insured Depositors

	(a) Interbank Deposit Turnover			(b) Log(Scaled Interbank Deposit Turnover)		
	(1)	(2)	(3)	(4)	(5)	(6)
Transfer Delay	-151.1***	-144.0***	-138.4***	-0.115***	-0.119***	-0.107***
	(3.062)	(3.601)	(3.433)	(0.00847)	(0.00831)	(0.00694)
Rate Dispersion	531.1***	523.9***	496.5***	0.103***	0.0921***	0.0781***
	(19.94)	(19.84)	(19.34)	(0.00376)	(0.00347)	(0.00308)
Transfer Delay × Rate Dispersion	-65.61***	-65.17***	-63.71***	-0.0217***	-0.0190***	-0.0174***
	(6.003)	(5.985)	(5.906)	(0.00328)	(0.00306)	(0.00281)
Financial Obligations		0.0194***	0.0172***		0.426***	0.291***
		(0.00133)	(0.00132)		(0.00813)	(0.00762)
Transfer Delay × Financial Obligations		-0.00131***	-0.00144***		-0.00283	-0.00171
		(0.000433)	(0.000427)		(0.00533)	(0.00475)
Month fixed effect	Y	Y	Y	Y	Y	Y
Depositor controls	Y	Y	Y	Y	Y	Y
N	1040062	1040062	1040062	401168	401168	401168
Adj. R^2	0.0218	0.0238	0.0316	0.0479	0.105	0.168

This table presents the relation between each depositor's transfer delays and rate exposures at time t and deposit turnover$_{i,t+1}$, which gauges the alertness with which a depositor i transfers deposits between accounts in month $t+1$, focusing on the cross-section of depositors, for the subset of depositors insured by FDIC. Deposit turnover is derived from interbank deposit transactions. Interbank deposit transactions include transfers between different banks that have any transfer delay, and immediate transfers facilitated by services such as Zelle, Cash App, and Venmo, along with a limited selection of transactions identified with ATM-related details. Transfer delays are measured in days. We capture interest rate exposures via two measures: on the asset side, we use the difference between the highest and lowest rate offered by bank accounts to capture potential shopping for rate incentives; on the liability side, we proxy rate exposure using monthly mortgage and personal loan repayment. Focusing on the heterogeneity of depositors, we introduce depositor-level controls including salary is the total monthly labor income of depositor i at month t, consumption smoothing efficiency, defined as the ratio of the rolling mean to the rolling standard deviation of consumption using monthly data from the previous 12 months for each depositor i at month t, digital adoption ratio which is the ratio between non-physical and total consumption for each depositor at month t. The dependent variable is Deposit Turnover$_{i,t+1}$, that is, the dollar amount moved among each bank account for depositor i at month $t+1$.

In Panel (b), to enable cross-individual comparisons, we present logged scaled deposit turnover adjusted by the depositor's average spending over the preceding year ($t-11$ to t). All depositor-level variables are scaled by the rolling average spending to reflect relative percentage changes and differences in depositors' behavior, taking into account their consumption patterns. All 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%.

4.4 Intrabank versus Interbank Deposit Transfers

Finally, we provide evidence beyond interbank transfers and investigate how the payment and interest channels play out in the context of intrabank transfers. Particularly, we examine whether intrabank depositor transfers serve as an alternative to interbank transfers, especially with higher interbank transfer frictions. We find that depositors with slower bank accounts tend to favor intrabank transfers as a strategy to bypass transfer delays, while as a placebo test, we show that these intrabank transfers show no significant correlation with interest rate risk since they are not subject to transfer delays.

Intrabank transfers between different deposit products, typically completed within the same day, may represent a response by depositors to avoid longer transfer delays across different banks. Table 6 provides evidence that depositors' intrabank transfers do not respond to longer interbank transfer delays, while overall deposit turnover (including both intra- and inter-bank transfers) decrease with longer interbank transfers, suggesting overall payment frictions lower depositing activities through lowered interbank transfers.

5 Identification: Impact of Fast Payments on Depositor Alertness

So far, we have provided evidence of depositor alertness, highlighting two underlying economic channels. Changes in interest rate risk at the macroeconomic level are likely exogenous to individual depositors' investment decisions (akin to the idea that individual depositors are price takers, as interest rates are perceived as the price of time in investment decisions), which gives a plausibly causal interpretation of the interest risk channel. However, regarding the payment channel, depositors who possess slower bank accounts are potentially also the "sleepy" depositors who have smaller deposit turnover, leading to an endogeneity concern of our results on deposit alertness being potentially driven by sleepy depositors self-selecting into slow bank accounts. In this section,

