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

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Abstract

Bank deposits are valuable for providing efficient payment services. Analyzing data from 50 billion transactions across 1,400 U.S. banks, we document that as transfers become faster, depositors initiate more bank-to-bank fund transfers, and have smaller deposit balances. We extend the Baumol–Tobin inventory model with uncertainty in transfer delays, and analyze the effect of faster payments on deposit demand through a precautionary motive. We characterize the model's solution, which qualitatively matches the observed empirical patterns. Using the empirical estimates to calibrate this deposit demand model, we quantitatively assess how faster payment systems and digital disruptions affect bank funding costs, accounting for depositor heterogeneity and fluctuations in interest rates.

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> This advantage (as a medium of exchange) of checking accounts does not give banks absolute immunity from the competition of savings banks... The community's demand for bank deposits is not indefinite, even though demand deposits do serve as means of payment.
>
> *Commercial Banks as Creators of "Money"*, Tobin, 1963.

1 Introduction

Deposits are a low-cost and stable funding source for banks, as deposit flows are mostly insensitive to the spread between policy rates and deposit rates. In other words, depositors hold substantial balances in bank accounts, despite these accounts may not be a good store of value even in nominal terms. In this paper, we demonstrate that American depositors value deposits for the liquidity services, and provide micro-founded, direct evidence that depositors respond to lower bank-to-bank transfer frictions by decreasing their account balances and engaging more actively in deposit fund transfers. These behaviors have significant implications for bank funding costs: smaller balances in low-interest bank accounts directly reduces the size of banks' deposit franchise, and the resulting increase in bank-to-bank payment flows increases payment risks, potentially leading to a higher demand for bank reserves. Based on the empirical findings, we develop and calibrate a new deposit demand model featuring settlement delays and provide counterfactuals on how adoption of fast payment systems like FedNow can influence depositor activeness and the size of bank deposits.

We begin with an empirical analysis of over 50 billion transactions from 1 million representative depositors across more than 1,400 U.S. banks and credit unions, revealing three new facts that prompt us to study depositor activeness through their fund transfer behaviors. First, during the sample period of 2014 to 2022, more than 95% of American depositors hold at least two bank accounts with significant average balances. Second, depositors actively manage their portfolios through bank-to-bank deposit fund transfers (hereafter *interbank transfers*), which account for

about 20% of all transactions. Third, 9% of transactions involve deposits moving between a given depositor's own accounts, often involving substantial amounts. In turn, we systematically track these interbank transfers at the individual level and, similar to the gross transfers recorded in Fed-Wire at the bank level, introduce a new measure of depositor activeness, *deposit turnover*, defined as the gross amount of funds transferred between accounts at different depository institutions for each depositor. This transaction-level analysis also allows us to quantify delays in bank-to-bank fund transfers (hereafter *transfer delays*), which, to our knowledge, is the first empirical measure of payment frictions at the depositor level.

We find that changes in payment frictions, in the form of transfer delays, have important impact on both deposit turnover and deposit balances. We first present the correlation between transfer delays and depositor activeness, where depositors with slower accounts tend to be less active and hold larger balances. The effect of transfer delays on depositor behavior varies in the cross section. Depositors with large balances, in particular uninsured depositors, are significantly more active when transfer delays is smaller, and will leave much less deposits in banks when bank-to-bank transfers becomes more efficient. Additionally, depositors who don't utilize or have access to credit lines through credit cards move less money out of their bank accounts when payment is more efficient. The evidence that depositor characteristics matter for depositor activeness and total balances suggests that analyses at the depositor level adds an essential layer of granularity to research on bank funding cost.

The negative correlation between transfer delays and depositor activeness could come from two possible sources. First, sophisticated or attentive depositors may be more likely to choose faster bank accounts, which allow them to transfer more funds across banks with less friction. Second, following exogenous decreases in transfer delays, depositors may adjust their activity levels and balances, as they face less friction and require lower low-interest deposit balances to fund their spending. Separating this second channel is important because our policy counterfactuals consider

exogenous shocks to payment technologies, such as the introduction of CBDC or FedNow.

We empirically distinguish this second channel through a natural experiment in which depositors are exposed to fast payment technologies via their social networks. During the sample period, instant payment applications such as Zelle, Venmo, PayPal, and Cash App experienced rapid growth. More than half of the depositors in the sample received or initiated fund transfers using these platforms. Not all depositors seek faster payments in the same way, and to address the potential endogeneity of fast payment usage driven by depositor characteristics, we focus on a subsample of depositors who had never used these fast payment applications before and treat the first time of receiving funds through these platforms as a shock to their access to the technology. The timing of receiving these inflows is most likely not determined by the depositors themselves but rather influenced by their exposure to these technologies through their peers.

