Payment Risk and Bank Lending*

Ye Li† Yi Li‡

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Abstract

Using confidential Fedwire data on payment settlements, we measure U.S. banks' exposure to liquidity risk arising from deposits' monetary role—their function as depositors' means of payment—which is fundamentally distinct from traditional run risk. We document that banks facing greater payment risk extend fewer loans, revealing a critical tension between banks' dual functions as money and credit suppliers. This payment-credit trade-off intensified after the Global Financial Crisis and became highly sensitive to aggregate liquidity conditions. Regulatory constraints amplify the effect. Our findings contribute to understanding the post-GFC liquidity dynamics and several ongoing structural changes in the financial system.

Keywords: Payment, deposits, bank lending, reserves, monetary system, liquidity shortage

JEL classification: E42, E43, E44, E51, E52, G21, G28

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†University of Washington (Foster School of Business). E-mail: liye@uw.edu

‡Board of Governors of the Federal Reserve System. E-mail: yi.li@frb.gov

1 Introduction

Banks supply money and extend credit—the core functions of the financial system. By allowing depositors to move funds in and out of their accounts, banks facilitate payments but expose themselves to liquidity risk. Banks also invest in illiquid loans, thereby facing a liquidity mismatch between assets and liabilities. Using confidential data from Fedwire, the primary payment system in the U.S., we measure banks' exposure to liquidity risk arising from depositors' payments. Our first contribution is to document that banks with greater payment risk extend fewer loans, underscoring a fundamental tension between banks' dual roles as money and credit suppliers.

Payment risk is distinct from the run risk (Diamond and Dybvig, 1983), which has been the traditional focus of the banking literature, as payment risk arises from banks' day-to-day operations rather than from isolated episodes of distress. Depositors move funds to pay, not out of concern for bank solvency. In fact, payment risk affects all deposits, including those fully insured. The scale of payment flows is enormous: the average weekly volume in Fedwire exceeds the annual U.S. GDP.

The negative impact of payment risk on bank lending reflects banks' sensitivity to liquidity risk more broadly. It suggests that the banking system is not satiated with liquidity; otherwise, banks' decisions to invest in illiquid loans would depend primarily on lending profitability and be largely insulated from concerns over payment-related liquidity issues.

Our second contribution is to compare banks' sensitivity to payment risk in two distinct regimes. In the decade before the Global Financial Crisis (GFC), U.S. banks collectively held below \$50 billion in reserves. After the GFC, their reserves increased more than twentyfold, but the negative impact of payment risk on bank lending has strengthened and become highly sensitive to aggregate liquidity conditions, such as interbank market tightness and fluctuations in the Treasury General Account (TGA). Moreover, in the post-GFC era marked by stricter regulations, banks closer to breaching regulatory constraints cut lending more sharply in response to increased payment risk.

Therefore, an increase in the sheer scale of reserves does not necessarily make the banking system less sensitive to liquidity risk. This finding contributes to the literature on post-GFC liquidity shortage that paradoxically coincided with a substantial expansion of central bank balance sheet (e.g., Afonso et al., 2022; Yang, 2022; Acharya et al., 2023; Copeland et al., 2024; d'Avernas and Vandeweyer, 2024; Afonso et al., 2025; Correa et al., 2025; d'Avernas et al., 2025). The unique focus of our paper is liquidity risk tied to deposits' payment role and its impact on bank lending.

Our third contribution is to show the heterogeneity in banks' business models. The negative relationship between payment risk and lending reflects cross-sectional differences across banks and within-bank variation over time. The former dominates before the GFC and remains important thereafter, indicating that banks' asset choices depend on payment risk as a persistent characteristic of depositor clientele.[1] Related, our findings shed light on structural changes in the financial system. For centuries, banks have combined the functions of payment and credit provision (e.g., Donaldson et al., 2018), and a long-standing literature emphasizes the synergy between deposit-taking and lending (e.g., Kashyap et al., 2002). However, the post-GFC era has witnessed the rapid rise of nonbank lenders. Regulatory pressure on banks played an important role (e.g., Gopal and Schnabl, 2022). While our paper does not directly assess the impact of regulations, we find that regulatory pressure amplifies the negative effect of payment risk on bank lending—that is, tighter regulations have challenged banks' traditional business model of bundling payment and credit.

Next, we summarize our measurements of payment risk and the main findings. We obtain records of interbank payment settlement from Fedwire, which is managed by the Federal Reserve. When a non-bank entity makes payments using deposits, the payment sender's bank must transfer an equal amount of reserves to the recipient's bank through Fedwire. A bank may rely on intraday

[1]Recent studies document several deposit characteristics that affect banks' assets, such as market power (e.g., Drechsler et al., 2017; Wang et al., 2022), market segmentation (e.g., Kundu et al., 2024), online banking (e.g., Koont, 2023; Jiang et al., 2025), instant transfer (e.g., Ding et al., 2025), and customer turnover (e.g., Egan et al., 2025).

netting—using payment inflows to cover outflows (Afonso et al., 2022)—but by the end of each day, it must settle any net outflow with reserve transfers.[2] Therefore, a net outflow drains liquidity on daily basis. We decompose the daily net outflow into the gross volume and the ratio of net outflow to gross volume (the "imbalance factor"). Since, for a given bank, the daily gross volume can almost be fully explained by time trend and seasonality, risk in the net outflow mainly arises from the imbalance factor. Therefore, for each quarter, we compute the volatility of a bank's daily imbalance factor ("$Flow\ volatility$"), thereby constructing a sample of bank-quarter observations.

We merge Fedwire data with Call Report and RateWatch data to construct a panel spanning 2000:Q1 to 2020:Q4, excluding the GFC quarters to focus on payment risk during normal times. We perform robustness checks using the full sample and more restrictive samples that exclude all NBER-defined recession periods (e.g., 2020:Q1-2020:Q2).

Our volatility measure reflects banks' ex ante risk consideration rather than the ex post realization of risk. Accordingly, our use of Fedwire data differs from that of Cipriani et al. (2024): their paper studies the ex post materialization of run risk during the 2023 regional banking crisis, while we focus on depositors' normal-time payment activities and construct an ex ante risk metric based on the volatility of payment imbalances. Taken together, our work and theirs underscore the value of using Fedwire data to study deposit dynamics—an area that remains underexplored.[3]

Our payment risk measure captures a unique characteristic associated with banks' depositor clienteles: banks' exposure to unpredictable payment imbalances. It is scale-free, thus applicable to banks of different sizes, and is constructed solely from Fedwire transactions rather than balance-

[2] In other payment systems, for example, Pix in Brazil that was introduced in November 2020, banks cannot rely on the intraday netting. Ding et al. (2025) measure such loss of netting efficiency and examines its effects on banks.

[3] Studies using Fedwire data and payment data in other countries often focus on bank-initiated transactions (rather than depositors-initiated transactions, which is our focus), particularly the interbank borrowing and lending transactions (e.g., Furfine, 2000; Ashcraft and Duffie, 2007; Afonso et al., 2011; Ashcraft et al., 2011; Acharya and Merrouche, 2012; Afonso and Lagos, 2015). Prior studies on banks' liquidity stress from payment settlement do not link it to lending (e.g., Poole, 1968; Hamilton, 1996; McAndrews and Potter, 2002; Bech and Garratt, 2003; Bech, 2008; Kahn and Roberds, 2009; Afonso and Shin, 2011; Bech et al., 2012; Ihrig, 2019; Denbee et al., 2021).

