The Making of an Alert Depositor:

How Payment and Interest Drive Deposit Dynamics*

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Abstract

Are depositors sleepy? We challenge the traditional view of depositor sleepiness by introducing a new notion, *depositor alertness*, and providing supporting evidence with novel transaction-level data from over a million U.S. depositors. Depositors shift their deposits across bank accounts more actively when the payment technology linked to their accounts is more efficient, and when they face higher interest rate risk, which we define as the *payment channel* and the *interest risk channel*, respectively. Furthermore, depositors facing higher payment frictions are also more attuned to interest rate risk and shift their deposits more actively, which we define as the *precautionary transfer channel*. Depositor alertness is particularly pronounced during periods of rate hikes but diminishes when rates fall. We further provide causal evidence with newly constructed exogenous shocks to payment frictions for depositors. Specifically, the exposure to fast payment technologies reduces transfer frictions, which consequently heightens depositor alertness. Our findings have significant policy implications, highlighting the impact of depositor behavior on bank funding costs and risks, especially amidst rapid developments in new payment technologies and during times of monetary tightening.

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1 Introduction

A defining feature of banks is their reliance on low-cost and stable deposit funding. Deposits constitute over 80% of the liabilities of an average U.S. bank, and depositors are considered "sleepy" in that they do not typically pay attention to fluctuations in the value of the bank assets. However, the collapse of Silicon Valley Bank and other high-profile regional banks in 2023 presents a new portrait of depositors: depositors may occasionally become "flighty", particularly for banks with better service quality and during times of increased interest rate risk.

Given the crucial importance of stable deposits to bank funding and the overall stability of the banking sector, this contrast between the "sleepy" view and the "flighty" behavior of depositors prompts several key questions: To what extent are depositors alert rather than sleepy? Which economic factors command depositors' alertness? Additionally, what are the economic drivers behind such depositor alertness, and how might this, in turn, influence their financial outcomes?

We study these questions by leveraging a new, comprehensive transaction-level dataset encompassing over 1,400 U.S. banks and credit unions and a million U.S. depositors, which allows for the uncovering of novel insights into depositor behaviors at the account level. Specifically, we analyze inter-bank transfers for over a million depositors based on billions of transactions. This distinctive data set allows us to introduce a new metric, *deposit turnover*, which quantifies the level of alertness among retail depositors. Specifically, deposit turnover measures the extent to which retail depositors actively transfer deposits across their own bank accounts at various depository institutions. This approach complements existing influential research on deposit flows such as Drechsler, Savov, and Schnabl (2017) and Xiao (2020) in two ways. First, by focusing on the intensive margin of deposit flows across depository institutions, our approach reveals how the traits of depositors affect the movement of deposits across banks, and thus it offers a fresh perspective that adds to the existing work on the extensive margin of bank deposits, i.e., the aggregate flows in and out of the entire banking sector. Second, we uniquely connect deposit movements to depositor account-level characteristics, uncovering new insights into bank funding and stability risks by examining the actions of individual depositors. We also provide a simple model that relates the empirical findings to two fundamental roles of deposits as money: a medium of exchange and a store of value.

To begin with, we find that depositors more actively shift their deposits between accounts when the payment technology attached to their accounts is more efficient. This underscores the significant role of deposits in household portfolios as a means of exchange. We identify this as the *payment channel*, which is fundamentally linked to the role of bank deposits as a payment instrument, or in other words, a medium of exchange. When the payment technology attached to a bank account becomes more efficient in the sense that the delay in transfer becomes shorter, deposits become more convenient in terms of the medium of exchange function, encouraging depositors to transfer them more actively across accounts to facilitate their transactional needs. This finding and the payment channel we uncover thus echo several recent studies showing that deposits at more digital banks are typically more flighty (e.g., Benmelech, Yang, and Zator 2023, Erel, Liebersohn, Yannelis, and Earnest 2023, Jiang, Yu, and Zhang 2023, Koont 2023, Koont, Santos, and Zingales 2023) because deposits at more digital banks tend to serve as a more convenient medium of exchange. In this sense, our paper offers one precise economic foundation for these observed effects of bank digitalization at the depositor level. In identifying the payment channel, 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).

Next, we find that depositors more actively shift their deposits when facing heightened interest rate risk, which we conceptualize as the probability of an increase in policy rates of an uncertain magnitude and which we track using the MOVE index (a measure of interest rate risk through bond market volatility). We identify this as the *interest risk channel*, which is in turn attached to the role of bank deposits as a store of value. Intuitively, a higher likelihood of increase in policy rates correlates with greater dispersion of expected deposit rate (Duffie and Krishnamurthy 2016), rendering each bank's deposits a less attractive store of value and prompting more frequent transfers among banks. In other words, to mitigate interest rate risk, depositors tend to move their deposits more actively between accounts instead of keeping them in one place. These findings thus echo the recent studies showing that interest rate risk may trigger large deposit outflows at the bank level (e.g., Drechsler, Savov, Schnabl, and Wang 2023, Haddad, Hartman-Glaser, and Muir 2023, Jiang, Matvos, Piskorski, and Seru 2023). Our findings add to this evidence by focusing on the granular behavior of individual depositors, specifically looking at the intensive margin of deposit transfers in response to interest risk.

Finally, the payment channel and the interest risk channel have an interactive effect, giving rise to what we describe as the *precautionary transfer channel*. Specifically, we find that depositors with bank accounts experiencing longer transfer delays are more alert in response to interest rate risks, tending to reallocate their deposits more actively when the MOVE index is elevated. Depositors engage in this active reallocation between accounts as a strategy to better navigate their exposure to interest rate risks, such as to assist with the servicing of floating-rate liabilities. Nevertheless, transfer delays impede their ability to manage this exposure efficiently, thereby amplifying the extent of unhedged interest rate exposure on household balance sheets. As a result, depositors precautionarily relocate their funds more to counteract the negative effects of transfer delays. In essence, depositors engage in precautionary transfers to alleviate the financial restrictions imposed by payment delays in managing interest rate risks. This behavior parallels the extensively documented precautionary savings motive in the consumption smoothing literature (e.g., Bewley 1983, Parker and Preston 2005, Carroll and Kimball 2006), where households save precautionarily to bolster their resilience against consumption risks with incomplete markets.

Notably, we find that depositors show heightened alertness during periods of rate hikes. In these times, all the identified economic channels are more pronounced compared to interest rate cuts. This pattern aligns our findings with extensive research emphasizing asymmetries in banks' rate-setting behaviors, especially the notable rate dispersion during rate increase periods (e.g., Driscoll and Judson 2013, Duffie and Krishnamurthy 2016, Drechsler, Savov, and Schnabl 2017). Our study contributes new, depositor- and account-level insights into this asymmetry. Specifically, Duffie and Krishnamurthy (2016) highlight that such asymmetry in banks' deposit rate-setting is likely driven by market power; banks tend to increase deposit rates less than proportionally in response to a rise in the policy rate, resulting in a broader dispersion of deposit rate offerings across banks. Conversely, they reduce deposit rates almost one-to-one when the policy rate decreases. This asymmetry suggests that the three channels we have identified become more prominent during rate hikes, as this is when the dispersion in deposit rates across banks is larger. Overall, our findings about depositor alertness, particularly during periods of rising interest rates, offer a fresh perspective on the financial stability risks associated with banks, as exemplified by the regional bank crisis of 2023.

We move on to provide causal evidence of the payment channel underlying deposit alertness. While individual depositors' alertness does not affect the aggregate interest risk, causally identifying the payment channel empirically is challenging: banks and depositors may choose each other based on payment needs. Such self-selection can lead to an endogenous sorting between depositors and the payment technologies of banks. To mitigate the identification challenges, we resort to the introduction of fast payment platforms such as Zelle, PayPal, Venmo, and Cash App. These platforms have an exogenous effect on the payment technologies available at the depositor level. For each depositor, we identify the first receipts of funds on these platforms and show that depositors who had *no* prior experience with these platforms start to actively use them for payments following their first receipt of inbound funds on these platforms. Economically, the exact timing and magnitude of the first receipt of fast-payment-based incoming funds are likely exogenous to the magnitude of transfer delay of the deposit accounts owned by the depositor in question, and thus serve as a plausibly exogenous shock. Specifically, We find the adoption of payment technologies is associated with a notable decrease in transfer delays, indicating a causal link between the adoption of fast payment technologies and changes in depositor behavior. Further analysis reveals that this reduction in transfer delays significantly increases deposit turnover.

We also show the impact of transfer delays on spending varies among depositor demographics, suggesting a distributional effect of interest rate pass-through via the deposit channel. Debit cards or bank accounts provide liquidity services with transfer delays. For depositors who predominantly rely on bank accounts for transactions, we anticipate them to benefit the most when transfer delays are shortened. Empirically, we show depositors who use debit cards or bank accounts for more than 90% of spending increase their consumption when transfer delays are reduced due to the availability of fast payment technologies.

To better understand the effect of depositor alertness on their economic outcomes, we present two pieces of supportive evidence grounded in the impact of interest rate fluctuations on household balance sheets. First, depositors who are highly alert about their deposits manage their repayments towards bank liabilities, such as mortgages, auto loans, student loans, and other personal loans (especially those with variable rates), more effectively. These liabilities add extra uncertainty in managing interest rate exposure across accounts receiving earnings or accumulating savings, and those covering such liabilities. At the account level, we find that for a given depositor, when an account with longer transfer delays faces a higher payment due to variable-rate debt, depositors tend to be more reluctant to transfer money out of it when the interest rate risk is high. Second, alert depositors may also engage in "interest shopping." This involves moving their deposits to accounts offering higher rates, thereby maximizing their interest earnings. Despite we do not directly observe account-level deposit rates, our findings reveal that depositors equipped with slower transfer technologies generally earn less interest income. However, in scenarios with high rate uncertainty, compared with depositors with shorter transfer delays, these depositors tend to earn more, aligning with the precautionary transfer motive underlying deposit alertness. Together, this evidence suggests that alert depositors gain tangible advantages by reducing the risks associated with interest rate fluctuations and payment frictions, through proactive financial behaviors, consistent with the three channels we discussed.