The empirical analysis gives us point estimates on how changes in payment convenience in deposits can affect bank deposits through depositor activeness. To quantify the aggregate implications of payment convenience on bank deposits, we introduce an inventory model of deposits with delays and spending/income uncertainty. Our model is a new extension to the classic Baumol-Tobin model. We account for both stochastic payment settlement and consumption uncertainty. We provide a general characterization of the optimal policy, summarized by two thresholds and two target balances, and obtained an analytical solution of the optimal policy for a limiting case, and use the closed form solution to calibrate the model and provide policy counterfactuals.

Specifically, calibrate the data to the distribution of depositors in sample and provide policy counterfactuals for the introduction of fast payment systems in various rate environment.

Literature. The payment-driven depositor activeness supports the view that deposits at digital banks are generally more volatile as deposits at digital banks tend to serve as a more convenient medium of exchange, and offers micro-founded evidence for these observed effects of digital disruption (Erel, Liebersohn, Yannelis, and Earnest 2023, Jiang, Yu, and Zhang 2023, Koont 2023,

Koont, Santos, and Zingales 2023). We further document that depositors using various transfer technologies demonstrate varying levels of activeness. 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).

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. 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.

Our findings suggest payment plays an important role in depositor activeness, 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), resulting in potentially less efficient lending and higher payment risk. 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.

Bank deposits are used to fund spending and receive income; the transactional demand of money is one important driver between the wedge of market interest rates and the deposit rates. 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 provides a micro-foundation for the documented market power in the deposit market, 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 introduces the key variables, including the notion of deposit turnover and transfer delay, and summarize the new stylized facts about depositors. Section 3 presents an extended Baumol-Tobin model to reconcile the new stylized facts and generate testable hypotheses. Section 4 empirically tests how payment frictions affect depositor activeness and deposit balances, and uses a natural experiment to separate the exogenous shocks to payment technology from endogenous sorting between depositors and technologies. Section 5 presents analytical results and numerical calibration of the model. Section 6 concludes.

2 Stylized Facts on Deposit Activeness and Transfer Frictions

In this section, we outline the dataset and detail the construction of key variables, including a novel metric for depositor activeness, termed *deposit turnover* and a measure of payment friction at the depositor level, the *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 January 2014 until October 2022. The databases include savings accounts, checking accounts, credit, and debit card activities but exclude other account types such as brokerages and investments. In particular, deposits and withdrawals are observable for both saving and checking accounts. Each transaction is rich in metadata, including date, amount, category, and often merchant name and location.

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. 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 the end of the section, and in the appendix, show the sample is representative by showing the matching trend between the total deposit balance changes inferred from the data versus the aggregate trends in Flow of Funds.

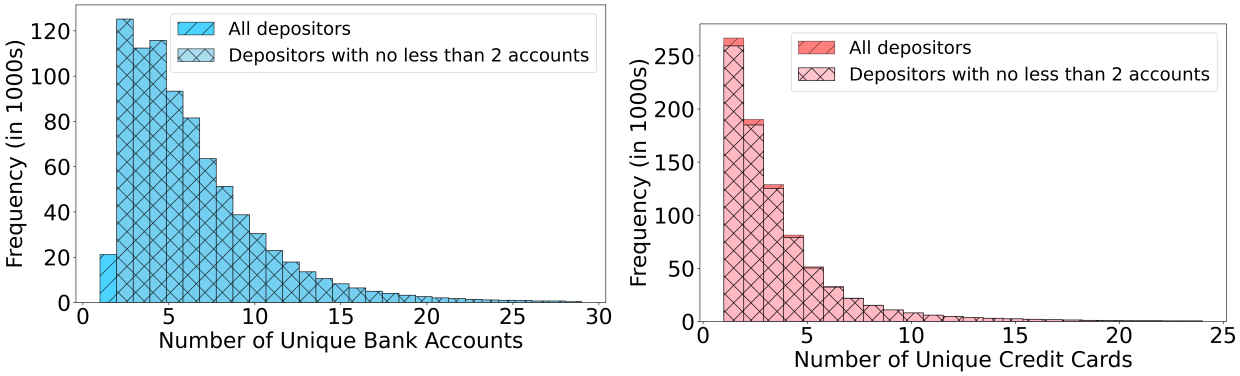
2.2 Deposit Turnover

We propose a new metric, *deposit turnover*, to assess how active retail depositors are. It measures the total gross amount of funds that a depositor transfers across her bank accounts within a given period, similar to the metrics in FedWire. Conceptually, higher deposit turnover is associated

with more bank funding risk; Bolton, Li, Wang, and Yang (2023) and Jermann and Xiang (2023) model deposits as a debt contract with random maturity, and a larger amount of debt maturing in a given period poses a higher risk on the bank. Before detailing the construction of the measure, we first highlight several important stylized facts that motivates the analysis on bank-to-bank fund transfers.