Table 6: Intrabank Transfers and All Transfers

	(I) Bank Transfers by Type				(II) Scaled Bank Transfers by Type			
	(a) Intrabank Transfers		(b) All Bank Transfers		(c) IntrabankTransfers		(d) All Bank Transfers	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Transfer Delay	219.9	-185.6	-802.5***	-864.3**	0.00662	0.000878	0.00352	-0.0280***
	(186.3)	(346.1)	(278.2)	(345.7)	(0.00768)	(0.0116)	(0.0114)	(0.00980)
Rate Dispersion	1908.4***	-1518.0	8519.8***	6328.0***	0.0202***	0.0236***	0.0220***	0.0634***
	(379.8)	(1016.8)	(601.7)	(1157.5)	(0.00421)	(0.00535)	(0.00518)	(0.00463)
Transfer Delay × Rate Dispersion		1543.7***		1297.4**		0.00470		0.00390
		(496.4)		(568.5)		(0.00692)		(0.00602)
Financial Obligations	1.844***	1.996***	2.123***	2.185***	0.289***	0.283***	0.285***	0.298***
	(0.0564)	(0.140)	(0.0824)	(0.141)	(0.0116)	(0.0130)	(0.0124)	(0.0121)
Transfer Delay × Financial Obligations		-0.0515		-0.0367		-0.00692		-0.00534
		(0.0559)		(0.0554)		(0.0123)		(0.0109)
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Depositor Controls	Y	Y	Y	Y	Y	Y	Y	Y
N	389303	188069	188069	188069	177261	94701	94701	94701
Adj. R^2	0.0410	0.0440	0.0474	0.0474	0.0568	0.0579	0.0580	0.0955

This table presents the relation between various depositor-specific attributes at time t and two alternative definitions of deposit turnover: in panel (a), intrabank deposit turnover is computed from the transactions with zero transfer delays and are not associated with instant payment platforms. In panel (b), deposit turnover is derived from all fund transfers including intrabank deposits and interbank deposits. Interbank deposit transactions include transfers between different banks that have any transfer delay, and immediate transfers facilitated by services such as Zelle, Cash App, and Venmo, along with a limited selection of transactions identified with ATM-related details. Transfer delays are measured in days. We capture interest rate exposures via two measures: on the asset side, we use the difference between the highest and lowest rate offered by bank accounts to capture potential shopping for rate incentives; on the liability side, we proxy rate exposure using monthly mortgage and personal loan repayment. Focusing on the heterogeneity of depositors, we introduce three relevant groups of depositor-level controls: 1) Budget constraint controls, including a) debt repayment ($), the payment to the amount of debt outstanding for depositor i at month t, b) Salary is the total monthly labor income of depositor i at month t; in panel b, all three variables are scaled by the rolling average of spending for the preceding year between months $t-11$ and t for depositor i to facilitate inter-person comparisons. 2) Liquidity and Sophistication constraint controls, including a) Consumption smoothing efficiency, defined as the ratio of the rolling mean to the rolling standard deviation of consumption using monthly data from the previous 12 months for each depositor i at month t, b) Digital adoption ratio which is the ratio between non-physical and total consumption for each depositor at month t; 3) Interest rate difference across accounts for depositor i at time t, defined as $max_{i,t}r_{i,a,t} - min_{i,t}r_{i,a,t}$. The dependent variable is Deposit Turnover$_{i,t+1}$, that is, the dollar amount moved among each bank account for depositor i at month $t+1$.

In Panel (II), to enable cross-individual comparisons, we present logged scaled deposit turnover adjusted by the depositor's average spending over the preceding year ($t-11$ to t). All depositor-level variables are scaled by the rolling average spending to reflect relative percentage changes and differences in depositors' behavior, taking into account their consumption patterns. All 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%.