To further support the identified payment channel and precautionary transfer channel, we present a placebo test leveraging the contrast between inter-bank and intra-bank deposit transfers. Intra-bank transfers, defined as deposit transfers across bank accounts within the same depository institution, are typically processed within the same day. When in need of transfers, depositors can use intra-bank transfers as a strategy to bypass the delays in inter-bank transfers. We show that when inter-bank transfer times increase, there is a corresponding rise in intra-bank deposit turnover, contributing to an overall increase in deposit turnover. Additionally, intra-bank deposit turnover, not directly affected by the delays in inter-bank transfers, is not affected by interest rate risk even with higher inter-bank transfer frictions. Our findings demonstrate that the interaction between transfer delays and MOVE index does *not* impact intra-bank deposit turnover, underscoring the unique influence of rate risk on inter-bank deposit transfers as opposed to intra-bank transfers.

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) find evidence that depositors substitute between liquidity services and deposit rates at a bank level. Our research adds an essential layer of granularity by analyzing data at the depositor level, offering a micro-founded understanding of the time-varying nature of deposit alertness, which is intricately connected to factors such as payment technology and household balance sheet variables.

Our findings bear important implications regarding the funding costs of banks and the financial stability risks of the banking system as a whole. It is well known that fractional-reserve banks' business models in liquidity creation depend critically on stable deposit funding (e.g., Gorton 1988, Hanson, Shleifer, Stein, and Vishny 2015, Drechsler, Savov, and Schnabl 2021, Egan, Lewellen, and Sunderam 2022), while panic runs are largely viewed as the top threat to bank liquidity transformation (e.g., Diamond and Dybvig 1983, Diamond and Rajan 2001, Goldstein and Pauzner 2005, Iyer and Puri 2012, Iyer, Puri, and Ryan 2016, Egan, Hortaçsu, and Matvos 2017), with the collapse of the Silicon Valley Bank as the most recent example(e.g., Drechsler, Savov, Schnabl, and Wang 2023, Haddad, Hartman-Glaser, and Muir 2023, Jiang, Matvos, Piskorski, and Seru 2023). Reconciling these two views as bank deposits being sleepy or flighty, recent work of Bolton, Li, Wang, and Yang (2023) and Jermann and Xiang (2023) highlights bank deposits as long-term liabilities of uncertain maturities.

Complementing this perspective, our research offers a new framework, supported by unique and detailed evidence to characterize the intensity of depositor alertness, highlighting the role of deposits as a medium of exchange and a store of value, and particularly, the conflict of these two roles (Goldstein, Yang, and Zeng 2023). As the demand for payment convenience becomes higher relative to that for storage convenience, banks face a more challenging liquidity management problem (e.g., Afonso, Kovner, and Schoar 2011, Afonso, Duffie, Rigon, and Shin 2022, Li and Li 2021, Li, Li, and Sun 2022, Lopez-Salido and Vissing-Jorgensen 2023), resulting in potentially less efficient lending or higher financial stability risks.

In essence, our research traces the origins of these 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 disintermediation and financial stability risks at the bank level.

The rest of the paper is organized as follows. Section 2 presents a straightforward model to introduce the concept of depositor alertness and the three channels. Section 3 describes the data and the construction of key variables, including the notion of deposit turnover and transfer delay. Section 4 empirically tests the predictions of the three channels. Section 6 further explores the motives underlying deposit alertness by analyzing to what extent deposits may benefit from such alertness in making cross-bank deposit transfers. 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 Theoretical Framework

In this section, we introduce a simple model along the lines of Duffie and Krishnamurthy (2016), Drechsler, Savov, Schnabl, and Wang (2023) and Haddad, Hartman-Glaser, and Muir (2023), to elucidate the concept of depositor alertness and the underlying economic channels. We intentionally keep the model stylized to reflect what we observe in the data, which are empirically examined subsequently in Sections 4, 5, and 6.

Time is continuous. There is a monopolistic bank i and a fringe of competitive banks. Note that modeling the fringe of competitive banks doesn't not imply all banks other than bank i process zero market power in reality; what is crucial is that bank i, which we take as the incumbent bank with which depositors initially bank, has some comparative market power over the other banks due to product differentiation (like certain bank services), search costs, or switch costs, which has been all well documented as important contributors to bank market power on the deposit market (e.g., Drechsler, Savov, and Schnabl 2017, Jiang, Matvos, Piskorski, and Seru 2023). For this reason, we assume that each unit of deposit at bank i delivers an exogenous relationship value or service flow at the rate of $\kappa > 0$ to its depositor, capturing such market power. The deposit rate offered by this monopolistic bank i, s_t, will then be determined in equilibrium. There is a continuum of depositors with log utilities, each endowed with a unit of bank deposits at bank i at $t = 0$.

To capture interest rate risk, we assume that there is a risk-free bond with exogenous return r_t, which can be viewed as, for example, the Fed Funds rate in the U.S., and the return on the risk-free bond follows

$$dr_t = \bar{r}dt + Y_{N_t}dN_t \,, \tag{1}$$

where N_t is a Poisson jump with an intensity $\phi > 0$, while Y_{N_t} is i.i.d. exponential with a parameter

$\alpha > 0$. Under this specification (1), the risk-free rate is subject to potential increases at random times of random sizes, capturing interest rate risk with a particular focus on monetary tightening cycles. When ϕ is larger, an interest rate hike is likely to happen more frequently. Similarly, when α is smaller, the interest rate hike is likely to be larger. Hence, both a larger ϕ and a smaller α would imply a larger interest rate risk.

To capture the notion of deposit alertness, we model depositors' endogenous deposit transferring decisions across different bank accounts, highlighting an underlying friction of payment inefficiency. Specifically, at $t = 0$, each depositor decides to transfer a portion of $x \in [0, 1]$ deposits to a competitive bank, which will be only settled at another independent Poisson arrival time with intensity $\lambda > 0$. Between $t = 0$ and the arrival time, the x deposits in the transfer process will not earn any interest rate. Here, the random settlement time captures potential payment delays and the risks involved; a larger λ implies a more efficient payment technology because it involves a shorter delay in settlement and hence a faster transfer.

As a benchmark, we first present a lemma showing that the monopolistic bank offers a lower deposit rate in equilibrium compared to the other banks.

Lemma 1. *The monopolistic bank i offers a deposit rate $s_t < r_t$, while the competitive banks offer the risk-free rate r_t.*

Lemma 1 has a simple interpretation when mapped to a more realistic setting with multiple banks: different banks respond to policy rate hikes differently in increasing their deposit rates, and a bank with comparative market power (due to various sources captured by κ) may increase its interest rate offering less. This is reminiscent of the result in Drechsler, Savov, and Schnabl (2017) that commercial banks with deposit market power compared to non-banks such as money market funds increase their deposit rates less than one-for-one in response to any increase in the policy rate. As shown there, despite the sticky rate-setting behavior, deposits flow out of the banking system regardless.

Similarly, in our framework, this economic force underlying Lemma 1 implies that deposits may also flow from an incumbent bank with relatively higher market power to another bank with relatively lower market power due to the interest rate difference $r_t - s_t$. The marginal contribution of our model is to pinpoint the determinants of such deposit flows in an interbank deposit transfer context. It is important to note that the interest rate difference $r_t - s_t$ does not only capture potential gains in terms of interest earnings by shifting deposits, but also any savings for preventing the deposits from incurring any interest-rate-related costs that derive from the failure of transferring deposits from one account to another. For example, a potential re-interpretation of the model is that staying banking with the incumbent bank may cost the depositor in question $r_t - s_t$, perhaps because of the mismatch between the asset and liability side of the household balance sheet due to the different exposure to interest rate risk. In this sense, a depositor optimally transfers deposits across different banks not to capture any interest earnings but to better manage the exposure to interest rate risk on the household balance sheet overall.

With these complementary interpretations of the model in mind, we now summarize the main theoretical results in the following proposition:

Proposition 1. *The optimal deposit transfer size:*

i). increases when the payment technology is more efficient (i.e., expected transfer delay is shorter), that is, $\frac{\partial x}{\partial \lambda} > 0$*, which we refer to as the payment channel;*

ii). increases when the interest rate risk is higher, that is, $\frac{\partial x}{\partial \phi} > 0$ *and* $\frac{\partial x}{\partial \alpha} < 0$*, which we refer to as the interest risk channel; and,*

iii). the sensitivity of optimal deposit transfer size to interest rate risk increases when the pay-

ment technology is less efficient (i.e., expected transfer delay is longer), that is, $\frac{\partial^2 x}{\partial\lambda\partial\phi} < 0$ *and* $\frac{\partial^2 x}{\partial\lambda\partial\alpha} > 0$*, which we refer to as the precautionary transfer channel.*

We elaborate on the three channels through which payment and interest drive deposit alertness. First, the payment channel implies that depositors more actively shift their deposits between accounts when the payment technology attached to their accounts is more efficient. Intuitively, when the settlement takes less time to transfer deposits from one bank to another, the depositor effectively loses less and bears a lower risk during this transfer process, encouraging her to transfer deposits to capture any potential gains from such transfers. This channel underscores the significant role of deposits in household portfolios as a means of exchange. When the payment technology attached to a bank account becomes more efficient in the sense that the delay in deposit transfer becomes shorter, deposits become more convenient in terms of the medium of exchange function, encouraging depositors to transfer them more actively across accounts to facilitate their transactional needs.