First, most American depositors have more than one bank account. The notion of interbank deposit transfers is only well-defined if depositors possess multiple bank accounts. Although the information about the number of bank accounts per American is limited, a 2019 survey by the Mercator Advisory Group indicated that the average number of bank accounts is 5.3 per person (Reville 2019). And in our sample, as illustrated in Figure 1, it is evident that the majority of depositors hold not just one but several bank and credit card accounts.

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.

Second, depositors hold significant funds across different accounts. Section 2.2 shows that]

Depositors manage funds across multiple bank accounts.

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

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

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).[1]
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

[1]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 transfer charges, please refer to Appendix A.

transaction, the one with the shortest time interval is selected.[2]

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 activeness 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 controls.

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 stability 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

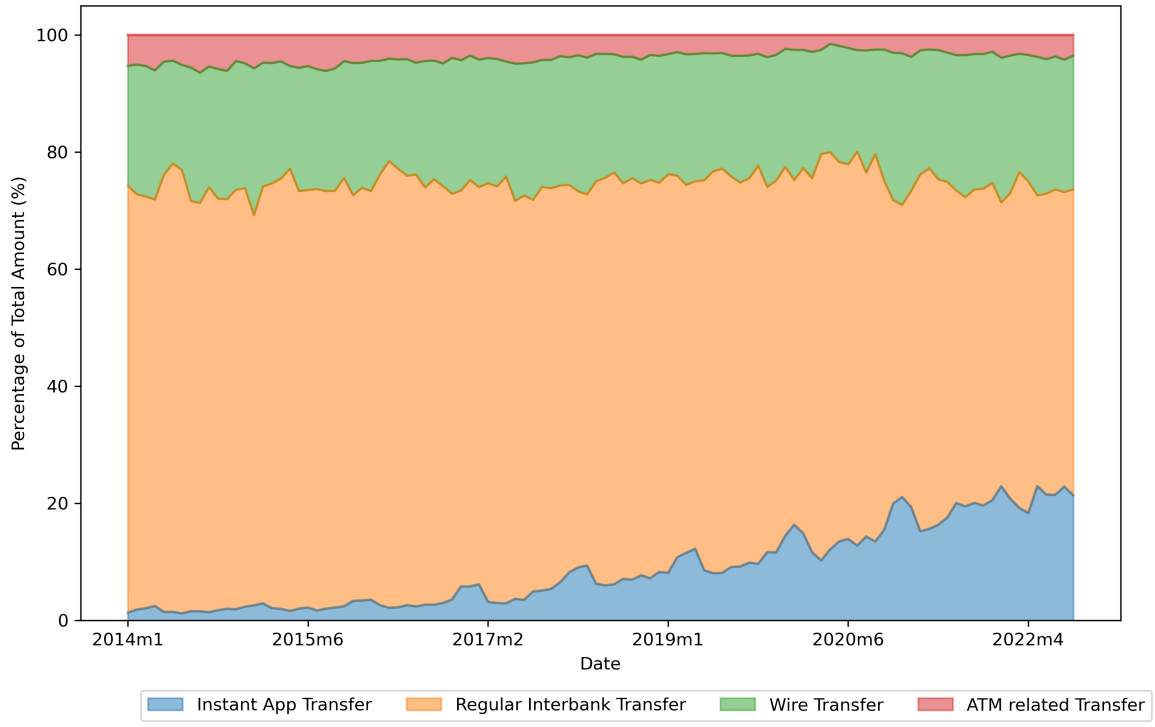
[2]This approach is designed to minimize the possibility of counting duplicate transactions. For example, if Tigger holds another account at Pooh Bank, he could transfer $100 to Pooh Bank before moving it to Bank Chestnuts. These steps would result in three separate records: (1) from Bank Adventures 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.

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.