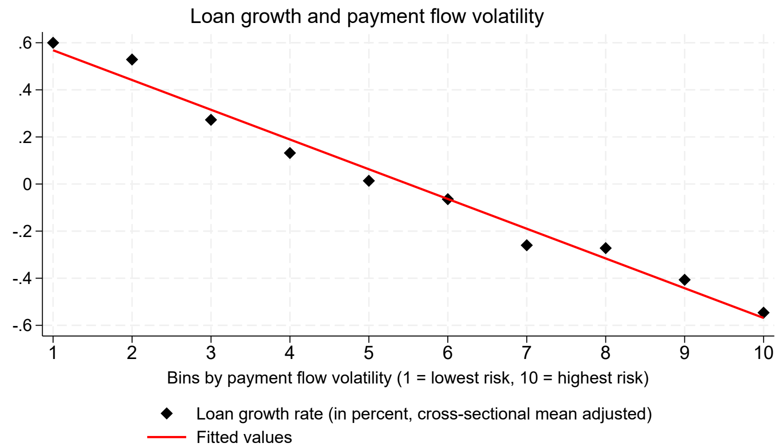

Figure 1: **Payment risk and loan growth.** This figure reproduces Figure C.2A. We sort bank-quarter observations into 10 bins based on their previous-quarter payment flow volatility (defined in Section 2) with bin 1 representing the group with the lowest payment risk, and bin 10 the group with the highest payment risk. We then calculate the average loan growth rate (adjusted for the cross-sectional mean) for each risk bin and mark their values with black diamonds. The sample spans 21 years from 2000:Q1 to 2020:Q4, excluding the financial crisis from 2008:Q1 to 2009:Q2.

sheet items, thereby minimizing mechanical relationships and endogeneity concerns. Unlike traditional, category-based measures of funding instability, it is built bottom-up from micro-level payment data and reveals time-varying and bank-specific features of deposit dynamics.[4]

After constructing our measures of payment risk, we examine its impact on bank lending. When banks face payment outflows, they cannot easily liquidate loans to cover the liquidity needs. Therefore, when facing heightened liquidity risk from depositors' payments, banks reduce lending. This is precisely what we find. In Figure 1, we sort bank-quarter observations into deciles of $Flow\ volatility$; within each decile, we plot the average loan growth rate in the next quarter adjusted by the cross-sectional mean to eliminate effects of macroeconomic cycles and seasonality.

In our main analysis, we regress lending growth on lagged payment risk, controlling for bank characteristics and fixed effects that have been shown in the literature to influence bank lending. We find that payment risk has a robust and statistically significant negative effect. An interquartile-

[4] For example, retail deposits are assigned 100%, and bonds with a maturity of at least one year are assigned 85%.

range increase in payment risk reduces bank lending by 0.55 percentage points—a sizable effect, given that the average lending growth rate in our sample is 2.0% and standard deviation of 6.3%.

We decompose the baseline payment risk measure, $Flow\ volatility$, into risks associated with inflows and outflows, constructing two separate measures that capture upside and downside liquidity risks, respectively. We find that the negative relationship between payment risk and bank lending is almost entirely driven by outflow risk, consistent with our hypothesis that banks' sensitivity to payment risk primarily reflects their aversion to potential liquidity losses.

To validate the underlying economic mechanism, we consider an alternative measure of payment risk based on the concentration (Herfindahl–Hirschman Index) of payment counterparty banks ("$Counterparty\ HHI$"). If a bank's depositors make payments to (or receive payments from) depositors of a small number of banks, the bank faces payment flows that are easily affected by shocks specific to these banks' depositor clienteles; in contrast, such shocks tend to be diversified away when a bank's depositors transact with many banks' depositors. The regression analysis shows that an interquartile-range increase in $Counterparty\ HHI$ is associated with a decrease in loan growth rate by 1.3 percentage points, an even larger effect than that of $Flow\ volatility$.

We examine a risk mitigation mechanism to further demonstrate that banks are aware of and respond to payment risk. Specifically, a bank can raise deposit rates to attract deposit inflows, thereby cushioning payment outflows and mitigating payment risk. Higher deposit rates also attract new depositors, and a larger depositor base allows more payment flows to be internalized within the bank, thereby reducing payment risk. Consistent with this mechanism, we find that banks facing greater payment risk offer higher deposit rates. This result aligns with Acharya and Mora (2015), who show that banks with greater liquidity risk raise deposit rates. Their focus is on a different source of liquidity risk in the GFC period, whereas we focus on payment risk during normal times.

A classic identification challenge is controlling for loan demand, since observed bank lending reflects both banks' willingness to lend—affected by payment risk that is our variable of interest—and borrowers' funding needs. Following the prior literature (e.g., Khwaja and Mian, 2008; Puri et al., 2011; Jiménez et al., 2012; Schnabl, 2012), we employ two approaches. First, we construct a subsample of single-state banks that represent 87% of bank-quarter observations and use the state×quarter fixed effects to control for state-level economic conditions driving loan demand. The results are consistent with full-sample estimates in both magnitude and statistical significance.

Our second approach uses HMDA annual data on mortgage lending. This method allows us to include all banks, and by observing their portfolios of mortgage lending across counties, and we include county×year fixed effects that capture economic conditions at a more granular level than state. The findings using HMDA data are consistent to our baseline results.[5]

So far, we have established the tension between banks' dual functions of facilitating payments and extending credit.[6] Next, we examine how our results vary across the pre- and post-GFC periods, which represent distinct liquidity and regulatory environments. The effects of payment risk on bank lending have become stronger after the GFC. Specifically, before the GFC, the relationship between payment risk and bank lending arises almost entirely from cross-sectional heterogeneity across banks: including bank fixed effects absorbs the effect of payment risk. This cross-sectional pattern suggests fundamental differences in banks' business models in line with the payment-credit trade-off: banks with depositor clienteles characterized by volatile payments lend less. While cross-sectional heterogeneity remains important after the GFC, within-bank variation over time emerges as a potent force, thereby amplifying the overall effects of payment risk on bank lending.

[5] Note that although it is unclear which omitted variables might correlate with both loan demand and the second moment of bank-level payment imbalances, $Flow\ volatility$ (or $Counterparty\ HHI$), controlling for local economic conditions through the fixed effects mitigates potential omitted variable bias.

[6] More broadly, our paper adds to the literature on funding risk and credit supply (e.g., Paravisini, 2008; Loutskina and Strahan, 2009; Ivashina and Scharfstein, 2010; Cornett et al., 2011; Iyer and Puri, 2012; Schnabl, 2012; Iyer et al., 2013; Dagher and Kazimov, 2015; Ivashina et al., 2015; Adelino and Ferreira, 2016; Benmelech et al., 2016; Gilje et al., 2016; Cortés and Strahan, 2017; Acharya et al., 2017; Kundu et al., 2021; Jiang et al., 2024; Drechsler et al., 2025). This literature mainly focuses on crisis periods or runs rather than payment risk in normal times.