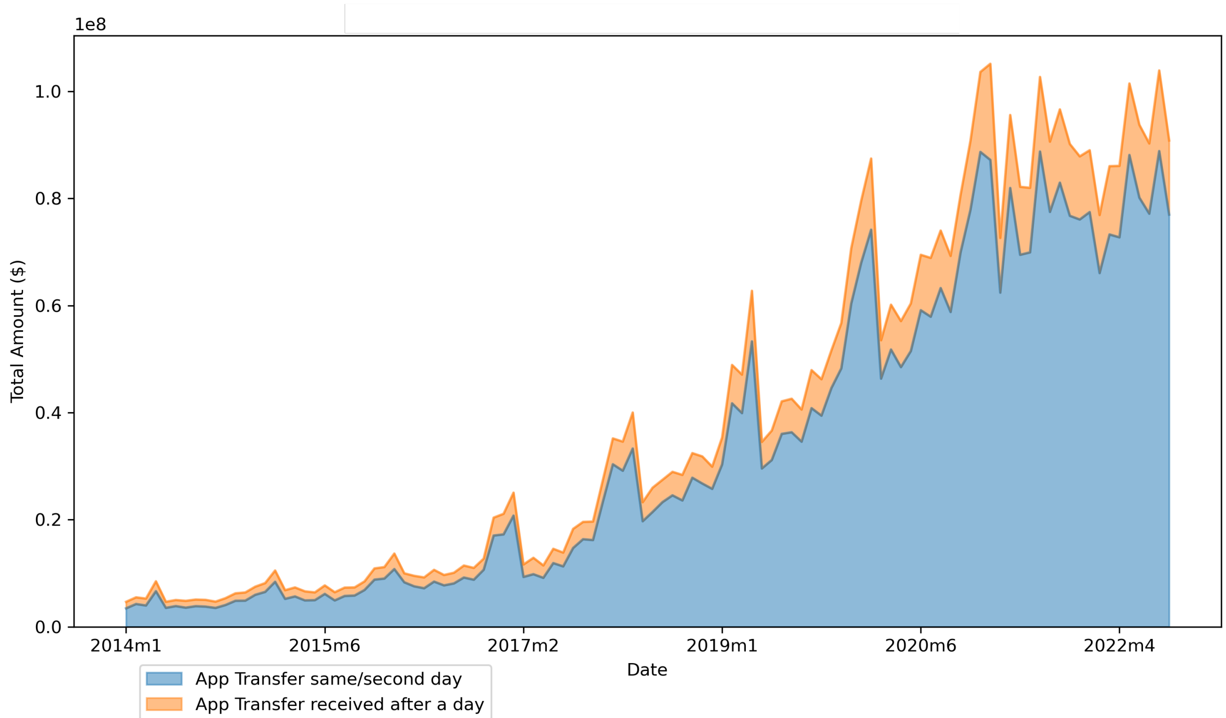
we introduce a natural experiment to causally identify the impact of payment delay on depositor alertness, that is, the payment channel.

Our identification strategy of the payment channel underlying depositor alertness relies on an instrument variable that is built upon the social connectedness of depositors. Previous studies have established that social connectedness and peer interactions affect households' investment decisions (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). Following this strand of literature, we infer depositor-level connectedness from the rich information in our transaction-level data. Specifically, we analyze the depositor-level "payment technology shocks" from another depositor, defined as a depositor's initial encounter with fast payment platforms, which is in turn triggered by an incoming fund transfer using such fast payment platforms from another depositor.

The rapid payment services under consideration in our study are Zelle, PayPal, Venmo, and Cash App — leading providers in the sector. Interbank transfers facilitated through these services typically endure considerably shorter delays. As shown in Figure 6, the bulk of interbank transfers conducted via these fast payment apps are concluded by the same or the following business day.

To give a concrete example, suppose depositor i had never used Zelle before date t. On date t, depositor i received an incoming Zelle transfer from depositor j, which would require depositor i to install and then use Zelle to be able to receive the funds. Such a fund transfer thus exposed depositor i to a payment technology shock in the sense that depositor would be more likely to use Zelle going forward, which would likely affect depositor i's alertness. In general, the adoption of fast payment technologies—marked by the first receipt of incoming funds from another depositor using such technologies—serves as an exogenous shock to the individual's transfer delays, offering a natural venue to observe changes in behavior due to the introduction of significantly faster payment processing speeds. The first time depositors experience the convenience and efficiency of

Figure 6: Transfer Delays and Fast Payment Applications



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

instant transfers, their perceptions and expectations of financial transactions can be substantially changed. This change is likely reflected in their subsequent transaction behavior, making them more inclined to engage in and initiate transfers that offer similar immediacy. This shock captures this exogenous variation in payment speed, likely unrelated to individual depositor characteristics, that induces a shift in the frequency and immediacy with which depositors conduct their banking activities.

To isolate the impact of fast payment technology, we narrow our analysis to the 193,787 depositors who *receive* money through fast payment platforms prior to utilizing them for their transactions. Notably, a majority—approximately 76%—of depositors initially employed these platforms for payment purposes to individuals and merchants before experiencing any inbound transactions through the same channels.

It is important to note that our network instrument hinges on the assumption that the *timing* of the initial rapid payment inflow is exogenous, which is considerably less demanding than the requirement for the exogeneity of a depositor's social network formation. Although depositors may engage in transactions with an endogenously formed set of individuals, these interactions are much less likely to predict the exact timing of the initial receipt of rapid payment inflow.