Second, the interest risk channel implies that depositors more actively shift their deposits when facing heightened interest rate risk, particularly for interest rate increases. Intuitively, when an interest rate hike becomes more likely or when the size of the interest hike shock becomes larger, the deposit rate difference between the incumbent bank and other competing banks widens, encouraging the depositor in question to leave the incumbent bank for a competing bank offering a potentially higher deposit rate. This channel is in turn attached to the role of bank deposits as a store of value. When interest rate risk becomes higher, deposits at the incumbent bank become a less attractive option as a store of value. This leads depositors to move their deposits more frequently between accounts instead of keeping them in one place.

Finally, the payment channel and interest risk channel interact with each other, leading to what we refer to as the precautionary transfer channel. The precautionary transfer channel implies that depositors whose bank accounts are subject to longer transfer delays respond more aggressively to interest rate risk, shifting their deposits across different accounts more actively. Intuitively, transfer delays hinder depositors' ability to manage interest risk exposure, increasing the exposure to interest rate risk on household balance sheets. Consequently, depositors proactively move their deposits to mitigate the adverse impacts of transfer delays. This is akin to the extensively documented precautionary savings motive (e.g., Bewley 1983, Parker and Preston 2005, Carroll and Kimball 2006), where households increase their savings as a precautionary measure to enhance their ability to cope with consumption risks under diverse constraints.

3 Data and New Metrics of Deposit Alertness and Delays

In this section, we outline the dataset and detail the construction of key variables, encompassing a novel metric for depositor alertness, termed *deposit turnover*, a measure of payment speed at the depositor level called *transfer delay*, along with a range of household balance sheet variables.

3.1 Data Description

We obtain transaction-level 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 over 60 million 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.

We categorize active users into four groups based on their transaction frequency since 2013: 1.26 million users with ten transactions each quarter, 1.42 million with 5, 2.8 million with ten transactions across 30 quarters, and 3.28 million with five transactions across 30 quarters. We use the 1.26 million user group as a benchmark following Buda et al. (2022). Even though the dataset does not contain supplementary demographic information, it provides a monthly estimate of users' current city of residence. The data vendor specializes in serving the banking and fin-tech industries, ensuring minimal user selection bias and attrition. To further validate the accuracy of these location estimates, we cross-referenced them with transaction data related to groceries, utility bills, and restaurant spending. Our cross-checking largely corroborated the location data supplied by the data vendor.

3.2 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.

In the data, we target transactions related to deposits and transfers. We record the dollar value of each credit transaction C and each debit transaction D. 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 25 and is an integer to capture the potential fees in deposit transfers.

4. Temporal constraint: The temporal difference between the two transactions does not exceed seven business days.

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

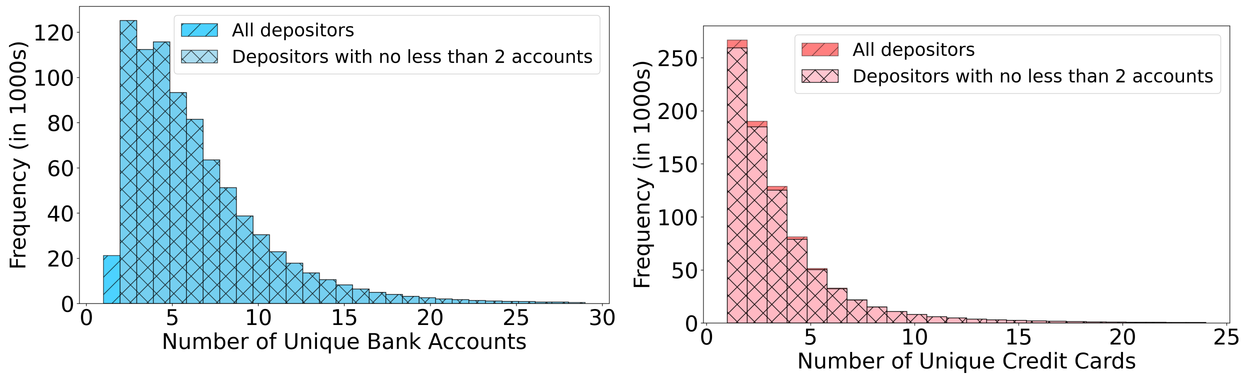
$$Deposit\ Turnover_{i,t} = \Sigma_k C_{i,t}^k.$$

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 inter-bank 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.

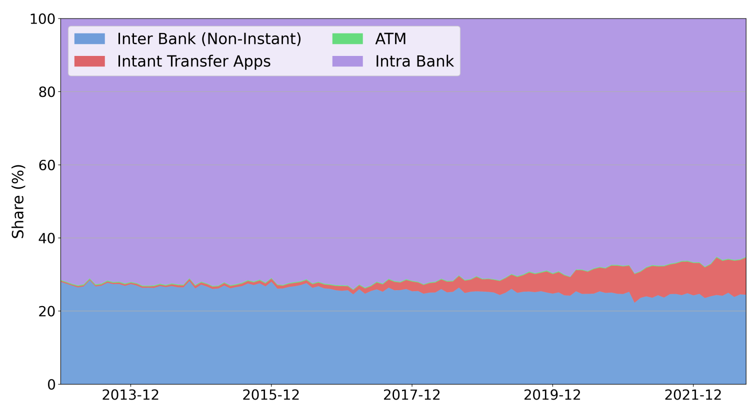
Types of Deposit Turnover. Using the meta information and transfer delays for paired deposit transactions, we further distinguish deposit turnover based on the method of transfer used, as illustrated in Figure 2. Transactions completed with fast payment services such as Zelle, PayPal, Cash App, and Venmo are classified as "Instant Transfer App" transactions. Over time, there has been a noticeable uptick in these types of transactions. We classify a transaction *intra-bank transfer* if it is completed within the same day without any fast payment technology marker in the transaction description. Intra-bank transfers account for the largest proportion of transactions and have main-

Figure 1: Bank Accounts and Credit Cards per Depositor



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

Figure 2: Types of deposit turnover

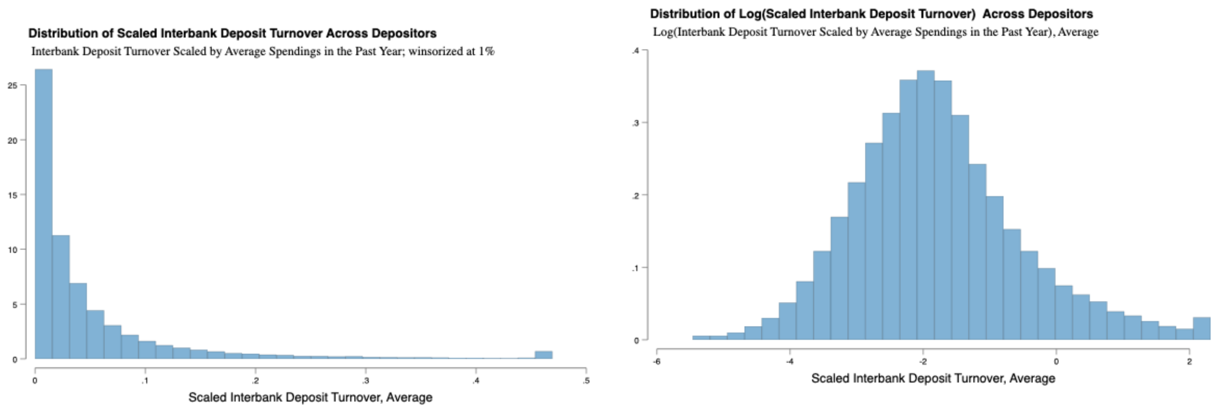


This graph delineates multiple types of deposit transfers. Depositors have the option to reallocate deposits between accounts held at the same financial institution or to transfer assets to an alternate bank. Transactions marked with fast payment services (such as Zelle, PayPal, Cash App, and Venmo) are classified as "Instant Transfer Apps" (red); if a transaction is completed *within the same day* without fast payment services, we infer it as an intra-bank transfer. Transactions with ATM related information in descriptions are categorized as ATM transactions. All remaining transactions are classified as inter-bank transfers, as shown at the bottom of the graph in blue.

tained a dominant position consistently through the years. 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 transactions that do not fall into the aforementioned categories are labeled as inter-bank transfers. These are depicted in blue at the bottom of our graph. The primary focus of our study is on inter-bank transfers, given their significant implications for overall financial stability.

Figure 3: Distribution of Scaled Interbank Deposit Turnover



These two hitograms present the distributions of interbank deposit turnover for depositors in our sample from 2013 to 2022. Plot on the left shows the density of average monthly interbank deposit turnover, scaled by average spendings in the past year at any point in time across depositors. Plot on the right shows the density of the logarithm of average monthly interbank deposit turnover, scaled by average spendings in the past year at any point in time across depositors; the logarithm is only defined for the months when depositors have positive interbank deposit 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, 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.