The effect from within-bank variation in the post-GFC era is driven by banks' heightened sensitivity to the aggregate liquidity conditions—specifically, the costs of interbank reserve borrowing and aggregate amount of reserves in the banking system. The interbank market can mitigate the effects of payment risk by allowing banks that receive inflows to lend to those experiencing outflows (Bhattacharya and Gale, 1987). We find that the interaction between $Flow\ volatility$ and the LIBOR-OIS spread, a measure of interbank market tightness, has an strong adverse impact on bank lending after the GFC.[7] In comparison, this interaction term has a smaller effect before the GFC. We obtain similar results when using $Counterpary\ HHI$ to proxy for payment risk.

After the GFC, banks substantially increased their reserve holdings, suggesting that variations in the aggregate amount of reserves in the banking system should not have played as important a role. Yet our findings point in the opposite direction. The interaction between payment risk measures and TGA growth, a proxy for aggregate reserve drain from the banking system, significantly reduces bank lending only in the post-GFC period, with no effect in the pre-GFC era.[8]

Regulatory pressure provides a potential explanation for banks' heightened sensitivity to payment risk after the GFC. We find that only in the post-GFC era does banks' proximity to regulatory constraints amplify the negative relationship between payment risk and lending, and this amplification exhibits strong nonlinearity. Specifically, the effect of interaction between payment risk measures and having a low regulatory capital intensifies as a bank's capital ratio declines.[9]

Finally, we place our findings in the broader context of post-GFC balance sheet dynamics in the

[7] From a different perspective, these findings indicate that the pass-through of interbank funding stress to credit supply—a key topic in the banking literature—is strengthened when banks face more payment risk.

[8] Related, there is an ongoing debate on the proper size of monetary base or M0 (e.g., Lagos and Navarro, 2023; Lopez-Salido and Vissing-Jørgensen, 2023). More broadly, our results shed light on the link between reserve supply and bank lending (e.g., Martin et al., 2016; Kandrac and Schlusche, 2021) and how central bank asset purchases affect bank lending by changing reserve quantity (e.g., Bernanke and Blinder, 1992; Kashyap and Stein, 2000; Jiménez et al., 2012; Rodnyansky and Darmouni, 2017; Chakraborty et al., 2020; Luck and Zimmermann, 2020; Peydró et al., 2021).

[9] It has been shown that capital requirements can reduce bank lending (e.g., Fraisse et al., 2020). Our findings shed light on a mechanism: capital requirements make banks more sensitive to payment risk.

U.S. banking sector. While payments are ultimately settled using reserves, banks' liquidity buffer depends not solely on reserves but also on other liquid assets available for sale, because a bank can liquidate assets to obtain reserves for settlement. The dramatic increase in reserve balances—largely a byproduct of the Federal Reserve's balance sheet expansion—should not be conflated with a fundamental strengthening of banks' liquidity positions. From 2010 to 2020, the median bank's holdings of reserves and other liquid assets grew at 4.6% annually, slightly lagging behind deposit growth (4.9%) and trailing the growth of payment volume (8.8%)—that is, while banks' liquidity buffer barely kept pace with their monetary liabilities (deposits), money velocity (the ratio of payment volume to deposits) has increased. Consequently, the banking system's overall liquidity conditions have actually tightened. This observation aligns with Acharya et al. (2023) and Acharya and Rajan (2024), though our analysis emphasizes different sources of liquidity risk.

2 Measuring Payment Risk

2.1 Data sources and summary statistics

Data sources and sample construction. For payment activities, we use confidential data from Fedwire Funds Service (Fedwire) from 2000 to 2020. Fedwire is the real-time gross settlement (RTGS) system operated by the Federal Reserve to settle large-value payments; the system processes trillions of dollars daily. Appendix A.1 provides more background information. The Fedwire database provides information such as the timestamp of each transaction, the identities of sender and receiver banks, payment amount, and transaction type.

In Fedwire, a reserve transfer happens between two banks either because a depositor at the sender bank makes payment to a depositor at the recipient bank ("customer-initiated transactions") or because the sender bank is actively paying the recipient bank to settle interbank debts or in exchange for assets or services ("bank-initiated transactions"). We focus on the former category.[10] After a depositor's payment instruction, the sender bank loses deposits on the liability side and reserves on the asset side to the recipient bank. Such liquidity churn among banks, roughly equivalent in magnitude to the U.S. GDP every two weeks, is driven by depositors' payment needs and thus out of banks' control, generating liquidity risk for banks. Such liquidity risk is different from the classic run risk in Diamond and Dybvig (1983) as deposit transfer from the payment sender bank to the recipient bank is not motivated by concern over the sender bank's solvency.

In Fedwire, the customer-initiated transactions account for 88% of the number of transactions. As we explain below, we construct quarterly measures of payment liquidity risk. Therefore, our sample is at bank-quarter level. If a bank processes customer-initiated payments for less than 10 business days in a quarter, we exclude that bank-quarter observation from our sample.

Next, we merge Fedwire data with quarterly data from the U.S. Call Report from 2000:Q1 to 2021:Q1 based on the Federal Reserve's internal identity system.[11] Call Report includes standard balance-sheet items such as total assets, loan amounts (by maturity), deposit amounts, equity capital, etc. Additionally, it provides information on banks' income statements.

We also obtain data on deposit rates and bank branch locations from RateWatch, which surveys deposit rates across over 90,000 bank branches on a weekly basis.[12] The data contains deposit rates for various products, including CDs of different maturities at the $10K tier and money market accounts (MMAs) at the $10K tier. We aggregate branch-level information to bank levels and merge the data with our Fedwire-Call Report merged sample using the FDIC bank identifier.

Finally, to conduct robustness tests that control for county-level loan demand, we construct a

[10] In particular, we exclude bank-initiated transfer of funds or banks' purchases and sales of federal funds (reserves) as these are banks' own management of reserves rather than reserve changes due to depositors' payments.

[11] As discussed in Section 2.2, we use Fedwire data lagged by one quarter to measure payment risk. Therefore, the last quarter in Fedwire, 2020:Q4 is matched with 2021:Q1 in Call Report.

[12] For multi-branch banks, only one branch per region is surveyed and matched with all other branches in that region.

subsample that merges our sample for the main analysis (Fedwire-Call Report-RateWatch) with HMDA data on banks' mortgage lending. The challenge stems from the lack of a ready-to-use identifier mapping between HMDA and Call Report, particularly prior to 2018. We have managed to backfill the bank identifier extending back to 2013. The details are provided in Appendix A.2.

Our focus is on bank operations outside of major financial disruptions, i.e., normal times when deposit outflows are mainly driven by depositors' transaction needs rather than concern over bank solvency. Therefore, our baseline sample excludes the period of global financial crisis (GFC) from 2008:Q1 to 2009:Q2, but we will provide results based on the full sample as well.