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. We find 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

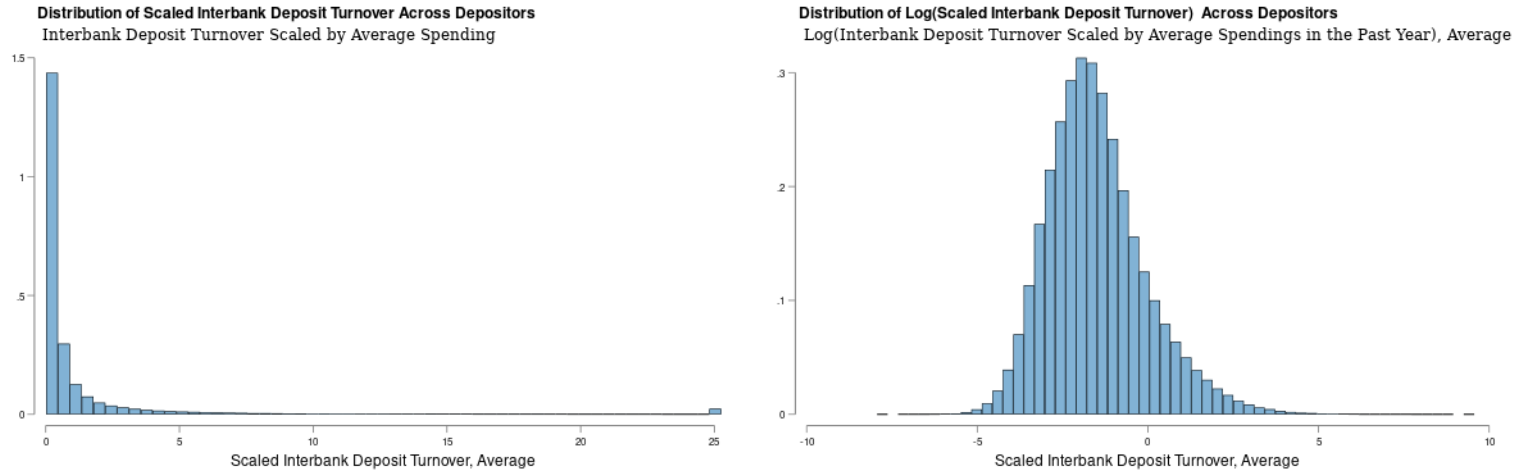
Figure 2: Types of interbank turnover



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.

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.

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,

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

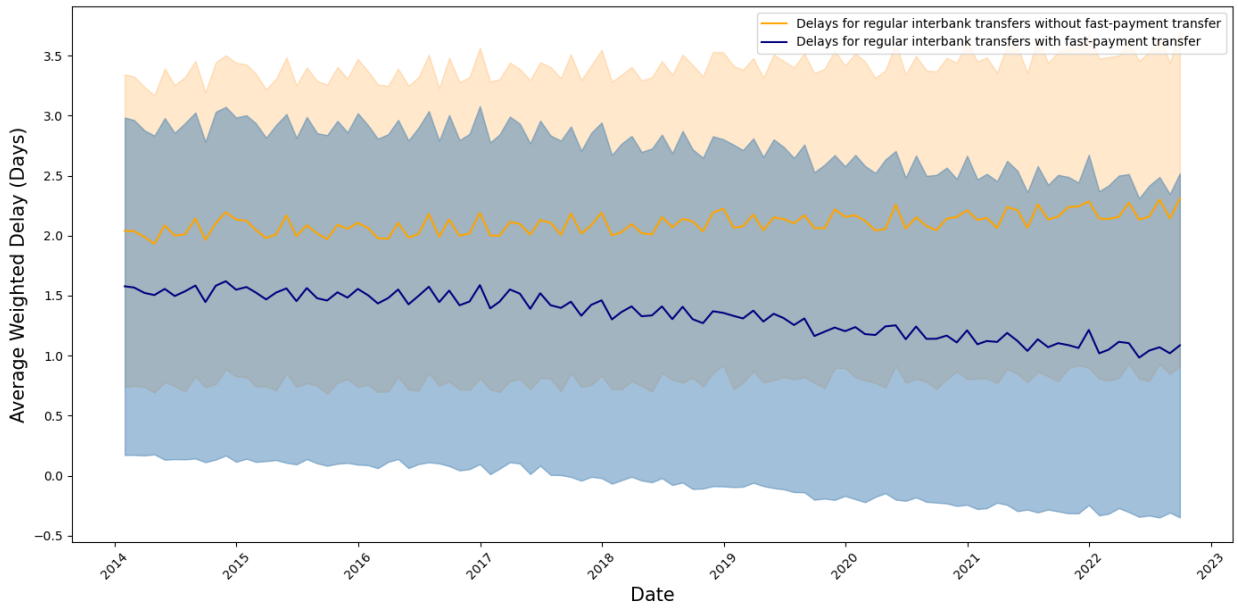
Given these individual account delays for month t, the depositor-month level *transfer delay*, factoring in the monetary values, can be written as:

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

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.[3]

Figure 4: 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.