Nevertheless, the initial receipt of funds from fast payment platforms could coincide with a change in financial habits, such as an increased propensity to engage with digital financial services, which could also affect depositor turnover independently of payment delays. Furthermore, the initial transaction made through a fast payment application might represent an unforeseen financial gain, similar to obtaining a bonus or a gift, which could also affect deposit turnover. To address these potential confounders, our analysis incorporates controls for depositor-level characteristics alongside the instrumented transaction delays. Specifically, we estimate a two-stage least square:

$$
\begin{aligned}
\text{Transfer Delay}_{i,t} &= \gamma_0 + \gamma_1 I(\text{Post } \widehat{\text{First Inflow}})_{i,t} + X_{i,t} + \delta_t + \varepsilon_{i,t}, \\
\text{Deposit Turnover}_{i,t} &= \beta_0 + \beta_1 \widehat{\text{Transfer Delay}}_{i,t} + \beta_2 (\widehat{\text{Transfer Delay}}_{i,t} \times \text{Rate Dispersion}_{i,t}) \\
&\quad + \beta_3 \text{Rate Dispersion}_{i,t} + \beta_4 (\widehat{\text{Transfer Delay}}_{i,t} \times \text{Debt Repayment}_{i,t}) \\
&\quad + \beta_5 \text{Debt Repayment}_{i,t} + X_{i,t} + \delta_t + \epsilon_{i,t}.
\end{aligned}
$$

Here, the indicator $I(\text{Post } \widehat{\text{First Inflow}})_{i,t}$ equals one for the periods after depositor i's first encounter with fast payment applications in month t, when we find his first *credit* transactions with markers related to Zelle, PayPal, Venmo, and Cash App. transfer_delay$_{i,t}$ is the dollar-weighted average delays for depositor i in the month t. In the second stage, we estimate the effect of transfer delays due to the technology shock on deposit turnover, using the predicted transfer delays in the first stage. 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 smoothing efficiency, digital adoption ratio, as in previous sections, along with the size of money first deposited via fast payment platforms.

Column 2 in Table 7 finds that after the initial deposit into depositors' accounts via fast payment platforms, the average delay in transferring deposits decreases by 0.013 days. Furthermore, the shorter delay corresponds with a higher rate of deposit turnover, as seen in Column 1. One reason for this reduced delay after the first deposit might be that depositors begin utilizing quick payment platforms for outgoing transfers after their initial receipt of funds via these services. This could be due to lowered setup costs or a better understanding of the technology, possibly influenced by a network effect. To delve deeper into how quick payment platforms impact the friction in fund transfers for depositors, we introduce a middle step in our analysis. We aim to determine if depositors begin to move money out of their accounts using these platforms after their first receipt. For this, we employ a three-stage-least-square (3SLS) methodology to capture the influence of receiving funds via quick payment services on technology adoption and, concurrently, how technology adoption affects transfer delays. Specifically, we estimate the following three equations:

$$
\begin{aligned}
I(\text{Post First Outflow})_{i,t} &= \zeta_0 + \zeta_1 I(\text{Post First Inflow})_{i,t} + \delta_t + v_{i,t}, \\
\text{Transfer Delay}_{i,t} &= \gamma_0 + \gamma_1 I(\widehat{\text{Post First Outflow}})_{i,t} + X_{i,t} + \delta_t + \varepsilon_{i,t}, \\
\text{Deposit Turnover}_{i,t} &= \beta_0 + \beta_1 \widehat{\text{Transfer Delay}}_{i,t} + \beta_2 (\widehat{\text{Transfer Delay}}_{i,t} \times \text{Rate Dispersion}_{i,t}) \\
&\quad + \beta_3 \widehat{\text{Rate Dispersion}}_{i,t} + \beta_4 (\widehat{\text{Transfer Delay}}_{i,t} \times \text{Debt Repayment}_{i,t}) \\
&\quad + \beta_5 \widehat{\text{Debt Repayment}}_{i,t} + X_{i,t} + \delta_t + \epsilon_{i,t}.
\end{aligned}
$$

Here, the first stage estimates how setting up an account on these platforms to receive funds for the first time can lead the depositors, who *never* used fast payment platforms before, to engage in initiating transfers in the future. $\mathbf{I}(\text{Post First Outflow})_{i,t}$ is a dummy that equals one if a depositor i has started using fast payment platforms to transfer money *out* before $\mathbf{I}(\text{Post First Inflow})_{i,t}$ is a