Descriptive statistics. Our sample includes 4,245 banks, covering 72% of total bank assets in the Call Report universe on average from 2000 to 2020.[13] Panel A of Table 1 provides the summary statistics. On average, banks have \$3.9 billion in assets, of which 28% are liquid assets and 64% are loans. Non-transaction deposits make up 61% of the funding source, and Tier-1 capital represents approximately 10%.[14] The average net return on assets for the quarter is 0.25%. Over the sample period, banks typically offer deposit rates lower than the target federal funds rate.

As the economy expands over time, payment volumes rise substantially, increasing the resulting liquidity churn in the banking system. In Panel A of Figure 2, we plot the evolution of payment volume distribution across banks in our sample. For any given quarter, we observe a cross section of banks and calculate the quarterly transaction volume for each bank. We show in Panel A the median and interquartile range. From 2000 to 2020, payment volume has increased significantly alongside deposits (see Panel B), but the growth of payment volume has outpaced that of deposits in the more recent years, indicating an increase in the money velocity. Specifically, in the post-GFC era, these depositor-initiated transactions in Fedwire grew at an annualized rate of 8.8% for

[13] Figure C.1 in the appendix plots the total assets in Call Report and those in our sample from 2000 to 2020.

[14] We use non-transaction deposits to calculate deposit-to-asset ratio (a proxy of banks' stable funding) that is controlled in our regressions. In contrast, our payment risk measures reflect funding instability in transaction deposits.

Table 1: **Summary statistics**

This table provides summary statistics for key variables in our empirical analysis. The sample is at the bank-quarter level and spans 21 years from 2000:Q1 to 2020:Q4, excluding the financial crisis from 2008:Q1 to 2009:Q2. $Asset$ is total bank asset, denominated in thousand dollars. $Liquidity\ ratio$ is defined as the sum of cash, balances due from depository institutions, Federal funds sold and securities purchased under agreements to resell, and available-for-trade securities, normalized by $Asset$ and winsorized at the top and bottom 0.5% levels. $Loan\ ratio$ (total loan amount divided by $Asset$), $Trading\ ratio$ (trading assets divided by $Asset$), $Capital\ ratio$ (Tier 1 capital divided by $Asset$), $Deposit\ ratio$ (nontransaction deposit divided by $Asset$), and $Return\ on\ asset$ (net income divided by $Asset$) are all winsorized at the top and bottom 0.5% levels. $Number\ of\ states$ is the number of states that a bank operates as a depository institution, based on RateWatch data. Deposit growth rate is defined as $Deposit_t/Deposit_{t-1} - 1$, winsorized at the top and bottom 0.5% levels. $Loan\ growth\ rate$ is defined as $loan_{t+1}/loan_t - 1$, winsorized at the top and bottom 0.5% levels. Spread of deposit rate is calculated as relative to target federal funds rate and winsorized at the top and bottom 0.5% levels. $Flow\ volatility$ is the standard deviation of a bank's daily excess payment flows, and $Counterparty\ HHI$ gauges the concentration levels of a bank's payment receivers and senders.

Variable	**N**	**Mean**	**S.D.**	**P25**	**P50**	**P75**
Asset (in thousands)	156588	3915423	50700000	141893.5	295987.5	680967.5
Liquidity ratio	156588	0.28	0.14	0.17	0.26	0.36
Loan ratio	156588	0.64	0.14	0.56	0.66	0.75
Trading ratio	156588	0.0001	0.0012	0.0000	0.0000	0.0000
Capital ratio	156588	0.10	0.03	0.08	0.10	0.11
Deposit ratio	156588	0.61	0.12	0.52	0.61	0.70
Return on asset	156588	0.0025	0.0025	0.0016	0.0025	0.0034
Number of states	156588	1.32	1.56	1	1	1
Deposit growth rate	156556	0.019	0.081	-0.014	0.008	0.035
Loan growth rate	156588	0.020	0.063	-0.007	0.013	0.035
spread of 10K 1-year CD	155754	-0.06	0.74	-0.51	0.11	0.40
spread of 10K MMA	150988	-0.91	1.29	-1.67	-0.30	0.01
Flow volatility	156588	0.55	0.23	0.37	0.55	0.73
Counterparty HHI	156588	0.57	0.26	0.36	0.60	0.79

the median bank from 2010 to 2019, compared to a 4.9% annual increase in deposits.

Banks hold liquid assets to buffer the uncertainty associated with payment-driven deposit flows (Afonso and Shin, 2011)—that is, when deposits flow out due to depositors' payment activities, the bank can directly transfer reserves to the payment recipients' banks or convert liquid assets into cash to cover outflows. Panel C of Figure 2 reports banks' holdings of liquid assets.[15] From 2010

[15]Liquid assets include cash, balances due from depository institutions including the Federal Reserve, Federal funds sold and securities purchased under agreements to resell, and available-for-trade securities.

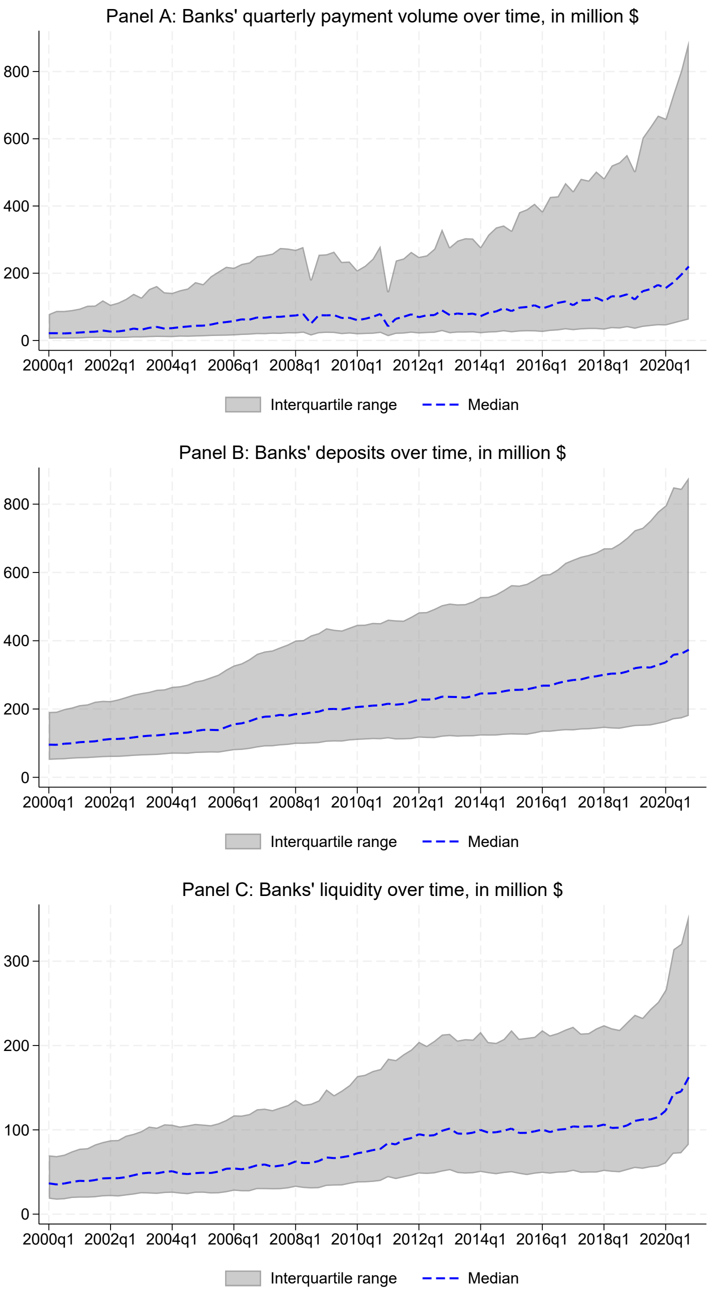

Figure 2: **The evolution of payment activities, deposits, and bank liquidity holdings**