3.3 Transfer Delay.

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,

$$Delay_k = Date(C_k) - Date(D_k), \tag{2}$$

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,

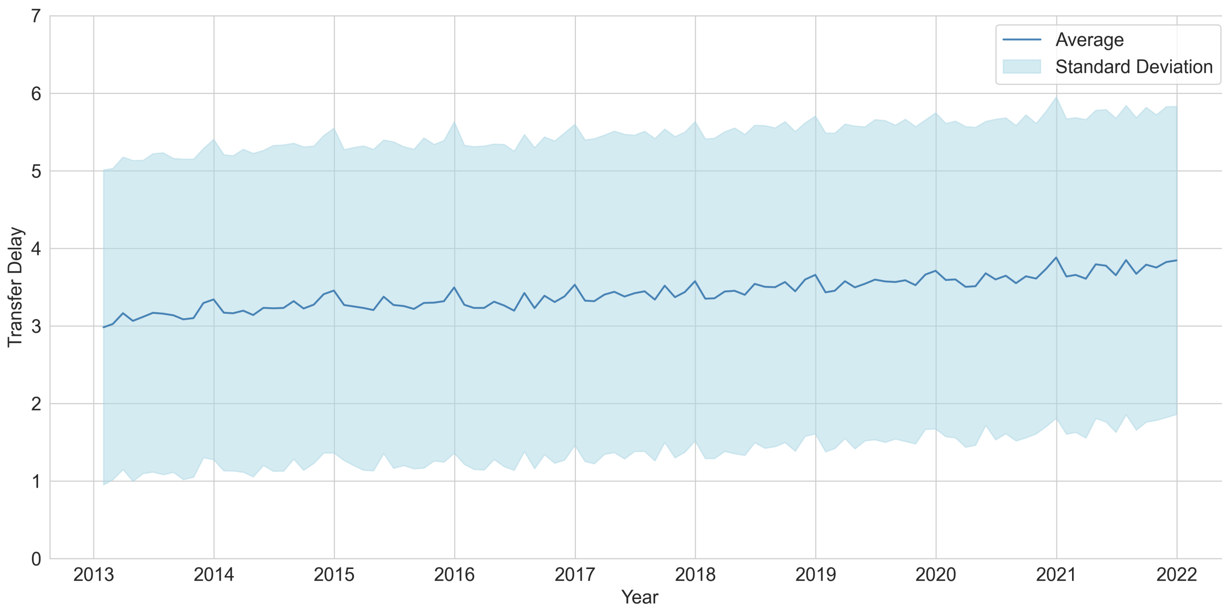
$$AvgDelay_{a,t} = \frac{\Sigma_k Delay_k \cdot \mathbf{I}(D_k \text{ is originated from account } a)}{\Sigma_k \mathbf{I}(D_k \text{ is originated from account } a)}. \tag{3}$$

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

$$PaymentDelay_{Depositor,t} = \frac{\Sigma_a D_{a,t} \times AvgDelay_{a,t}}{\Sigma_a D_{a,t}}. \tag{4}$$

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.[1]

Figure 4: Transfer Delays Over Time



This graph shows the average weighted delay in inter-bank deposit transfers from 2013 to before June 2022, computed using the dollar-weighted transfer delays across interbank deposit transfer transactions for each depositor at any given month. 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 despite the development of payment technologies in recent decades, American depositors still face economically significant delays in

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

transferring their deposits across different banks. Specifically, transfer delays remain consistently around a mean of 4 days throughout the sample period.

Table 1 further offers an overview of the average transfer sizes correlated with various transfer delays. Specifically, this table summarizes the average transaction values for each specific transfer delay across depositors. For each month, we determine the average amount transferred by each depositor for each value of transfer delay (in days). We then summarize the average transfer related to different delays across all depositors and months.

Table 1: Average Amount by Transfer Delay

delay	mean	sd	median	p10	p90	count
0	1,360.04	1,563.11	833.90	300.60	2,986.11	806,992
1	646.46	1,279.54	232.06	91.17	1,475.00	600,888
2	572.18	1,241.59	200.00	84.44	1,125.00	557,006
3	541.04	1,132.34	200.00	87.50	1,050.00	586,849
4	521.98	1,112.12	200.00	86.76	1,000.00	580,660
5	488.25	1,075.69	187.33	82.50	1,000.00	534,883
6	477.00	1,029.20	192.25	84.93	1,000.00	567,725
7	482.97	1,016.57	200.00	88.33	1,000.00	615,765

This table presents a summary of average monthly deposit transfer sizes, categorized by the transfer delays (measured in days). For each month, we first compute the average amount transferred by each depositor for every value of transfer delay (in days), and then aggregate the average amount transferred for each specific value of transfer delay across depositors and months.

3.4 Characteristics and Constraints of Depositors

Floating-Rate Liabilities. To assess the interest rate exposure at the individual depositor level for both mortgages and loans, we start by extracting all transactions specifically labeled as mortgage payments, keeping only those with at least 24 payments for further analysis. Next, we examine fluctuations in these monthly payments, filtering out any changes greater than 10% as these are likely due to factors like prepayment or financial constraints on the borrower. To gauge the impact of interest rate changes, we correlate these payment fluctuations with the 3-Month LIBOR.[2] Following this, we calculate both the average and modal frequencies between payment changes to classify the types of mortgages. Fixed-rate mortgages are identified if the modal frequency is absent or if the average frequency of changes is longer than six months. On the other hand, mortgages are considered to be of the floating-rate variety if either the average or modal frequency of changes is less than six months and is highly correlated with 3M LIBOR. For identifying N-year adjustable rate mortgages (ARMs), we look for annual adjustments in the first N years, followed by more frequent changes. A similar procedure is applied for loan payments, excluding the ARM categorization.

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. To validate the reliability of our approach, we compared the labor income dynamics of depositors in our dataset to those in the Panel Study of Income Dynamics (PSID), and found the trends to be similar.

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.

[2]We chose LIBOR over SOFR because LIBOR's availability throughout the sample period makes it a more reliable metric for our study. In addition, Duffie et al. (2023) shows that on average, over 70% of floating-rate credit lines and term loans are benchmarked to LIBOR by the end of 2019.

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 control for financial sophistication and debt-to-income ratio, to address potential self-selection effects. Depositors with floating-rate liabilities may inherently exhibit specific characteristics that differentiate them from others. For instance, they can be more financially sophisticated or have higher incomes. Such characteristics could predispose them to be more proactive depositors. By controlling for financial sophistication and debt-to-income ratio, we aim to disentangle the effects of holding floating-rate liabilities from the potential confounding influence of these underlying attributes.

The *debt-to-income ratio* is calculated by dividing the combined payments of fixed and variable rate loans and mortgages by the salary earned within the same month.[3] To capture sophistication

[3]Investment income was excluded from consideration for now due to the difficulty in distinguishing pension income and irregular inflows from inheritances or proceeds from trading activities.

in payments, we construct a variable, *digital adoption ratio*, that captures online versus total consumption for each depositor. This measure can serve as an indicator of a user's adoption of digital payment methods, reflecting their comfort with and reliance on online transactions. The digital adoption ratio highlights a depositor's trust in technology, accessibility to digital platforms, and preference for transactional convenience. However, this measure might be influenced by the inherent nature of certain expenditures, and individual security concerns, and might not encompass the broader aspects of financial sophistication, such as investment knowledge or budgeting skills.

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.

Interest Income. Despite we do not directly observe deposit rates in the data, to quantify the income generated from interests on deposits at the individual account level, we select transaction records with a description containing the word "interest" and are credited to the account. We manually filtered out transactions that might misrepresent genuine interest income. This included but was not limited to, transaction descriptions associated with bonuses, overdraft fees, loans, and rents. The controls for financial sophistication and debt-to-income ratio help to address potential self-selection effects. Depositors who possess floating-rate liabilities may inherently exhibit specific characteristics that differentiate them from others. For instance, they might be more financially sophisticated, living in urban areas, or have higher income. Such characteristics could predispose them to be more proactive depositors. By controlling for financial sophistication and debt-to-income ratio, we aim to disentangle the effects of holding floating-rate liabilities from the potential confounding influence of these underlying attributes.

Macro Series. The three-month London Interbank Offered Rate (LIBOR3M) data is gathered from S&P Global Market Intelligence through the Wharton Research Data Services (WRDS). Additionally, we source the ICE Bank of America Merrill Lynch Option Volatility Estimate (MOVE) Index from Investing.com. The MOVE Index quantifies volatility in U.S. interest rates by tracking fluctuations in U.S. Treasury yields, reflecting uncertainties about future rate changes. During the observed period from 2013 to 2022, the MOVE Index averaged 69.429, with a standard deviation of approximately 21.019. Throughout this timeframe, the correlation between the MOVE Index and the three-month LIBOR stood at around 0.168.

In the above variables related to depositors, we adjusted the data by winsorizing at the 1% level across users and dates to mitigate the influence of extreme outliers. Table 2 provides summary statistics for the variables, highlighting substantial volatility in deposit turnover ($11,397.16 mean, $27,403.48 SD) and dollar-weighted delays (3.91 days mean, 1.1 days SD). It's important to note that calculations for deposit turnover and transfer delays in the table are based solely on inter-bank self-deposit transactions, as intra-bank transfers are instantaneous and present minimal payment risk for banks. One factor contributing to the high rate of deposit turnover is account specialization. Figure A-1 in Internet Appendix A 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. The data also reflects diverse mortgage and loan values, with significant variations in fixed and floating rate mortgages. Additionally, the percentage of depositors using fast payment applications stands at 17%, suggesting a notable but not predominant use fast payment platforms.