Table 7: Turnover, Consumption, Interest Income and Fast Payment Adoption

	(a) Interbank Deposit Turnover (T)					(b) C	(c) *Bal.*	(d) log(T)	(e) log(C)	(f) log(*Bal.*)
	T	Delay	T	Delay	$\mathbf{I}_{PostFirstOutflow}$					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Transfer Delay	-57.63***		-57.63***			-40.42*	898.9***	-0.157***	-0.0140***	0.0374***
	(1.615)		(1.615)			(22.54)	(212.3)	(0.00473)	(0.000779)	(0.00136)
Rate Dispersion	491.9***	-0.154***	491.9***	-0.146***	-0.00287***	496.3***	1503.0*	0.189***	0.0189***	0.00668***
	(6.059)	(0.00853)	(6.059)	(0.00738)	(0.000331)	(84.56)	(796.6)	(0.00262)	(0.000594)	(0.00104)
Transfer Delay × Rate Dispersion	-70.79***		-70.78***			63.88*	-1908.0***	-0.0314***	0.00375***	-0.00678***
	(2.748)		(2.748)			(38.36)	(361.3)	(0.00332)	(0.000649)	(0.00113)
Financial Obligations	0.0124***	0.00000481***	0.0124***	0.00000356***	0.000000173***	0.554***	9.122***	-0.0152***	-0.00312***	0.00203
	(0.000500)	(0.000000748)	(0.000500)	(0.000000667)	(2.88e-08)	(0.00697)	(0.0657)	(0.00478)	(0.000938)	(0.00164)
Transfer Delay × Financial Obligations	-0.00134***		-0.00134***			-0.0157***	0.245***	-0.0152***	-0.00312***	0.00203
	(0.000210)		(0.000210)			(0.00293)	(0.0276)	(0.00487)	(0.000816)	(0.00142)
$\mathbf{I}_{PostFirstInflow}$		-0.0130***			0.957***					
		(0.00487)			(0.000471)					
$\mathbf{I}_{PostFirstOutflow}$				-0.0108**						
				(0.00443)						
Month FE	Y		Y			Y	Y	Y	Y	Y
Depositor Controls	Y		Y			Y	Y	Y	Y	Y
N	1339432		1339432			1338737	1024351	234927	1301470	978642

This table summarizes the effect of fast payment technology adoption on deposit turnover and consumption. Deposit turnover is derived from interbank deposit transactions. Interbank deposit transactions include transfers between different banks that have any transfer delay, and immediate transfers facilitated by services such as Zelle, Cash App, and Venmo, along with a limited selection of transactions identified with ATM-related details. Transfer delays are measured in days.

Columns 1-2 reports the 2SLS results, where the first stage (column 2) estimates transfer delay on the first outflow from fast payment platforms for the bank accounts of depositors who received money from fast payment technology before. Columns 3-5 adopts 3SLS to further incorporate the effect of receiving funds from fast payment platforms on technology adoption: in the first-stage regression(columns 5) we first obtain predicted values of technology adoption (a dummy that equals one if a depositor has started use fast payment platforms to transfer money *out*, $\mathbf{I}$(Post First Outflow)) from the receipt of funds from such platforms (a dummy that equals one if a depositor has received funds from fast payment platforms, $\mathbf{I}$(Post First Inflow)); then we use the predicted technology adoption to understand how it affects transfer delays; finally, we estimate effects on consumption (C), total balance (*Bal.*), and deposit turnover (T) from the predicted changes in transfer delays, both in levels and in percentage changes. We include time-fixed effects in all stages and depositor-level controls to estimate changes in delays and outcome variables (turnover and consumption), including debt repayments, salary, CSE, digital adoption ratio, and the amount received from fast payment platforms. Specifically, we estimate: $Y_{i,t} = \beta_0 + \beta_1 \widehat{\text{Transfer Delay}}_{i,t} + \beta_2(\widehat{\text{Transfer Delay}}_{i,t} \times \text{Rate Dispersion}_{i,t}) + \beta_3 \text{Rate Dispersion}_{i,t} + \beta_4(\widehat{\text{Transfer Delay}}_{i,t} \times \text{Debt Repayment}_{i,t}) + \beta_5 \text{Debt Repayment}_{i,t} + X_{i,t} + \delta_t + \epsilon_{i,t}$, $\text{Transfer Delay}_{i,t} = \gamma_0 + \gamma_1 I(\text{Post First Outflow})_{i,t} + X_{i,t} + \delta_t + \varepsilon_{i,t}$, $\text{Transfer Delay}_{i,t} = \gamma_0 + \gamma_1 I(\text{Post First Outflow})_{i,t} + X_{i,t} + \delta_t + \varepsilon_{i,t}$, and $I(\text{Post First Outflow})_{i,t} = \zeta_0 + \zeta_1 I(\text{Post First Inflow})_{i,t} + \delta_t + v_{i,t}$. 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.