This figure illustrates the quarterly evolution of three bank-level metrics: total customer-initiated payment volume within each quarter (encompassing both payments received and payments sent), the amount of total deposits at quarter end, and liquid holdings (the sum of cash, balances due from depository institutions, federal funds sold, securities purchased under agreements to resell, and securities available for trading) at quarter end. The blue line represents the cross-sectional median and the gray area the interquartile range.

to 2020, the median bank's holdings of liquid assets grew by only 4.6% annually, roughly in line with deposit growth but lagging the growth of payment volume. The fact that payment volumes have grown faster than banks' liquidity holdings suggests that, in the post-GFC era, banks may have become less prepared for liquidity risk arising from depositors' payment activities.

2.2 Payment risk: flow imbalance volatility

During a payment settlement period (a business day), gross outflows can be partly offset by inflows as a bank's depositors make payments to other banks' depositors and receive payments as well. As highlighted by Afonso et al. (2022), banks can rely on incoming payments throughout a business day to fund outgoing payments, thereby conserving scarce liquidity. By the end of a day, it is the payment-flow imbalance (net flow) that ultimately determines a bank's liquidity gain or loss. In what follows, we introduce a measure of payment risk based on the volatility of these payment-flow imbalances. First, we compute the daily flow imbalance factor.

For each day d in quarter t, we calculate bank i's net outflow scaled by gross volume:

$$Flow\ imbalance_{i,t,d} = \frac{Amount\ sent_{i,t,d} - Amount\ received_{i,t,d}}{Amount\ sent_{i,t,d} + Amount\ received_{i,t,d}} = \frac{Net\ outflow_{i,t,d}}{Gross\ flow_{i,t,d}}, \qquad (1)$$

where $Amount\ sent_{i,t,d}$ is depositors' payment outflow and $Amount\ received_{i,t,d}$ is inflow that banks i's depositors receive from ohter banks' depositors. By construction, this imbalance factor takes values between -1 and 1, with 1 representing the case when all payments are outflows and -1 the case when all payments are inflows (i.e., the two extreme forms of imbalance).

At the end of day d in quarter t, bank i faces a net outflow given by

$$Net\ flow_{i,t,d} = Gross\ flow_{i,t,d} \cdot Flow\ imbalance_{i,t,d}. \qquad (2)$$

The first component is highly predictable: time trend and seasonality explain the gross flow with an R^2 of 92% (see Table B.1 in the Appendix B.1). Therefore, liquidity risk in the net flow arises from the imbalance factor. This is why our measure of payment liquidity risk focuses on the volatility of $Flow\ imbalance_{i,t,d}$.[16] Specifically, for bank i in quarter t, we calculate its standard deviation:

$$Flow\ volatility_{i,t} = S.D.(Flow\ imbalance_{i,t,d})\,. \tag{3}$$

In other words, banks can largely predict depositors' gross payment volume but face risk in the direction and magnitude of imbalances. In Appendix B.2, we develop a simple model that captures this feature of payment activities and provides a unified framework for our empirical hypotheses.

Our payment risk measure, $Flow\ volatility_{i,t}$, represents a unique characteristic of bank i's depositor base that is tied to the role of deposits as means of payment. It has several attractive properties. First, it is scale-free, comparable across banks of different sizes. Second, when constructing $Flow\ volatility_{i,t}$, we only use Fedwire records of bank i's depositors sending and receiving payments and do not involve bank balance-sheet items. By doing so, we avoid potential mechanical relationship and minimize endogeneity concerns when examining the impact of payment risk on bank lending. Third, our Fedwire-based measure is derived from micro-level transaction data in a bottom-up manner. This differs from traditional measures of funding instability, which are often based on categorical assumptions—such as those used in the Basel III Net Stable Funding Ratio.[17] Finally, our measure of payment risk reflects the dominant component of deposit liquidity risk induced by payment activities as Fedwire covers around two thirds of aggregate payment volume in the U.S. This stands in contrast to other measures of deposit flightiness that emphasizes the run risk, which is distinct from payment risk, and relies on tail events or stress episodes.

[16] To have enough observations of $Flow\ imbalance_{i,t,d}$ for calculating the standard deviation, we include banks that have payment sent or received on at least 10 business days in quarter t.

[17] For example, retail deposits are assigned 100%, and bonds with a maturity of at least one year are assigned 85%.

It is worth emphasizing that our measure of payment risk—the volatility of the payment imbalance factor—reflects banks' ex ante risk consideration rather than the ex post realization of risk. Accordingly, our use of Fedwire data to characterize deposit instability differs from that of Cipriani et al. (2024). First, while they study run risk during the 2023 regional banking crisis, we focus on depositors' normal-time payment activities. Second, whereas they trace the unfolding of deposit withdrawals during a crisis (the ex post materialization of risk), we measure volatility, a standard ex ante risk metric. Taken together, our work and theirs underscore the value of using Fedwire data to study deposit dynamics—an area that remains underexplored.[18]

2.3 Payment risk: counterparty concentration

We introduce an alternative measure of payment risk—counterparty Herfindahl-Hirschman Index ("counterparty HHI"). It captures how concentrated a bank's payment counterparty banks are in the Fedwire system. Intuitively, when a bank's depositors transact with depositors from a very large set of banks, the idiosyncratic component of payment flows associated with any specific bank's depositor base tends to be diversified away, resulting in less volatile imbalance and a lower level of payment risk. In contrast, when a bank has only a limited number of counterparty banks, shocks to payment activities of these banks' depositor base cannot be "averaged out", resulting in significant liquidity risk for the bank. Next, we describe how the counterparty HHI is calculated.