Based on our notion of payment delay, Figure 4 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

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

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 with discount rate β is endowed with two bank accounts, account C and account S, which may be offered by different banks, starting at time $t = 0$. Motivated by the evidence of account specialization discussed earlier, and without loss of generality, we assume that deposits in bank account C are non-interest-bearing yet are used by the depositor 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 $r > 0$. Suppose the total repayment amount is exogenous yet uncertain: let $g > 0$ denote the constant flow of consumption from bank account C. Specifically, c follows a Brownian motion: $dc = -gdt + \sigma dw$ where w is a standard Wiener process, and $g > 0$ and $\sigma > 0$ are the drift and standard deviation, respectively. Additionally, denote by m the balance of bank account C, which, as we will show, is a crucial state variable in the model. It is important to note that the assumption of account C being non-interest-bearing is not critical. What is essential is that the two accounts offer different interest rates, and 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_j made at t_j 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_k are made at t_k, when the balance in account C hits 0:

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

where positive (negative) transfers indicate a transfer from account S to account C (from account

C to account S), the first term captures the expected interest losses due to carrying a positive deposit balance in account C rather than in account S, the second term captures the additional expected interest losses due to delayed transfers 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

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

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 two optimal targets for m: $0 < \underline{m} < m^* < m^{**} < \overline{m}$. 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:

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

where the first term rm gives the carry cost of balance in account C, the second term $crV'(m) -$

$\frac{1}{2}c^2\sigma^2 V''(m)$ gives the change in the value function due to the use of deposit balance to repay interest liabilities per unit of time conditional on no transfers, 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 two optimality conditions:

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

and

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

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

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

and

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

two "smooth pasting" conditions:

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

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 thresh-

olds, and further, 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 second-order derivative are both continuous at the two thresholds.

Finally, the value function should grow at a finite rate when m goes to infinity:

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

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 when r is not too large. 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.*

Analytical solution in a limiting case. In general, the optimal deposit policy cannot be solved in close-form given the complexity of the second-order differential equations.[4] We therefore analyze a limiting case where spending has no drift ($g = 0$) and the discount rate approaches zero ($\beta \to 0$). This special case is also in Constantinides and Richard (1978), but the stochastic transfer arrival in our framework leads to value functions in the action regions being transcendental equations with two exponential terms, rather than a degenerate homogeneous solution as found in their work. We are able to characterize the optimal policy ($\underline{m}, m^*, m^{**}$, and $\bar{m}$) as functions of (r, κ, σ, b) without solving the entire system explicitly, and the results, along with proofs, are presented in the

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

appendix.

4 Payment and Depositor Behavior

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. We then split the sample to understand the heterogeneous effect payment technology has in the cross section: uninsured depositors are significantly more sensitive to payments, while the hand-to-mouth (without access to credit lines through credit cards) increase their activeness but do not have a lower balance as the efficiency in payment also leads to a slightly higher consumption to fund for this group. Finally, we disentangle the endogenous depositor-bank sorting with depositor's reaction to exogenous payment shock through a payment network exposure instrument.

4.1 Faster payment is associated with more deposit turnover and smaller balances.

We investigate the effects of transfer frictions, in the form of transfer delays in interbank deposit transfers, on depositor activeness 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 activeness 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. The data indicate that, when accounting for both time fixed effects and depositor-specific controls, each additional day of delay in interbank transfers reduces deposit turnover, a significant and consistent result across various models.

4.2 Uninsured depositors are payment is associated with more deposit turnover and smaller balances.

Bank run risk is partially 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). We restrict our sample to depositors with total balances higher than $\$250,000$ during the sample period. Table 4 shows that the uninsured depositors are much more responsive to reductions in payment frictions, holding significantly less balances in bank accounts.

4.3 Identifying the impact of fast payments on depositor behaviors.

So far, we have provided evidence of depositor activeness, 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

Table 3: Transfer Delays and Depositor Behaviors

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

This table presents the relation between each depositor's transfer delays at time t and deposit turnover$_{i,t+1}$, which gauges the activeness 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%.