Table 2: Summary Statistics

	mean	sd	median	p10	p90	count
Interbank deposit turnover ($)	4701.92	18752.24	1321.60	286.80	8400.00	623,367
Scaled interbank deposit turnover	0.35	0.38	0.20	0.05	0.87	556,899
Number of interbank transfers	8.66	4.96	9.00	2.00	13.83	623,367
Interest income ($)	19.93	467.24	1.61	0.13	21.95	623,367
Fixed-rate mortgages ($)	487.77	1158.48	0.00	0.00	1599.34	623,367
Fixed-rate mortgage + loans ($)	556.55	1436.16	27.11	0.00	1719.70	623,367
Floating rate mortgage + loans ($)	436.83	1215.48	163.79	0.00	1101.68	623,367
Floating rate mortgage ($)	52.79	294.22	0.00	0.00	0.00	623,367
Debt payment to income ratio	1.26	25.30	0.19	0.00	1.14	466,913
Consumption smoothing efficiency	2.67	1.27	2.49	1.29	4.25	417,439
Salary ($)	2951.00	4162.56	1662.71	0.00	7562.38	623,367
Digital adoption ratio	0.79	189.13	0.50	0.19	0.87	461,490
Dollar-weighted delays (days)	2.92	1.44	2.83	1.15	4.75	623,367
Number of Employers	1.28	0.47	1.00	1.00	2.00	466,913
% with ATM use	0.29	0.45	0.00	0.00	1.00	623,367
% with fast payment services	0.19	0.39	0.00	0.00	1.00	623,367
Salary ($)	2951.00	4162.56	1662.71	0.00	7562.38	623,367
Digital adoption ratio	0.79	189.13	0.50	0.19	0.87	461,490
Dollar-weighted delays (days)	2.92	1.44	2.83	1.15	4.75	623,367
% with ATM use	0.29	0.45	0.00	0.00	1.00	623,367
% with fast payment services	0.19	0.39	0.00	0.00	1.00	623,367

This table provides a summary of financial statistics for a sample of 623,367 depositors, actively tracked from transaction data across more than 1,400 U.S. banks and credit unions as a balanced panel between 2013 and 2022. It summarizes key variables at monthly frequency: interbank deposit turnover represents the total dollar amount transferred across bank accounts in different banks. Additionally, to facilitate more meaningful cross-sectional comparisons, we report the scaled interbank deposit turnover as interbank deposit turnover scaled by the average monthly spending in the past year. The number of interbank deposit transfers reflects the average number of deposit transfer transactions per depositor. Interest Income is the income earned from interest on deposits in bank accounts. Mortgages and Loans, both fixed and floating rates, are the values of monthly payments to outstanding mortgages and loans, illustrating depositor debt exposure. Debt Payment to Income Ratio shows the portion of income used for debt repayment, and Consumption Smoothing Efficiency is computed as 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. Salary is the monthly labor income, and the Digital Adoption Ratio reveals the extent of digital payment methods adoption among users, defined as online versus total consumption for each depositor. Dollar-weighted Delays indicate the average processing days for inter-bank transfers weighted by the dollar amount of outflows from each account, and the Number of Employers provides an average count of employers per depositor. Lastly, the percentage of depositors using Fast Payment Services summarizes the percentage of depositors who have used fast payment services such as Zelle, PayPal, Cash App, and Venmo in their transactions. All variables are winsorized at the 1% threshold to mitigate the impact of extreme outliers.

4 What Drives Deposit Alertness: Testing the Channels

In this section, we empirically test the predictions of the three channels that we highlight in Section 2: the *payment channel*, the *interest risk channel*, and the *precautionary transfer channel*, and explore their implications. We first provide baseline estimates, and then provide a series of tests that further substantiate the existence and magnitude of these channels in Section 6.

4.1 Baseline Estimates: Determinants of Deposit Turnover

We study how transfer frictions, particularly delays in inter-bank deposit transfers, impact depositor alertness both unconditionally and conditional on interest rate risk with the empirical model:

$$\begin{aligned} \textit{Deposit Turnover}_{i,t+1} = \beta_0 + \beta_1 \times \textit{Transfer Delay}_{i,t} + \beta_2 \times \textit{MOVE}_t + \\ \beta_3 \times \textit{Transfer Delay}_{i,t} \times \textit{MOVE}_t + \Gamma \times \mathbf{X}_{i,t} + \delta_t + \epsilon_{i,t}. \end{aligned}$$

Deposit Turnover$_{i,t+1}$ represents the deposit movements across different banks for depositor i within the month $t+1$, scaled 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). *Transfer Delay*$_{i,t}$ is the dollar-weighted average time in days it takes for depositor i within the month t, standardized by subtracting the mean and then dividing by the standard deviation; i.e., a one unit increase is equivalent to a one-standard-deviation increase in *Transfer Delay*$_{i,t}$ throughout the analysis. The MOVE index measures fluctuations in U.S. Treasury yield volatility. 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 financial constraints (such as payments towards floating-rate and fixed-rate debts and monthly income). Second, we also consider financial savvy through the digital adoption ratio, which compares non-physical to total consumption and reflects a depositor's inclination towards newer, faster technologies. These individual-specific variables are all scaled by the average spending in the past year to facilitate comparisons across depositors. Additionally, we account for the interaction between *Transfer Delay*$_{i,t}$ and interest rates, represented by the three-month London Interbank Offered Rate (LIBOR), to adjust for possible deposit activeness due to reaching for income incentive. Finally, we factor in economic constraints using the debt-to-income ratio and the consumption smoothing efficiency, calculated as the ratio of the rolling mean to the rolling standard deviation of consumption.

Table 3 summarizes baseline estimates aligning with the three channels outlined in Section 2. First, accounting for time-specific effects and depositor-specific factors, it's observed that each additional day of delay in inter-bank transfers reduces deposit turnover by approximately $233.8 (Column 4), a significant and consistent result across various models. This supports the *payment channel*, where faster payment technology is correlated with increased deposit turnover. This suggests that depositors are alert to the efficiency of the payment technology at their disposal, actively shifting their deposits between accounts when they can do so with less delay. Conversely, when considering the interaction between transfer delays and interest rate volatility (as indicated by the MOVE index), there's a positive effect on deposit turnover. With controls in place, each standard deviation increase in interest rate volatility coupled with an additional day of transfer delay correlates with a $52.5 rise in deposit turnover (Column 4), endorsing the *precautionary transfer channel*, implying that depositors who face higher interest rate risk may be more likely to shift their deposits when facing longer transfer delays.

Moreover, while the main emphasis of this research is on the cross-section of depositors, in Column 1, we omit the time-fixed effect to further analyze the unconditional impact of interest rate volatility on deposit turnover. With an average transfer delay of 3.9 days, a one standard deviation rise in interest rate volatility correlates with a $285.7 increase in deposit turnover. This suggests an unconditional greater sensitivity of depositors to fluctuations in interest rates, consistent with the *interest risk channel*, which indicates increased alertness among depositors when the risk associated with interest rates is elevated.

Table 3: Deposit Turnover & Transfer Delays

	(1)	(2)	(3)	(4)
Transfer delay	-0.0271***	-0.0274***	-0.0273***	-0.0271***
	(0.00135)	(0.00137)	(0.00136)	(0.00135)
Transfer delay $\times$ MOVE	0.00444***	0.00428***	0.00428***	0.00421***
	(0.000984)	(0.00100)	(0.00100)	(0.000993)
MOVE	-0.00610***	0	0	0
	(0.00134)			
Time FE	N	Y	Y	Y
Interest rate controls	Y	Y	Y	Y
Budget constraint controls	N	N	Y	Y
Liquidity & sophistication controls	N	N	N	Y
Time FE	N	Y	Y	Y
N	338672	338672	338672	338672
Adj. R^2	0.00721	0.00958	0.0101	0.0115

This table presents the relation between various depositor-specific attributes 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 computed from inter-bank paired deposit transactions 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. Transfer delay is the dollar-weighted average time in days it takes for depositor i to transfer self-deposits within the month tMOVE index tracks the movement in U.S. Treasury yield volatility. For interpretation purposes, transfer delay and MOVE index are standardized by first subtracting their mean and then dividing by their standard deviation, respectively. Focusing on the heterogeneity of depositors, we introduce three relevant groups of depositor-level controls: 1) Budget constraint controls, including a) Floating rate mortgage ($), the payment to the amount of floating-rate debt outstanding for depositor i at month t, b) Salary is the total monthly labor income of depositor i at month t, and c) Fixed-rate mortgages and loans for depositor i at time t; 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) the debt-to-income ratio for depositor i at time t, and c) Digital adoption ratio which is the ratio between non-physical and total consumption for each depositor at month t; 3) Interest rate controls, including the 3-month LIBOR rate and its interaction with transfer delays. The dependent variable is Deposit Turnover$_{i,t+1}$, that is, the dollar amount moved among each bank account for depositor i at month $t+1$. 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%.

In Internet Appendix B, we revisit the analyses that underpin Table 3, this time centering on an alternative metric of depositor alertness: the average amount of inter-bank transfers per individual transfer within a given month, as opposed to the total dollar value of inter-bank transfers used in our benchmark specifications. Aligning with the theoretical framework outlined in Section 2, our findings indicate that the depositor alertness observed in Table 3 is primarily attributable to depositors engaging in more active and substantial transfers with each transaction (corresponding to a larger equilibrium x in the model), rather than an increase in the frequency of their transfers. To focus on the implications for bank funding and financial stability risks, however, we opt to employ the initial concept of depositor alertness as our benchmark. This approach focuses on the total dollar value of inter-bank transfers, thereby providing a more accurate representation of the funding pressures a bank faces during a specific period.

4.2 Asymmetric Deposit Turnover Behaviors along Interest Rate Cycles

Previous research suggests the stickiness of deposit rates is asymmetric during interest rate cycles (Driscoll and Judson 2013). Particularly, Duffie and Krishnamurthy (2016) suggest that such asymmetry in bank's deposit rate setting behaviors is driven by bank market power in that banks increase deposit rates less than one-to-one in response to an increase in the policy rate, leading to a larger dispersion of deposit rate offerings at the cross-section of banks, while they decrease deposit rates almost one-to-one in response to a decrease in the policy rate. In light of our model in Section 2, this asymmetry implies that the three channels we highlighted above would be stronger during interest rate hikes because the equilibrium deposit rate differential between the monopolistic bank and the competitive bank would only exist during interest rate hikes. In other words, the monopolistic bank and the competitive bank would become observationally equivalent during interest rate cuts, dissolving any motive for a depositor to transfer deposits between the two bank accounts.

To explore this implied asymmetry, we explore the magnitude of depositor alertness during periods of rate hikes and cuts, showing that deposit alertness indeed exhibits a form of asymmetry between hikes and cuts. Specifically, we repeat the specifications in the previous section but separate the sample into periods of interest hikes and cuts.