We first compute bank i's receiver HHI on day d in quarter t:

$$Receiver\ HHI_{i,t,d} = \sum_{j \neq i} \left(\frac{Amount\ sent_{i,j,t,d}}{Amount\ sent_{i,t,d}} \right)^2, \tag{4}$$

[18] Prior research using Fedwire data and payment-system data in other countries has typically focused on bank-initiated transactions, particularly interbank borrowing and lending (e.g., Furfine, 2000; Ashcraft and Duffie, 2007; Afonso et al., 2011; Ashcraft et al., 2011; Afonso and Lagos, 2015).

where $Amount\ sent_{i,j,t,d}$ is defined as depositor-instructed payment from bank i to j on day d in quarter t. We then take the average of $Receiver\ HHI_{i,t,d}$ across all business days in quarter t and obtain $Receiver\ HHI_{i,t}$. Next, we calculate bank i's sender HHI on day d in quarter t:

$$Sender\ HHI_{i,t,d} = \sum_{j \neq i} \left(\frac{Amount\ received_{i,j,t,d}}{Amount\ received_{i,t,d}} \right)^2, \tag{5}$$

where $Amount\ received_{i,j,t,d}$ is defined as depositor-instructed payment received by bank i from bank j on day d in quarter t. We then take the average of $Sender\ HHI_{i,t,d}$ across all business days in quarter t and obtain $Sender\ HHI_{i,t}$. Finally, we define $Counterparty\ HHI$ as:

$$Counterparty\ HHI_{i,t} = (Receiver\ HHI_{i,t} + Sender\ HHI_{i,t})/2. \tag{6}$$

By definition, $Counterparty\ HHI_{i,t}$ is between zero and one. It captures the network topology of depositors' payment flows across banks.

Figure 3 plots the frequency distributions of the two payment risk measures. These two measures bear substantial variation. Panel A of Table 1 shows that the interquartile range is 0.36 ($= 0.73 - 0.37$) for $Flow\ volatility$ and 0.43 ($= 0.79 - 0.36$) for $Counterparty\ HHI$. In the last two rows of Table 1, we report additional statistics of the two payment risk measures.

3 The Impact of Payment Risk on Bank Lending

In this section, we examine the impact of payment liquidity risk on banks' lending decisions. In the next section, we explore the mechanism behind this relationship and compare the pre- and post-GFC eras. In Appendix B.2, we develop a simple model that captures how we measure payment risk and provides a unified framework for the hypotheses underpinning our empirical exercises.

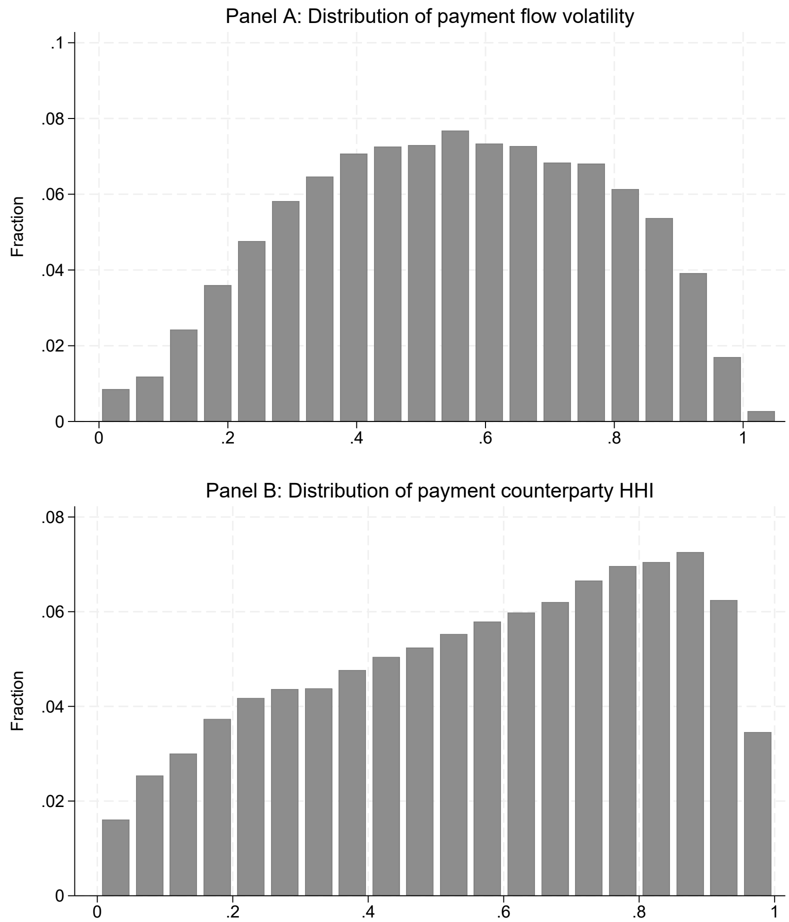

Figure 3: **The distributions of payment risk measures**

This figure shows the distribution of two measures that gauge the instability of banks' payment flows: $Flow\ volatility$ (Panel A) and $Counterparty\ HHI$ (Panel B). $Flow\ volatility$ is defined as in equation (3), and $Counterparty\ HHI$ is defined as in equation (6). The sample is at the bank-quarter level and spans from 2010:Q1 to 2020:Q4, excluding the financial crisis from 2008:Q1 to 2009:Q2.

3.1 The baseline findings

Our hypothesis is that when facing greater liquidity risk from depositors' payment activities, banks reduce their investment in illiquid loans. We test this hypothesis through the following regression:

$$Loan\ growth_{i,t+1} = \alpha + \beta\, Flow\ volatility_{i,t} + \gamma\, Controls_{i,t} + \mu_{state,t} + \mu_{type,t} + \mu_i + \epsilon_{i,t+1}, \quad (7)$$

where the dependent variable is defined as the loan growth rate of bank i over quarter $t+1$ and winsorized at the top and bottom 0.5% levels, $Loan\ growth_{i,t+1} = (Loan_{t+1} - Loan_t)/Loan_t$, and explanatory variables are at quarter t. We cluster standard errors at the bank and quarter levels.

We control for bank characteristics that are commonly included as explanatory variables for loan growth (see, e.g., Loutskina and Strahan, 2009) and include multiple fixed effects. Specifically, we control for the following bank characteristics: $Liquidity\ ratio$ (the sum of cash, balances due from depository institutions, Federal funds sold and securities purchased under agreements to resell, and available-for-trade securities, divided by total assets), $Loan\ ratio$ (the ratio of loan amount to total assets), $Trading\ ratio$ (the ratio of trading assets to total assets), $Capital\ ratio$ (the ratio of Tier-1 capital to total assets), $Deposit\ ratio$ (the ratio of non-transaction deposit amount to total assets), and $Return\ on\ asset$ (net income divided by total assets), all calculated from Call Report data as of quarter t and winsorized at the top and bottom 0.5% levels. We also include both the logarithm of bank size (total assets) and its squared term to control for potential nonlinear effects of bank size (e.g., Kishan and Opiela, 2000). In addition, we control for the number of states that the bank operates as a depository institution based on branch information from RateWatch. Finally, we control for state×quarter fixed effects $\mu_{state,t}$ (with state based on banks' headquarter locations), bank type×quarter fixed effects $\mu_{type,t}$ (with bank types including banks, credit unions, and savings & loan institutions), and in stricter specifications, bank fixed effects (μ_i).