Table 4: Transfer Delays and Depositor Behaviors: The Uninsured Depositors

	(a) In dollars				(b) Scaled by the moving average of spending			
	(i) Deposit Turnover		(ii) Bank Balances		(iii) Deposit Turnover		(iv) Bank Balances	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Delay	-53.51***	-51.02***	1887.1***	2325.1***	-0.143***	-0.132***	0.0372***	0.0367***
	(1.068)	(1.065)	(477.1)	(468.1)	(0.0115)	(0.0107)	(0.00318)	(0.00317)
max		169.8***		-11345.7***		0.197***		0.00347
		(5.893)		(2491.3)		(0.00543)		(0.00347)
Transfer Fees (		(55.04)		(17915.5)		(0.256)		(0.126)
sd of c_total in a 12 periods rol. wind.		0.00585***		3.873***				
		(0.000248)		(0.198)				
Payment Advance Ratio		-11.29***		17817.8***		0.156***		0.219***
		(2.969)		(1565.3)		(0.0154)		(0.0110)
Salary		0.000719		-0.402*				
		(0.000433)		(0.217)				
scale_vol						-0.000419***		0.0000275
						(0.000143)		(0.0000239)
Scaled Salary						0.00345***		0.0000115***
						(0.00115)		(0.00000103)
Constant	465.2***	385.9***	304755.8***	271904.9***	-1.602***	-1.685***	3.146***	3.074***
	(3.500)	(4.177)	(1465.5)	(2262.9)	(0.00946)	(0.00975)	(0.00526)	(0.00645)
Depositor FE	N	N	N	N	N	N	N	N
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
N	2276841	2275366	2276841	2275366	422409	422336	2219764	2218417
Adj. R^2	0.00793	0.0163	0.0684	0.0861	0.0294	0.0681	0.0830	0.0864

This table presents the relation between each depositor's transfer delays at time t and deposit turnover$_{i,t+1}$, which gauges the activeness 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%.

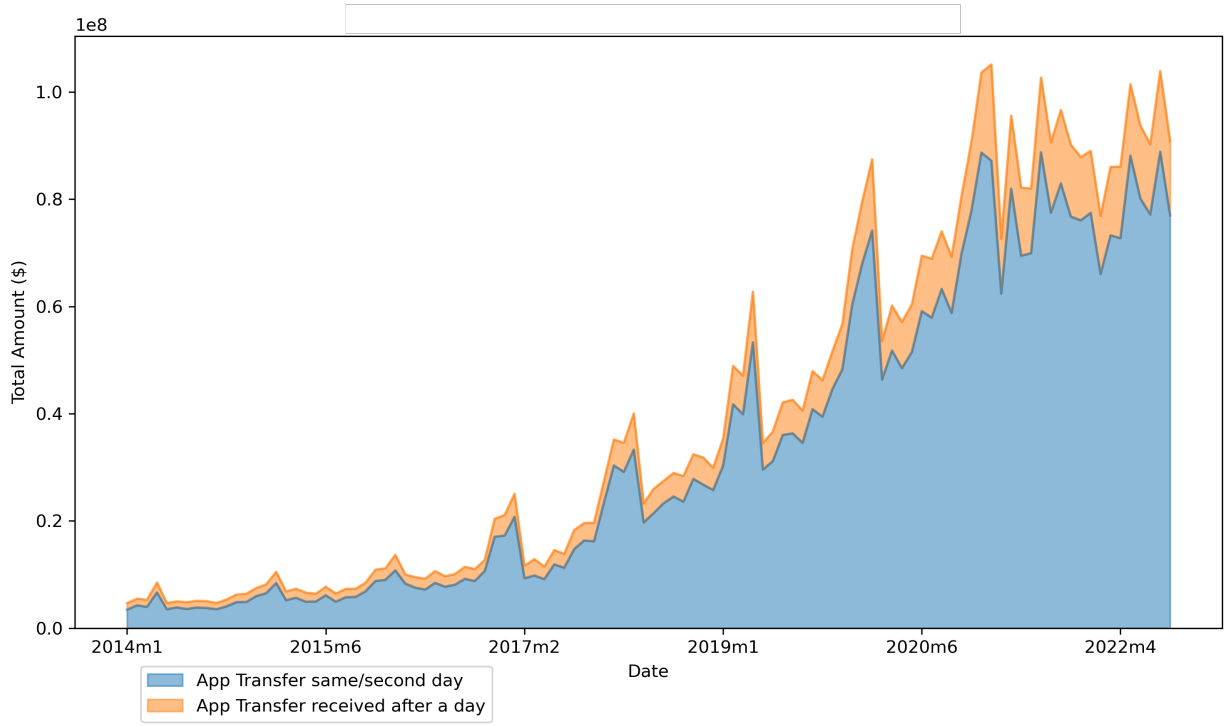
interest rates are perceived as the price of time in investment decisions), which gives a plausibly causal interpretation of the interest risk channel. However, regarding the payment channel, depositors who possess slower bank accounts are potentially also the "sleepy" depositors who have smaller deposit turnover, leading to an endogeneity concern of our results on deposit activeness being potentially driven by sleepy depositors self-selecting into slow bank accounts. In this section, we introduce a natural experiment to causally identify the impact of payment delay on depositor activeness, that is, the payment channel.

Our identification strategy of the payment channel underlying depositor activeness 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 5, 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

Figure 5: 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.