The findings of this analysis are compiled in Table 4. During rate hikes, the impact of each additional day of delay in inter-bank transfers on deposit turnover is magnified significantly. Specifically, the reduction in deposit turnover due to transfer delays is approximately \$491.3, a figure that is almost two times as large as the standard reduction of \$233.8 observed in the full sample. This finding is robust with and without depositor fixed effects and lends strong support to the payment channel hypothesis. It suggests that, especially during rate hikes, depositors are highly sensitive to the efficiency of payment technology, actively moving more deposits between accounts if their payment technology is more efficient. In contrast, the interaction between transfer delays and interest rate volatility (as measured by the MOVE index) shows a different pattern. In the full sample (Column 1), each standard deviation increase in interest rate volatility, combined with an additional day of transfer delay, correlates with a \$52.5 increase in deposit turnover under normal circumstances. However, during rate hikes, this effect escalates significantly, with the corresponding increase in deposit turnover rising to 1.7 times larger, at approximately \$90 (Column 2). This pronounced effect suggests that during periods of interest rate hikes, depositors become more reactive to changes in interest rate volatility, adjusting their deposit turnover more aggressively in particular with slower payment technologies.

The results in Table 4 provide further support to the interest risk channel and the precautionary transfer channel discussed in Section 2, which, as discussed above, would be present only during

Table 4: Deposit Turnover & Transfer Delays: Rate Cycles

	(a)			(b)		
	Full-Sample (1)	Rate Hikes (2)	Rate Cuts (3)	Full-Sample (4)	Rate Hikes (5)	Rate Cuts (6)
Transfer delay	-233.8***	-491.3***	93.74	-65.46*	-127.7**	14.29
	(63.69)	(70.42)	(70.88)	(38.77)	(50.03)	(56.57)
Transfer delay $\times$ MOVE	2.503***	4.291***	-0.624	0.992*	1.330*	0.557
	(0.873)	(0.885)	(1.225)	(0.573)	(0.686)	(0.985)
Time FE	Y	Y	Y	Y	Y	Y
Interest rate controls	Y	Y	Y	Y	Y	Y
Budget constraint controls	Y	Y	Y	Y	Y	Y
Liquidity & sophistication controls	Y	Y	Y	Y	Y	Y
Depositor FE	N	N	N	Y	Y	Y
N	3,440,794	2,015,557	1,425,237	3,359,185	1,930,222	1,337,538
Adj. R^2	0.00330	0.00351	0.00255	0.241	0.240	0.281

This table presents the associations between various depositor-specific attributes at time t and deposit turnover$_{i,t+1}$, which gauges the alertness with which a depositor i transfers deposits between accounts in month $t+1$. Panel (b) includes two-way fixed effects. Transfer delay (day) is the dollar-weighted average time in days it takes for depositor i to transfer self-deposits within the month t. MOVE index tracks the movement in U.S. Treasury yield volatility. Focusing on the heterogeneity of depositors, we introduce three relevant groups of depositor-level controls: 1) Budget constraint controls, including a) Floating rate mortgage ($), the payment to the amount of floating-rate debt outstanding for depositor i at month t, b) Salary is the total monthly labor income of depositor i at month t, and c) Fixed-rate mortgages and loans for depositor i at time t; 2) Liquidity and Sophistication constraint controls, including a) Consumption smoothing efficiency, defined as the ratio of the rolling mean to the rolling standard deviation of consumption using monthly data from the previous 12 months for each depositor i at month t, b) the debt-to-income ratio for depositor i at time t, and c) Digital adoption ratio which is the ratio between non-physical and total consumption for each depositor at month t; 3) Interest rate controls, including the 3-month LIBOR rate and its interaction with transfer delays. The dependent variable is Deposit Turnover$_{i,t+1}$, that is, the dollar amount moved among each bank account for depositor i at month $t+1$. All standard errors are clustered and are reported in parentheses. *, **, and *** indicate statistical significance level at 10%, 5%, and 1%.

interest rate hikes. To see this, note that, as predicted by Duffie and Krishnamurthy (2016), the across-bank dispersion of deposit rates is larger during interest rate hikes than cuts. This implies that a representative depositor, as modeled in Section 2, would more likely face a differential between deposit rates between her different bank accounts. Thus, the two channels are more likely to be observed during such rate hike periods because otherwise the need for deposit transfers is muted during interest cuts. The results in Columns 2 and 5 compared to those in Columns 3 and 6 in Table 4 are indeed consistent with the interest risk channel and the precautionary transfer channel being present only during interest rate hikes but not cuts. Note that we cannot separately test the interest risk channel in Table 4 because MOVE index is absorbed by time fixed effects.

5 Identification: Impact of Fast Payments on Depositor Alertness

So far, we have provided evidence of depositor alertness, highlighting three underlying economic channels. Particularly, 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 and precautionary transfer 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, 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 fast payment platforms we consider include Zelle, PayPal, Venmo, and Cash App, the major service providers. 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 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. This evidence suggests that depositors in our sample set up accounts to receive deposits via fast payment platforms predominantly driven by network effects rather than an arbitrary change in financial habits.

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:

$$\begin{aligned}
\text{Transfer Delay}_{i,t} &= \gamma_0 + \gamma_1 I(\text{Post}\ \widehat{\text{First Inflow}})_{i,t} + X_{i,t} + \delta_t + \varepsilon_{i,t}, \\
\text{Deposit Turnover}_{i,t} &= \beta_0 + \beta_1 \widehat{\text{Transfer Delay}}_{i,t} + \beta_2 (\widehat{\text{Transfer Delay}}_{i,t} \times \text{MOVE}_t) \\
&= + X_{i,t} + \delta_t + \epsilon_{i,t}.
\end{aligned}$$

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 floating rate and fixed rate liabilities, salary, DTI ratio, CSE, digital adoption ratio and the interactions between delays and LIBOR3M, 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 0.127 days. This indicates that using quick payment methods significantly reduces this delay for depositors, as evidenced by an F-statistic of 42.9. 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:

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

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 floating rate and fixed rate liabilities, salary, DTI ratio, CSE, digital adoption ratio, as above, and the amount received from fast payment platforms. Panel (a) and (b) 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.

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

Table 5: Consumption, Turnover, and Fast Payment Adoption

	(a) Deposit Turnover					(c) Consumption					
	(a) 2SLS		(b) 3SLS			(c) Full Sample			(d) Debit Card>90%		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Transfer delay	-554.5***		-554.2***			-84.21			-2019.4**		
	(168.3)		(168.3)			(508.3)			(886.3)		
Transfer delay × MOVE	5.991***		6.020***			5.582			31.89***		
	(2.143)		(2.143)			(6.690)			(12.10)		
I(Post First Inflow)		-0.133***			0.971***			0.971***			0.983***
		(0.0161)			(0.00119)			(0.00121)			(0.00251)
I(Post First Outflow)				-0.161***			-0.164***			-0.253***	
				(0.0184)			(0.0183)			(0.0637)	
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Depositor Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	243,462	243,462	243,462	243,462	243,462	239,261	239,261	239,261	19,653	19,653	19,653

This table summarizes the effect of fast payment technology adoption on (inter-bank) deposit turnover and consumption. Panel (a) 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. Panel (b)-(d) adopts 3SLS to further incorporate the effect of receiving funds from fast payment platforms on technology adoption: in the first-stage regressions (columns 5, 8, and 11) 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 and deposit turnover from the predicted changes in transfer delays. We include time-fixed effects in all stages and depositor-level controls to estimate changes in delays and outcome variables (turnover and consumption), including floating rate and fixed rate liabilities, salary, DTI ratio, CSE, digital adoption ratio, and the amount received from fast payment platforms. Specifically, we estimate: $Y_{i,t} = \beta_0 + \beta_1 \widehat{\text{Transfer Delay}}_{i,t} + \beta_2(\widehat{\text{Transfer Delay}}_{i,t} \times \text{MOVE}_t) + \beta_3(\widehat{\text{Transfer Delay}}_{i,t} \times \text{LIBOR3M}_t) + X_{i,t} + \delta_t + \epsilon_{i,t}$, $\text{Transfer Delay}_{i,t} = \gamma_0 + \gamma_1 I(\text{Post First Outflow})_{i,t} + X_{i,t} + \delta_t + \varepsilon_{i,t}$, $\text{Transfer Delay}_{i,t} = \gamma_0 + \gamma_1 I(\text{Post First Outflow})_{i,t} + X_{i,t} + \delta_t + \varepsilon_{i,t}$, and $I(\text{Post First Outflow})_{i,t} = \zeta_0 + \zeta_1 I(\text{Post First Inflow})_{i,t} + \delta_t + v_{i,t}$. Finally, panel (d) reports results with a subsample of depositors who use debit cards (bank accounts) for more than 90% of their spending only since credit card spending does not result in fast-payment related penalties (overdraft, non-sufficient fee, etc) hence the ability to pay via a fast payment platform should affect consumers who rely on debit cards to consume the most. 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-statistic (column 1) is 42.905.

findings. However, again, as illustrated in Figure 4 above, throughout the sample period, transfer delays do not exhibit a temporal trend and remain consistently around a mean of 4 days.

Furthermore, we narrow our focus to a specific subset of depositors to understand how transfer delays can affect consumer welfare. Recognizing that depositors who mainly use credit cards are generally not subject to penalties like overdraft fees or non-sufficient funds charges due to transfer delays, we hypothesize that the implications of transfer delays will predominantly influence the spending behaviors of those who mainly use debit cards or bank accounts. Panel (d) of Table 5 highlights the outcomes for a subset primarily using debit cards for transactions, contrasting with panel (c), which examines the impact of transfer delays on the consumption of all depositors in our sample who have experienced the payment technology shock. As we anticipated, the benefits of faster payment methods are more significant and impactful for those heavily dependent on debit cards for their spending. Panel (d) reveals that the influence of rapid payment technology is notably more substantial and meaningful for this demographic, which is most affected by—and stands to gain the most from—reductions in transfer delays.

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. The greater responsiveness and shifts in financial habits among depositors reliant on debit cards for expenditures underscore the economic benefits and inclusivity implications of payment system innovations beyond the scope of deposit flows and financial stability.