dummy that equals one if a depositor i has received funds from fast payment platforms before time t. We include time-fixed effects to control for the common trend of technology improvement over time. The second stage uses the predicted values of $\mathbf{I}$(Post First Outflow)$_{i,t}$ from the first stage, along with depositor-level controls and time-fixed effects to estimate changes in transfer delays. In the last stage, we estimate the effect of transfer delays due to the technology shock on deposit turnover, using the predicted transfer delays in the second stage. We include time-fixed effects and depositor-level controls in both stages as in Section 4. Controls include debt repayment, salary, CSE, digital adoption ratio, as above, and the amount received from fast payment platforms. Panel (a) in Table 7 show that the instrumented measure of transfer delays exerts a significantly negative effect on deposit turnover. Columns 1-2 estimate a two-stage least-square using the receipt of the initial fast payment transfer as an instrument for transfer delays, and Columns 3 to 5 expand upon this by assessing the effect of the technology shock on the depositor's selection of payment technology. Column 5 indicates that after receiving funds via fast payment services, depositors are significantly more likely to incorporate this quicker payment method into their transactions. Panel (d) presents the log-transformed scaled depositor turnover; conditional on one-standard-deviation of rate volatility, an additional day of delay instrumented by the payment technology adoption is associated with a 14% increase in deposit turnover.

It is important to note that the study's methodology relies on temporal variations in delays. Thus, we restrict the analysis to depositors with over five years of transaction data. Additionally, there is a potential confounder regarding technology adoption timing: later adopters may inherently experience faster transfer delays, independent of technology use, which could potentially skew the findings. However, again, as illustrated in Figure 5 above, throughout the sample period, transfer delays do not exhibit a significant trend and remain consistently around a mean of two days.

In summary, this natural experiment, leveraging the adoption of fast payment platforms, provides robust evidence that advancements in payment technology not only reduce transfer delays but also significantly influence depositor behavior. The significant decrease in transfer delays post-adoption of the fast payment platforms and the subsequent increase in deposit turnover illustrate the critical impact of efficient payment systems on deposit flows. Moreover, the heterogeneous consumption responses to faster payment platforms across different depositor segments highlight the broader implications of these technological changes on consumer welfare.

6 Implications on Monetary Policy and Payment Fragility

In this section, we solve for the optimal policy $(\underline{m}, m^*, \overline{m})$ for the model in Section 3, to match the key data moments and evaluate the effect of reduced payment delays jointly with monetary policy, to shed light on the interactive effect of introducing faster payment technology, such as FedNow, in a changing rate environment with mounting consumer debt.

As the interest rate rises, the cost of holding money in a non-interest-bearing account increases, prompting depositors to transfer funds more frequently between accounts. They balance the cost of keeping funds idle against the need for liquidity to meet financial obligations. We solve the optimal deposit balance rule using the Bellman equation, along with boundary, value matching, and smooth pasting conditions. Figure 7 illustrates how a depositor's balance evolves under a 2% interest rate, a 2-day payment delay, and \$3,000 in financial obligations.

We also present analytical characterization of the target deposit balance m^* and the lower bound of the active region $\underline{m}$ in Figure 8. Given that interest and consumption spending cr over any typical time unit (days, months, years) is significantly larger than the Poisson arrival rate $\kappa \in (0, 1)$, our calibration falls within the monotonically decreasing segment of the solution. This is intuitive: the difference $(m^* - \underline{m})$ captures the "leeway" before the depositor reacts; in turn, a smaller $(m^* - \underline{m})$ suggests a more alert depositor.

Table 8 presents the key parameters, data moments, and corresponding model moments from 1,000 simulations. In the benchmark scenario (Column 2), the depositor's optimal target deposit