Zelle going forward, which would likely affect depositor i's activeness. 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 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 en-

counter 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 5 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:

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

Table 5: Scaled Depositor Turnover and Fast Payment Adoption

	OLS	2SLS		3SLS		
	(1)	(2)	(3)	(4)	(5)	(6)
Transfer Delay	-0.140***	-0.111***		-0.140***		
	(0.0108)	(0.00327)		(0.00401)		
$\mathbf{I}_{PostFirstInflow}$			-0.101***			0.955***
			(0.00231)			(0.000756)
$\mathbf{I}_{PostFirstOutflow}$					0.0603***	
					(0.00507)	
Depositor Controls	Y	Y			Y	
Month FE	Y	Y			Y	
N	528699	702972			528692	

This table summarizes the effect of fast payment technology adoption on deposit turnove. 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 reports results from OLS for this subsample, and column 2-3 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 4-6 adopts 3SLS to further incorporate the effect of receiving funds from fast payment platforms on technology adoption: in the first-stage regression(columns 6) 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*, **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, **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: $Y_{i,t} = \beta_0 + \beta_1 \text{Transfer Delay}_{i,t} + \beta_2(\widehat{\text{Transfer Delay}}_{i,t} \times \text{Rate Dispersion}_{i,t}) + \beta_3 \text{Rate Dispersion}_{i,t} + \beta_4(\widehat{\text{Transfer Delay}}_{i,t} \times \text{Debt Repayment}_{i,t}) + \beta_5 \text{Debt Repayment}_{i,t} + X_{i,t} + \delta_t + \epsilon_{i,t}$, $\text{Transfer Delay}_{i,t} = \gamma_0 + \gamma_1 I(\text{Post First Outflow})_{i,t} + X_{i,t} + \delta_t + \varepsilon_{i,t}$, $\text{Transfer Delay}_{i,t} = \gamma_0 + \gamma_1 I(\text{Post First Outflow})_{i,t} + X_{i,t} + \delta_t + \varepsilon_{i,t}$, 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.

$$+ \beta_5 \text{Debt } \widehat{\text{Repayment}}_{i,t} + X_{i,t} + \delta_t + \epsilon_{i,t}.$$

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 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 $\mathbf{I}(\text{Post First Outflow})_{i,t}$ 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 5 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 4 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.

5 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 6 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 characterization of the target deposit balance m^* and the lower bound of the active region $\underline{m}$ in Figure 7.[5] 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

[5] In fact, for $r << \kappa$, $m^* - \underline{m} = c \cdot f(\frac{\kappa}{r+\kappa}) \approx \frac{c}{\kappa+r} - \frac{c}{r}\sqrt{\frac{2r}{\kappa+r}} + O(\frac{\kappa}{\kappa+r})$.

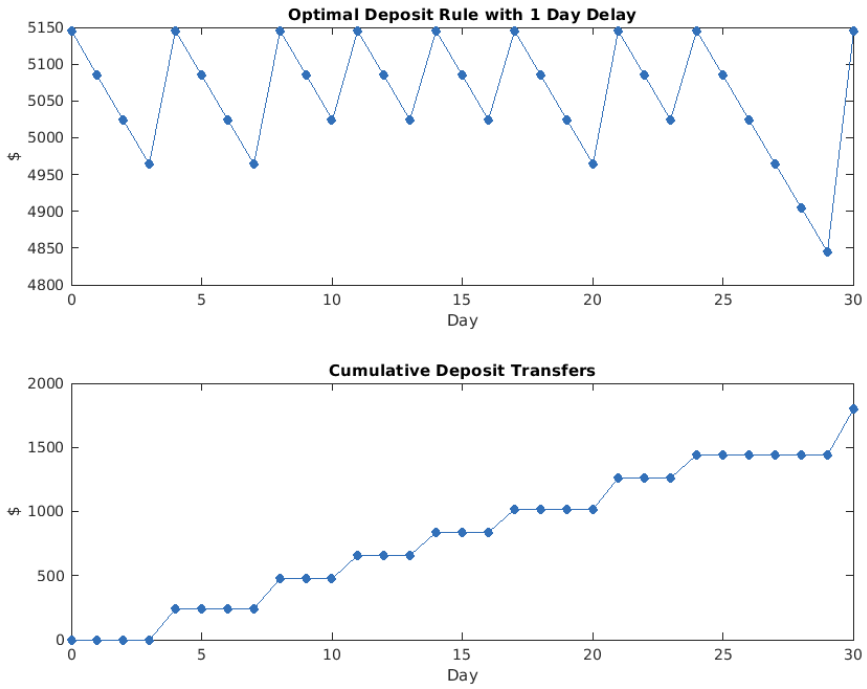


Figure 6: Optimal Depositing Activity

difference $(m^* - \underline{m})$ captures the "leeway" before the depositor reacts; in turn, a smaller $(m^* - \underline{m})$ suggests a more alert depositor.