6 What Deposit Alertness Implies: Understanding the Outcomes

Having shown how the three channels introduced in Section 2 drive depositor alertness and particularly identified the payment channel, we perform further tests to explore why deposit alertness is important to depositors, helping highlight the economic significance of depositor alertness. In doing so, we examine the underlying motives for deposit transfers, and we show how depositor alertness helps meet these motives, highlighting the channels illustrated in Section 2.

Depositors' motives for deposit transfers across bank accounts could stem from two possible reasons. First, to manage repayments for bank liabilities such as mortgages, auto loans, student loans, and other personal loans, depositors may constantly move deposits from one account that receives salary earnings or accumulates savings to another that carries such liabilities. Second, as noted by Samphantharak and Townsend (2006), depositors may directly engage in "interest shopping" by moving deposits from one account to another that offers a higher deposit rate to maximize returns on their interest earnings. At the same time, however, inter-bank deposit transfers can be hindered by slower transfer speeds between different banks, which may pose a risk in managing the mismatch between fixed-rate earnings flows and floating-rate debt repayments or delay interest earnings. This risk might be mitigated if depositors transfer their deposits between different bank accounts within the same bank.

6.1 Deposit Alertness and Account Risk Management

In this section, we further study deposit alertness at the account level, which is even more granular than the depositor-level analysis above. The account-level data provides us with a unique opportunity to delve deeper into the reasons behind the precautionary transfer motive: what drives depositors to redistribute funds across different bank accounts? One consideration may be the need to manage the unpredictability of interest payments on debts with floating rates. Consequently, depositors may opt to retain more funds in accounts linked to payments on floating-rate debts.

To empirically test the precautionary transfer motive, we test if depositors, when faced with high and uncertain payables in accounts that typically have longer average money transfer times, tend to reduce the amount of money they transfer out of these accounts. This behavior is presumed to be more pronounced during times when interest rate uncertainty is high. Complementary to the deposit turnover metric defined in Section 3, our account-level analysis focuses on the *directional* outflow of deposits at various bank accounts for a given individual depositor. Specifically, we consider the triple difference estimation below:

$$\begin{aligned}\textit{Deposit Outflow}_{i,a,t+1} = \gamma_0 + \gamma_1 \textit{Account Delay}_{i,a,t} \times \textit{MOVE}_t \times \textit{Account Debt}_{i,a,t} + \\ \gamma_2 \textit{Account Delay}_{i,a,t} \times \textit{MOVE}_t + \gamma_3 \textit{Account Debt}_{i,a,t} \times \textit{MOVE}_t + \\ \gamma_4 \textit{Account Debt}_{i,a,t} \times \textit{Account Delay}_{i,a,t} + \gamma_5 \textit{Account Debt}_{i,a,t} + \\ \gamma_6 \textit{Account Delay}_{i,a,t} + \Gamma \mathbf{X}_{i,t} + \delta_i + \delta_t + \varepsilon_{i,t}.\end{aligned}$$

$\textit{Deposit Outflow}_{i,a,t+1}$ represents the deposit outflows from account a of depositor i during the month $t+1$, account-level transfer delay $Acct.\ Delay_{i,a,t}$ is defined as the 12-month rolling average transfer delays for withdrawal transactions from account a of depositor i, and account-level floating rate debt payment $Acct.\ Debt_{i,a,t}$, defined as the 12-month rolling average floating rate debt payment from account a of depositor i. The MOVE index measures fluctuations in U.S. Treasury yield volatility. We incorporate time-fixed effects δ_t to highlight differences in deposit activity across various depositors, along with a set of depositor-specific covariates in $\mathbf{X}_{i,t}$ to address other characteristics across depositors that can affect deposit alertness as in previous sections. Additionally, we control for depositor fixed effects in Column 3 to focus on the transfer activities across accounts for a given depositor i.

Table 6: Account-level Deposit Outflows

	(1)	(2)	(3)
$Acct.\ Delay_{i,a,t}$	8364.4***	8678.3***	9339.3***
	(395.1)	(397.1)	(1028.4)
MOVE $\times$ $Acct.\ Delay_{i,a,t}$	6.600	6.227	7.023
	(5.783)	(5.794)	(7.055)
MOVE $\times$ $Acct.\ Delay_{i,a,t}$	-0.0268***	-0.0266***	-0.0204**
$\times Acct.\ Debt_{i,a,t}$	(0.00740)	(0.00733)	(0.0103)
Time FE	Y	Y	Y
Acct. Level Debt Controls	Y	Y	Y
Depositor Controls	N	Y	Y
Depositor FE	N	N	Y
N	791772	791772	791772
Adj. R^2	0.0350	0.0421	0.293

This table presents the account-level analysis on deposit *outflows*. The regressors include account-level transfer delay $Acct.\ Delay_{i,a,t}$, defined as the 12-month rolling average transfer delays for withdrawal transactions from account a of depositor i, account-level floating rate debt payment $Acct.\ Debt_{i,a,t}$, defined as the 12-month rolling average floating rate debt payment from account a of depositor i. MOVE index tracks the movement in U.S. Treasury yield volatility. The dependent variable is Deposit $\text{Outflow}_{i,a,t+1}$, that is, the dollar amount moved out of account a for depositor i at month $t+1$. Focusing on the heterogeneity of depositors, we control for depositor-level characteristics, including a) Floating rate mortgage ($), the payment to the amount of floating-rate debt outstanding for depositor i at month t, b) Salary is the total monthly labor income of depositor i at month t, c) the debt-to-income ratio which serves as a proxy for the financial constraints of depositor i, d) Fixed-rate mortgages and loans for depositor i at time t; e) 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, and f) Digital adoption ratio which is the ratio between non-physical and total consumption for each depositor at month t. Finally, for the triple-difference analysis, we add additional controls *Acct. Level Debt Controls* for account-level floating rate debt payments, the interactions between account-level floating rate debt payments and MOVE index, along with the interactions between account-level floating rate debt payments and transfer delays. All standard errors are clustered and are reported in parentheses. *, **, and *** indicate statistical significance level at 10%, 5%, and 1%.

Table 6 shows that when an account with longer transfer delays is used for payments on floating rate debts, depositors tend to precautiously transfer less money out of these accounts during times of elevated interest rate risk. Controlling for depositor level fixed effect, Column 3 in Table 6 suggests that for any given depositor, on average, conditional on the average bond market volatility and transfer delays, an additional dollar of floating debt payment from the account is associated with $69 \times 3.9 \times 0.0204 = 5.48$ dollar decrease in the outflow of deposits from the same account, consistent with the notion of a precautionary transfer motive.

6.2 Deposit Alertness and Interest Earnings

Second, we offer complementary evidence on how depositor alertness may help with interest rate shopping, that is, to help maximize interest earnings over an depositor' entire deposit portfolio. To this end, we explore how transfer delays and interest rate risk impact interest income.

Specifically, we consider the empirical model similar as before:

$$
\begin{aligned}
\textit{Total Interest Earnings}_{i,t+1} &= \beta_0 + \beta_1 \times \textit{Transfer Delay}_{i,t} \\
&\quad \beta_2 \times \textit{Transfer Delay}_{i,t} \times \textit{MOVE}_t + \Gamma \times \mathbf{X}_{i,t} + \delta_t + \epsilon_{i,t}.
\end{aligned}
$$

Table 7 presents the results that further support the payment and the precautionary transfer channels. First, depositors with slower bank accounts tend to accrue less interest earnings. Together with the finding in Row 1 of Table 3, this is consistent with an interpretation of depositors with slower accounts being less alert, capturing less interest earnings by less actively moving deposits between their various bank accounts, consistent with the payment channel.

At the same time, however, this effect is less pronounced when the interest rate risk, indicated by the MOVE index, is elevated. Specifically, although depositors with slower bank accounts tend to capture lower total interest earnings, this negative effect of payment delay on interest shopping is offset when interest rate risk become higher, suggesting that depositors become more alert and thus more actively transfer their deposits given the payment delays. Again, together with the finding in Row 2 of Table 3, this lends further support to the precautionary transfer channel in that depositors who face payment delays tend to transfer deposits more actively amid higher interest rate risk.

Table 7: Interest Income & Fund Transfer Delays

	(1)	(2)	(3)	(4)
Transfer delay	-0.437***	-0.437***	-0.409***	-0.0551
	(0.0654)	(0.0654)	(0.0629)	(0.0357)
Transfer delay × MOVE	0.00237***	0.00237***	0.00222***	0.000908*
	(0.000833)	(0.000832)	(0.000799)	(0.000496)
Time FE	Y	Y	Y	Y
Interest rate controls	Y	Y	Y	Y
Budget constraint controls	N	Y	Y	Y
Liquidity & sophistication controls	N	N	Y	Y
Depositor FE	N	N	N	Y
N	2,131,080	2,131,080	2,131,080	2,131,080
Adj. R^2	0.00168	0.00169	0.00745	0.415

This table presents the associations between various depositor-specific attributes at time t and interest income$_{i,t+1}$, which gauges the interest income for a depositor i in month $t+1$. transfer_delay$_{i,t}$ is the dollar-weighted average delays for depositor i within the month t. Focusing on the heterogeneity of depositors, we control for depositor-level characteristics, including a) Floating rate mortgage ($), the payment to the amount of floating-rate debt outstanding for depositor i at month t, b) Salary is the total monthly labor income of depositor i at month t, c) the debt-to-income ratio which serves as a proxy for the financial constraints of depositor i, d) Fixed-rate mortgages and loans for depositor i at time t; e) Consumption smoothing efficiency, defined as the ratio of the rolling mean to the rolling standard deviation of consumption using monthly data from the previous 12 months for each depositor i at month t, and f) Digital adoption ratio which is the ratio between non-physical and total consumption for each depositor at month t. The dependent variable is Deposit Turnover$_{i,t+1}$, that is, the dollar amount moved among each bank account for depositor i at month $t+1$. Interest rate controls include interactions between Transfer delay and LIBOR3M, LIBOR3M, along with a rate volatility tracker, MOVE index. All standard errors are clustered and are reported in parentheses. *, **, and *** indicate statistical significance level at 10%, 5%, and 1%.