We also control for loan growth and deposit growth over quarter t. When a bank extends loans, it typically finances them by issuing deposits in a debt-swap process known as "money creation": the borrower obtains the bank's liabilities (newly issued deposits) while the bank acquires the borrower's liabilities (the new loans); in the process, both loans and deposits are created (e.g., Tobin, 1963; Donaldson, Piacentino, and Thakor, 2018; Bianchi and Bigio, 2022). Borrowers may use these deposits to make payments, implying that loan and deposit creation over quarter t can be associated with payment outflows and potentially the volatility of payment imbalances. In addition, lending and deposit growth over quarter t may correlate with lending growth over quarter $t+1$, the dependent variable. Therefore, in summary, we control for the loan and deposit growth from over quarter t due to their potential correlations with $Flow\ volatility_{i,t}$ and $Loan\ growth_{i,t+1}$.[19]

We report the regression results in Table 2. Column (1) shows that loan growth rate is negatively associated with $Flow\ volatility$, significant at the 1% level. The economic magnitude is large. An interquartile-range increase in $Flow\ volatility$ is associated with a decrease in loan growth rate by 0.55 percentage points ($0.36 \times (-0.0154) = -0.55\%$). For comparison, the average and standard deviation of loan growth rate in our sample is 2.0 and 6.3 percentage points, respectively. In column (2) we add bank fixed effects and the coefficient of $Flow\ volatility$ remains highly significant, though smaller in magnitude, suggesting that cross-sectional differences across banks contribute notably to the negative relationship between payment risk and bank lending.

Next, we replace $Flow\ volatility_{i,t}$ with $Counterparty\ HHI_{i,t}$, our alternative measure of payment risk, in equation (7). As previously discussed, a higher $Counterparty\ HHI_{i,t}$ indicates more payment risk for bank i as the "averaging out" of payment shocks to its counterparty banks' depositor clienteles is less effective. The results, presented in columns (3)–(4) of Table 2, show that loan growth rate is negatively associated with counterparty concentration, significant at the 1% level and robust across specifications. The economic magnitude is even greater than that for $Flow\ volatility$. Column (3) shows that an interquartile-range increase in $Counterparty\ HHI$ is associated with a decrease in loan growth rate by 1.3 percentage points ($0.43 \times (-0.0256) = -1.1\%$), which is equivalent to 17.5% of the standard deviation of loan growth rate. Figure C.2 in the appendix graphically illustrates the negative relationship between the two payment risk measures and bank lending.

[19] Our results remain qualitatively similar when we exclude lagged lending and deposit growth as control variables.

Table 2: **Payment risk and bank lending**

The sample is at the bank-quarter level from 2000:Q1 to 2020:Q4, excluding the financial crisis from 2008:Q1 to 2009:Q2. The dependent variable is the loan growth rate in quarter $t+1$, winsorized at the top and bottom 0.5% levels. $Flow\ volatility$ is the standard deviation of a bank's daily payment flows, and $Counterparty\ HHI$ gauges the concentration levels of a bank's payment counterparties. $Loan\ growth$, $Deposit\ growth$, $Liquidity\ ratio$, $Loan\ ratio$, $Trading\ ratio$, $Capital\ ratio$, $Deposit\ ratio$, and $Return\ on\ asset$ are defined as in Table 1 and calculated as of quarter t, all winsorized at the top and bottom 0.5% levels. $Size$ is bank asset. $Number\ of\ states$ is the number of states that a bank operates based on RateWatch data. Bank type includes: bank, credit union, and saving and loan bank. Standard errors are clustered at the bank and quarter levels, with corresponding t-values in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Dependent variable: Loan growth rate$_{t+1}$				
	(1)	(2)	(3)	(4)
Flow volatility	-0.0154***	-0.0067***		
	(-7.06)	(-3.24)		
Counterparty HHI			-0.0256***	-0.0156***
			(-6.51)	(-3.79)
Liquidity ratio	0.0090***	0.0333***	0.0091***	0.0337***
	(2.78)	(4.72)	(2.79)	(4.78)
Loan ratio	0.0091**	-0.0492***	0.0070*	-0.0500***
	(2.48)	(-5.98)	(1.90)	(-6.07)
Trading ratio	-0.1702	-0.2928	-0.1268	-0.2925
	(-0.65)	(-0.78)	(-0.49)	(-0.79)
Capital ratio	0.1037***	0.2836***	0.1068***	0.2820***
	(5.95)	(7.88)	(6.18)	(7.85)
Deposit ratio	0.0002	0.0027	0.0009	0.0027
	(0.10)	(0.75)	(0.37)	(0.74)
Return on asset	-0.4040*	0.0743	-0.3948	0.0637
	(-1.68)	(0.42)	(-1.64)	(0.36)
log(Size)	0.0060*	-0.0296*	-0.0013	-0.0350**
	(1.85)	(-1.91)	(-0.42)	(-2.29)
log(Size)^2	-0.0003**	0.0003	-0.0001	0.0005
	(-2.07)	(0.62)	(-0.59)	(0.89)
Number of states	0.0013***	-0.0017	0.0014***	-0.0017*
	(4.49)	(-1.65)	(4.61)	(-1.70)
Loan growth$_t$	0.1466***	0.0954***	0.1457***	0.0955***
	(12.25)	(9.63)	(12.22)	(9.64)
Deposit growth$_t$	0.0253***	0.0118***	0.0251***	0.0120***
	(5.23)	(2.93)	(5.22)	(2.96)
State $\times$ Quarter FE	Yes	Yes	Yes	Yes
Type $\times$ Quarter FE	Yes	Yes	Yes	Yes
Bank FE		Yes		Yes
Adjusted R^2	0.116	0.169	0.117	0.169
N of Obs.	156466	156368	156466	156368

It is worth noting the difference in the coefficients on payment risk between the regressions with and without bank fixed effects. Payment risk measures contain both cross-sectional and time-series variations. Controlling for bank fixed effects absorbs most of the cross-sectional differences across banks, leaving only the within-bank, time-varying component to identify the effect. As a result, the magnitude of the coefficients decreases notably. This pattern suggests that the negative relationship between payment risk and bank lending is partly driven by cross-sectional heterogeneity across banks. In particular, it implies a form of heterogeneity in specialization between facilitating payments (through bearing the payment risk) and lending: banks that face greater uncertainty in depositors' payment flows tend to extend fewer loans.

Effects on long-term lending. Next, we replace the growth rate of all loans with that of loans maturing in three years or longer, while maintaining the regression specification. For Table 3 and the regression results that follow, all control variables, state$\times$quarter fixed effects, and type$\times$quarter fixed effects are included. To conserve space, the coefficients on control variables are not shown.

The results in Table 3 show that compared to the baseline results, both $Flow\ volatility$ and $Counterparty\ HHI$ have larger effects. Loans with longer maturities tend to be less liquid, as they are riskier and more information-sensitive, which exacerbates asymmetric information in secondary markets. In addition, by definition, loans with longer maturities require banks to wait longer for repayment. The stronger effects of payment risk on long-term lending are consistent with our hypothesis that payment risk reduces bank lending because banks seek to mitigate the liquidity mismatch between assets (loans) and liabilities (deposits).