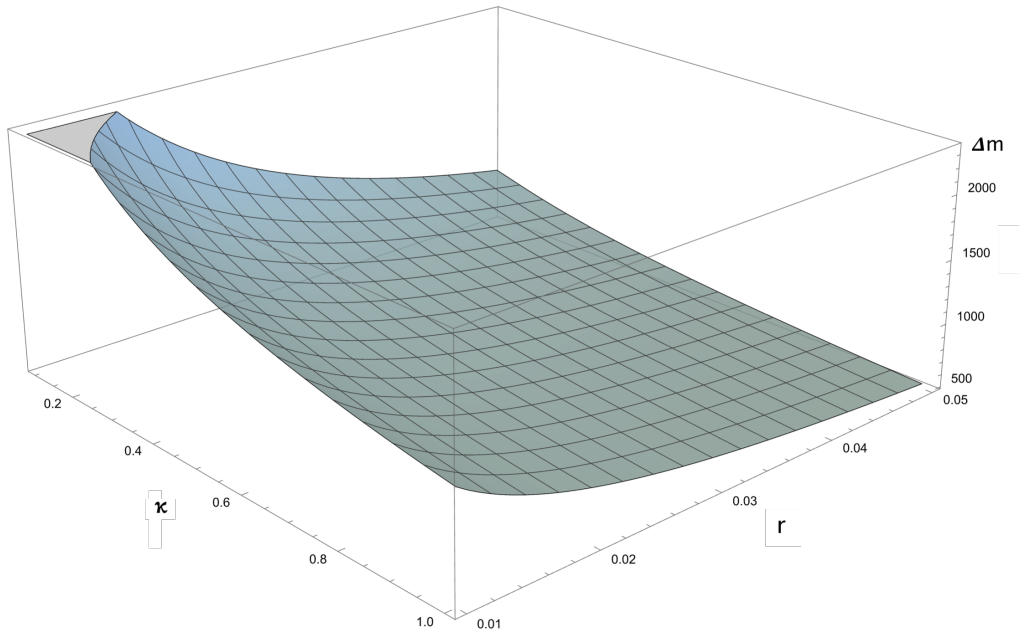


Figure 7: Analytical results on $m^* - \underline{m}$

Table 6 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 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 6: 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 ($-ln(1-\kappa)/\kappa$)		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 6), which aligns with the estimates in Table 3 and Section 4.3. At the same time, total deposit balances fall by $1,472, consistent with the results in Section 4.3, 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 6 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 6 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.

6 Conclusion

Our paper reveals new, micro-founded facts about depositor behavior and how faster payment services can affect bank funding cost through depositor behavior. By introducing the novel concept of deposit turnover to quantify depositor activeness, 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 both consumption and 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 cost. 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

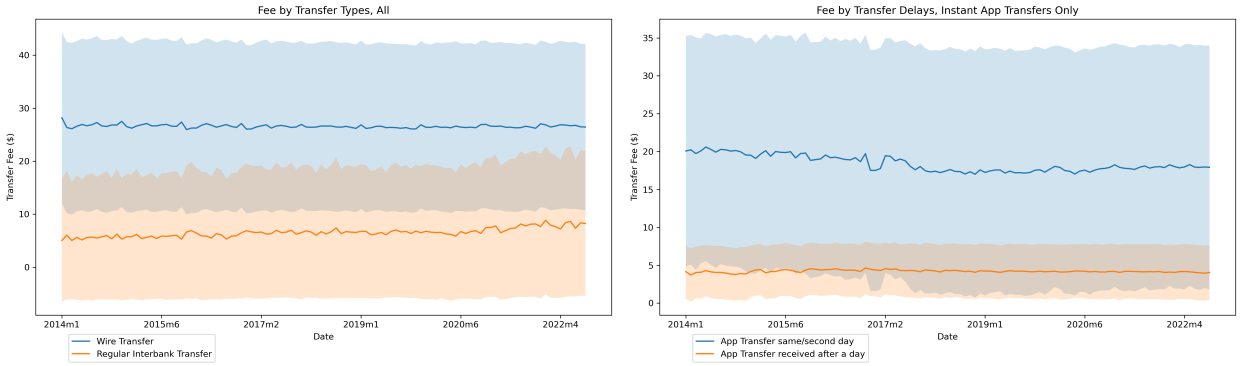
A Bank Wire Transfer Fees

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