6.3 Intra-bank versus Inter-bank Deposit Transfers

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

Table 8: Intra-bank Transfers and All Transfers

	(a) Intra Bank Transfers		(b) All Bank Transfers	
	(1)	(2)	(3)	(4)
Transfer delay	1739.9***	1878.9***	1094.3***	1236.4***
	(151.4)	(157.4)	(151.3)	(144.4)
Transfer delay $\times$ MOVE	-1.474	-1.756	2.190	1.735
	(2.101)	(2.062)	(1.998)	(1.859)
Depositor Controls	N	Y	N	Y
Time FE	Y	Y	Y	Y
N	1,482,996	1,482,996	1,482,996	1,482,996
Adj. R^2	0.00943	0.0225	0.00741	0.0206

This table presents the associations between various depositor-specific attributes at time t and deposit turnover$_{i,t+1}$, which gauges the alertness with which a depositor i transfers deposits between accounts in month $t+1$. In panel (a), deposit turnover is computed from intra-bank paired deposit transactions, that is, the deposit transfers happened between two bank accounts within the *same bank*. In panel (b), the computation of deposit turnover also includes the inter-bank transfers in the main analysis to provide a holistic view of depositor alertness. Transfer delay (day) is the dollar-weighted average time in days it takes for depositor i to transfer self-deposits within the month t. Depositor controls include depositor-level covariates (DTI, salary, floating-rate mortgage and loans, fixed-rate mortgage and loans, CSE, digital adoption ratio, and delays interacted with LIBOR3M, the three-month LIBOR rate). All standard errors are clustered and are reported in parentheses. *, **, and *** indicate statistical significance level at 10%, 5%, and 1%.

Intra-bank 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. Panel (a) in Table 8 provides evidence that depositors increase intra-bank transfers in response to longer inter-bank transfer delays, which in turn contributes to an overall higher deposit turnover in Panel (b). This indicates that the adverse effects of the payment channel due to extended payment delays may be partially mitigated as depositors proactively transfer deposits within the same bank.

As a placebo test, using the same specifications as in Section 4.1, we demonstrate that intra-bank transfers, unaffected by transfer delays, would not exhibit a correlation with interest rate risk. In other words, the precautionary transfer channel would not exist for intra-bank transfers. Supporting this view, Table 8 demonstrates that the interaction between inter-bank transfer delays and the MOVE index does not significantly affect deposit turnover derived solely from intra-bank transactions. This lack of significance underscores the different dynamics governing intra-bank deposit turnover, decoupled from the interaction between payment delays and interest rate risk that may influence inter-bank fund movements through the precautionary transfer channel.

7 Conclusion

Contrary to the traditional belief that depositors are "sleepy," recent events such as the Silicon Valley Bank collapse and the 2023 regional bank crisis suggest that depositors can be unexpectedly "flighty." Utilizing an extensive dataset covering over 1,400 U.S. banks and credit unions and a million U.S. depositors, we provide the first holistic analysis of depositor behaviors from the standpoint of individual depositors. We introduce *deposit turnover*, a novel metric to assess depositor alertness at the intensive margin. This metric measures the amount of which retail depositors shift deposits across their bank accounts, offering a comprehensive view of depositor activities compared to previous studies that mainly used aggregate bank data.

Our findings reveal three primary drivers of depositor alertness. First, the efficiency of payment technology attached to bank accounts, or the *payment channel*, encourages more active transferring of deposits across accounts. This aligns with the concept of deposits as a convenient medium of exchange. We observe that developments in digital banking and faster payment technologies influence depositor behaviors, highlighting the impact of transfer delays on deposit dynamics and banks' liquidity management. Second, depositors often shift their funds across accounts to reduce interest rate risk, termed the *interest risk channel*. This channel is linked to bank deposits' function as a reliable store of value. It becomes more evident when higher interest rate fluctuations, indicated by the MOVE index, lower the appeal of deposits as secure value storage. Third, our research also identifies a *precautionary transfer channel*, where depositors with accounts subject to longer transfer delays are more alert to interest rate risk, actively shifting deposits to manage exposure. This behavior is akin to the precautionary savings motive, where households save more under constraints to buffer against consumption risks.

In conclusion, our analysis of depositor behaviors at the individual level provides new insights into the dynamics of bank deposits, challenging the traditional view of depositors as passive actors. Our findings have profound implications for understanding the funding costs of banks and the financial stability risks of the banking system. As we reconcile the seemingly contrasting views of bank deposits being either sleepy or flighty, we highlight the importance of considering deposits both as a medium of exchange and a store of value. These dual roles of deposits can conflict, posing challenges for banks' liquidity management and potentially leading to less efficient lending or heightened financial stability risks. Our study underscores the significance of depositor demands and preferences, particularly in the context of modern banking, where the demand for payment convenience is increasingly juxtaposed with the need for a store of value. This nuanced understanding of depositor behavior is crucial for policymakers and financial institutions as they navigate the complex landscape of banking stability and efficiency.

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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 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).

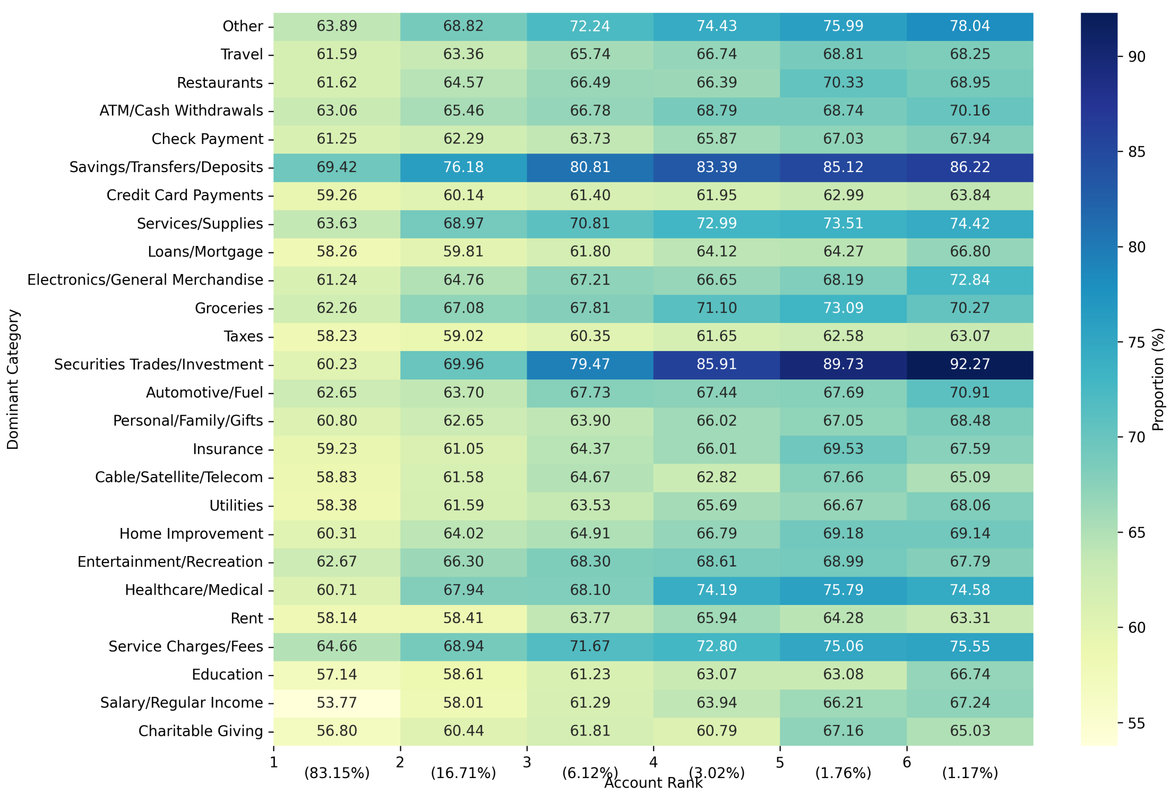
3. Color Intensity: The shade in the heatmap denotes the level of dominance; darker colors represent a stronger alignment to a particular category. For example, a dark cell in a column

(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 A-1: Dominant Transaction Categories for Multi-Account Depositors



B Average Amount of Transfers

Table A-1: Average Amount of Inter-Bank Transfers

	Full-Sample		Hikes	Cuts
	(1)	(2)	(3)	(4)
Transfer delay	-56.31***	-55.18***	-74.85***	-32.24***
	(4.856)	(4.719)	(4.994)	(5.506)
Transfer delay × MOVE Index	0.191***	0.186***	0.317***	-0.0232
	(0.0601)	(0.0582)	(0.0546)	(0.0971)
Depositor Controls	N	Y	Y	Y
Time FE	Y	Y	Y	Y
N	2,195,784	2,195,784	1,266,168	929,616
Adj. R^2	0.00871	0.0184	0.0198	0.0172

This table presents the associations between depositor-specific transfer delays at time t and average amount of transfers$_{i,t+1}$. Panel (b) includes two-way fixed effects. Transfer delay (day) is the dollar-weighted average time in days it takes for depositor i to transfer self-deposits within the month t. MOVE index tracks the movement in U.S. Treasury yield volatility. Controls include depositor-level covariates (DTI, salary, floating-rate mortgage and loans, fixed-rate mortgage and loans, CSE, digital adoption ratio, and delays interacted with LIBOR3M, the three-month LIBOR rate). All standard errors are clustered and are reported in parentheses. *, **, and *** indicate statistical significance level at 10%, 5%, and 1%.