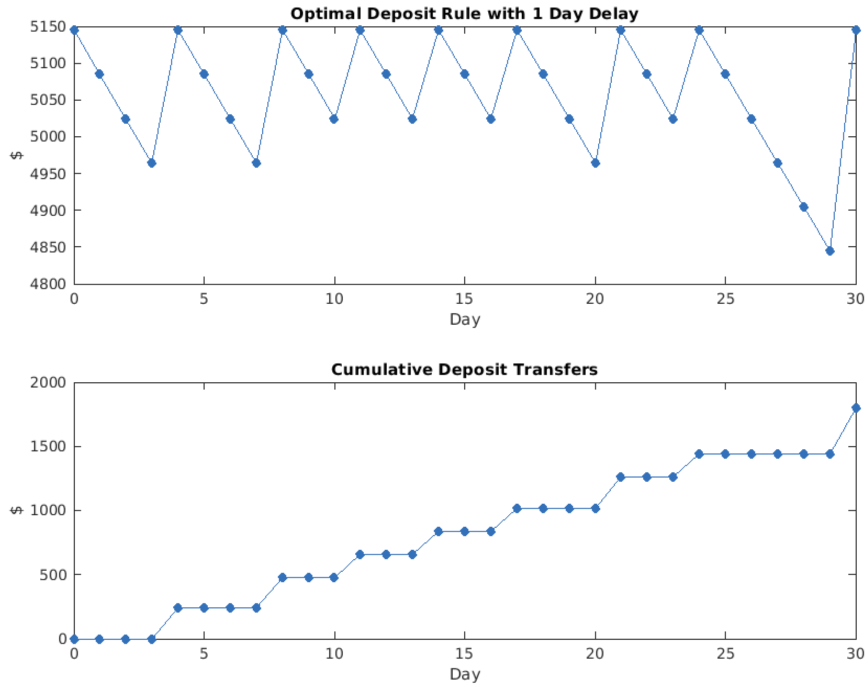


Figure 7: Optimal Depositing Activity

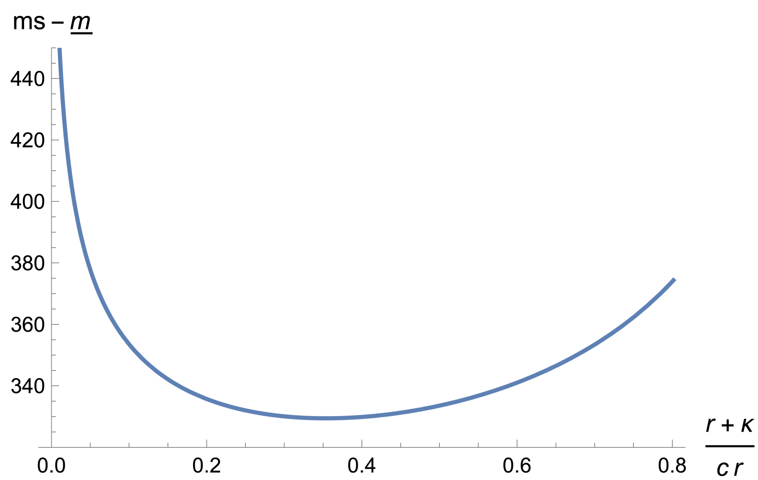


Figure 8: Analytical results on $m^* - \underline{m}$

of $M^* = 6,617.23$ (for the median depositor in sample, he has \$6,617 end of month balance), with \$1,637 deposit turnover (in-sample median of \$1,612).

Table 8: The Interactive Effects Between Payment Delays, Monetary Policy, and Consumer Debt

	Data (median) (1)	Benchmark (2)	No Lag (3)	No Lag & 50bps Cut (4)	Indebted (5)	No Lag & Indebted (6)
Moments						
Deposit Balance (M^*)	6,671.17	6,617.23	5,144.57	5,560.32	8,344.53	6,482.21
Deposit Turnover ($\Sigma_t \lvert X_t \rvert$)	1,612.68	1,637.82	1,724.76	1,616.96	2,063.65	2,176.15
Parameters						
Interest rate (r)		2.00%	2.00%	1.50%	2.00%	2.00%
Payment Delay ($-ln(1-\kappa)$)		2.00	1.00	1.00	2.00	1.00
Financial Obligations (C)		900.00	900.00	900.00	1,134.00	1,134.00

The effect of payment system upgrade on deposit dynamics. We calibrate the model assuming a one-day payment delay, representing a scenario where depositors face no transfer delays (e.g., widespread use of FedNow with next-day settlement). Under this condition, average monthly deposit turnover per depositor increases by $87 (Column 3 of Table 8), which aligns with the estimates in Table 3 and Section 5. At the same time, total deposit balances fall by $1,472, consistent with the results in Section 5, where a one-day reduction in payment delays leads to a $899 decline in balances. It's also important to note that the model currently excludes income shocks to the operating account, resulting in a larger balance change than observed in the data. These findings show two key effects of upgrading the payment system: first, the increased "payment efficiency" per dollar deposit means depositors need to hold less in low-interest accounts to fund the same level of spending; second, lower transfer friction leads to higher deposit turnover, causing gross deposit flows to increase relative to the total amount held in banks.

The rate-equivalent payment system upgrade. While faster settlement reduces transaction costs and enhances economic efficiency, it also introduces new risks for banks by triggering large and volatile deposit flows, raising concerns about payment fragility and financial stability (Li and Li 2021, Goldstein, Yang, and Zeng 2023, Cipriani, Eisenbach, and Kovner 2024). The question is: what kind of monetary policy can offset these additional flows caused by reduced transfer frictions? Column 4 in Table 8 shows that if payment delays are reduced from 2 days to 1 day, a 50 basis point rate cut would keep depositing activity unchanged. The intuition is straightforward: while faster transfers provide depositors with more incentive to move funds, the lower rates reduce their motivation to shop for better interest deals, neutralizing the impact of the upgrade.

Consumer debt and payment system upgrade. In Section 4, we find depositors' financial debt amplifies the effects of payment delays. Consumer debt grew 26% from the pre-pandemic level. Column 5 in Table 8 shows that 26% higher than median financial obligations will lead to both higher deposit turnover and balances. And with higher consumer debt, the effect of a decrease in payment delays is also significantly more pronounced: with 26% higher than median financial obligations, deposit turnover would raise by 33% with a 1-day deduction in delays.

7 Conclusion

Our paper reveals new, micro-founded facts about depositor behavior, central to understand coordinated deposit flows that is important for bank funding stability and payment fragility. By introducing the novel concept of deposit turnover to quantify depositor alertness, we find significant variation in how depositors move their funds across institutions. Our findings demonstrate that the efficiency of payment technologies and the degree of financial uncertainty faced by depositors are key determinants of these flows. We show that payment delays and uncertainties related to interest rate dispersion prompt depositors to be more active in reallocating their balances.

We rationalize the new empirical findings through an extended inventory model that accounts for lumpy transfer behavior and uncertainty in transfer settlement times. Our model aligns closely with the observed data and allows us to explore how policy changes – specifically, the adoption of faster payment technologies, such as FedNow – interact with monetary policy and consumer debt levels. The results suggest that the adoption of faster payment technologies, like FedNow, could substantially alter depositor behavior, and the effect interacts with monetary policy and depositor indebtedness. Policymakers need to recognize this interplay between payment efficiency and interest rate conditions, as it introduces novel risks and opportunities for financial stability. Our findings therefore offer fresh policy implications, pointing to the need for careful coordination between payment system innovations and the broader economic environment to ensure financial resilience.

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Internet Appendix for

The Make of Alert Depositors: How Payment and Interest Drive Deposit Dynamics

Xu Lu   Yang Song   Yao Zeng

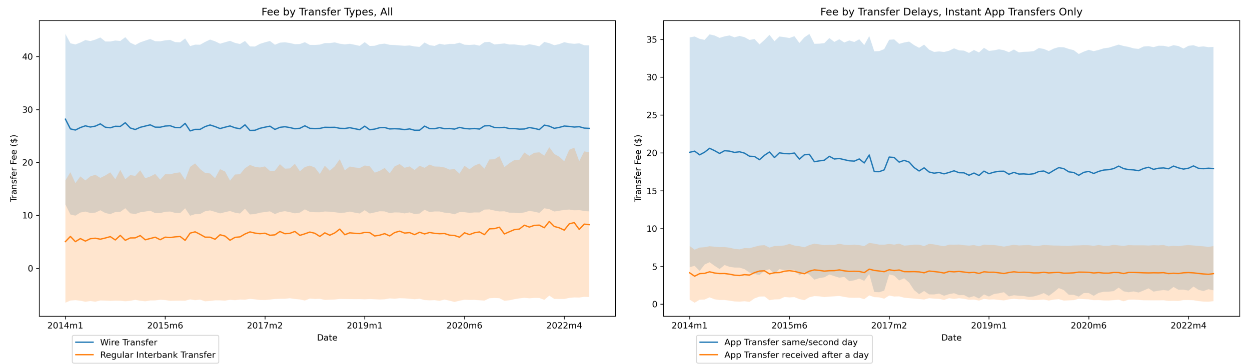
A Bank Wire Transfer Fees

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 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 1: Distribution of Fees by Transfer Type



These two hitograms 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.

B Bank Account Specialization

Most 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.

The heatmap below details the transaction distribution patterns among depositors who have at least two bank accounts.

1. Dominant Category: An account's primary usage is characterized by its dominant category—where more than 50% of the total transaction in dollars belongs to this category. More than 90% of the depositors in the data have an account with a dominant category.

2. Account Rank: On the x-axis, accounts are ranked by their importance based on dollar usage. A rank of "1" represents the account with the most transactions in dollar terms, while "6" indicates the sixth most used account (assuming a depositor has 6 accounts).

3. Color Intensity: The shade in the heatmap denotes the level of dominance; darker colors represent a stronger alignment to a particular category. For example, a dark cell in a column (pertaining to an account) for a category means many users mainly use that account for transactions in that domain.

4. Percentage Annotations: The percentages adjacent to the account ranks convey the total transaction volume of an account relative to a user's entire transaction history, shedding light on each account's importance.

Notably, specialization for a single purpose isn't necessarily tied to the account's popularity. The dominance of a transaction type within an account appears to be independent of its rank, signifying that an account's primary use is unrelated to its popularity among users.

Figure 1: Dominant Transaction Categories for Multi-Account Depositors