Moreover, it is worth noting that the adjusted R^2 declines noticeably in the regression for long-term loans compared with the baseline analysis using all loans. This suggests that while payment risk remains a strong predictor for bank lending when loan maturities extend, the explanatory

Table 3: **Payment risk and loan growth: long-maturity loans**

The sample spans from 2000:Q1 to 2020:Q4, excluding the financial crisis from 2008:Q1 to 2009:Q2. The dependent variable is the loan growth rate in quarter $t+1$ (restricted to loans with maturities longer than three years), winsorized at the top and bottom 0.5%. $Flow\ volatility$ is the standard deviation of a bank's daily payment flows, and $Counterparty\ HHI$ gauges the concentration levels of a bank's payment counterparties. Control variables are calculated as of quarter t and include $Loan\ growth$, $Deposit\ growth$, $Liquidity\ ratio$, $Loan\ ratio$, $Trading\ ratio$, $Capital\ ratio$, $Deposit\ ratio$, $Return\ on\ asset$, $\log(Size)$, squared $\log(Size)$, and $Number\ of\ states$, as defined in Table 2. Bank type includes: bank, credit union, and saving and loan bank. Standard errors are clustered at the bank and quarter levels, with corresponding t-values in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Dependent variable: 3+ year loan growth rate$_{t+1}$				
	(1)	(2)	(3)	(4)
Flow volatility	-0.0202***	-0.0107***		
	(-7.50)	(-3.04)		
Counterparty HHI			-0.0387***	-0.0262***
			(-9.18)	(-4.66)
Bank controls	Yes	Yes	Yes	Yes
State × Quarter FE	Yes	Yes	Yes	Yes
Type × Quarter FE	Yes	Yes	Yes	Yes
Bank FE		Yes		Yes
Adjusted R^2	0.043	0.061	0.043	0.061
N of Obs.	154728	154630	154728	154630

power of other control variables diminishes substantially. This finding underscores the importance of incorporating payment risk when analyzing banks' lending decisions.

Inflow risk vs. outflow risk. Next, we separately compute payment inflow risk and outflow risk and examine their relative effects on bank lending. Two decomposition methods are used. First, we calculate the volatility of $Flow\ imbalance_{i,t,d}$ for days with a net inflow ("*inflow-day volatility*") and for days with a net outflow ("*outflow-day volatility*"). Second, we decompose the numerator of the payment-flow imbalance factor, $Flow\ imbalance_{i,t,d}$, and compute the standard deviations of $\frac{Amount\ received_{i,t,d}}{Gross\ flow_{i,t}}$ and $\frac{Amount\ sent_{i,t,d}}{Gross\ flow_{i,t}}$ separately for bank i in quarter t, thereby defining, respec-

Table 4: **Payment risk and bank lending: payment inflow vs. outflow risk**

The sample spans from 2000:Q1 to 2020:Q4, excluding the financial crisis from 2008:Q1 to 2009:Q2. The dependent variable is the loan growth rate in quarter $t+1$, winsorized at the top and bottom 0.5% levels. $Inflow\text{-}day\ volatility$ is the standard deviation of a bank's daily payment flows in quarter t calculated for days with positive payment flows, and $Outflow\text{-}day\ volatility$ is the standard deviation of a bank's daily payment flows calculated for days with negative flows. $Payment\text{-}received\ volatility$ and $Payment\text{-}sent\ volatility$ are defined as the standard deviations of a bank's daily payment amounts received and sent, respectively, in quarter t, each normalized by the bank's average daily transaction volume in that quarter. Control variables are calculated as of quarter t and include $Loan\ growth$, $Deposit\ growth$, $Liquidity\ ratio$, $Loan\ ratio$, $Trading\ ratio$, $Capital\ ratio$, $Deposit\ ratio$, $Return\ on\ asset$, $\log(Size)$, squared $\log(Size)$, and $Number\ of\ states$, as defined in Table 2. Bank type includes: bank, credit union, and saving and loan bank. Standard errors are clustered at the bank and quarter levels, with corresponding t-values in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Dependent variable: Loan growth rate$_{t+1}$				
	(1)	(2)	(3)	(4)
Inflow-day volatility	-0.0028	-0.0023		
	(-0.94)	(-0.63)		
Outflow-day volatility	-0.0130***	-0.0074**		
	(-4.16)	(-2.56)		
Payment-received volatility			-0.0016***	0.0002
			(-3.34)	(0.44)
Payment-sent volatility			-0.0029***	-0.0010**
			(-5.78)	(-2.05)
Bank controls	Yes	Yes	Yes	Yes
State × Quarter FE	Yes	Yes	Yes	Yes
Type × Quarter FE	Yes	Yes	Yes	Yes
Bank FE		Yes		Yes
Adjusted R2	0.118	0.173	0.115	0.169
N of Obs.	147642	147559	156466	156368

tively, "*Payment-received volatility*" and "*Payment-sent volatility*".[20]

In the regression, we replace the total payment risk, $Flow\ volatility$, with either *inflow-day* and *outflow-day* volatilities or *payment-received* and *payment-sent* volatilities, while keeping the rest of model specifications unchanged. The results in Table 4 show that outflow risk has a more

[20]Note that the denominator is the average daily gross flow for quarter t. If we normalize inflows and outflows with daily gross volume as we have done for $Flow\ imbalance_{i,t,d}$, the resulting standard deviations would be identical for inflows/gross flow and outflows/gross flow because these two ratios sum up to one.

pronounced effect and primarily drives the negative impact of payment risk on bank lending—that is, when making lending decisions, banks are more concerned about the downside risk to deposit funding (i.e., the risk associated with depositors' payment outflows) than the upside risk.

Robustness. We next conduct several robustness checks. Table C.1 in the appendix reports results in which the dependent variable is the loan-to-asset ratio. The results remain consistent.

Our baseline sample excludes the Global Financial Crisis (GFC) period from 2008:Q1 to 2009:Q2. As discussed earlier, our analysis focuses on banks' operations during normal times—periods when deposit outflows are primarily driven by transaction needs rather than concerns about bank solvency. We show that our findings are robust across different time periods and economic cycles between 2000 and 2020. Columns (1)–(2) of Table C.2 analyze a sample that excludes all NBER-defined recessions from 2000 to 2020: the dot-com bubble burst (2001:Q2–2001:Q4), the GFC (2008:Q1–2009:Q2), and the COVID-19 pandemic (2020:Q1–2020:Q2). Conversely, Columns (3)–(4) include all quarters from 2000 to 2020, encompassing these recession periods. The results from both samples closely align with those in Table 2, with the negative impact of payment risk on bank lending appearing even stronger when recession periods are included.

Evidence on deposit rates. While our analysis focuses on the impact of payment risk on bank lending, evidence on deposit rates further demonstrates banks' awareness of payment risk and active responses to it. A bank can raise deposit rates to mitigate payment risk. Higher deposit rates attract deposit inflows that offset potential payment outflows. Moreover, by offering higher rates, the bank can expand its depositor base. This in turn helps internalize payment flows and directly reduce payment risk—that is, a larger depositor base increases the likelihood that payment recipients are also depositors of the same bank. Therefore, we expect that banks facing greater payment risk set higher deposit rates and test this hypothesis by estimating the following regression:

$$Deposit\ spread_{i,t+1} = \alpha + \beta \times Payment\ risk_{i,t} + \gamma \times Controls_{i,t} + \mu_{state,t} + \mu_{type,t} + \epsilon_{i,t+1}\,. \quad (8)$$

The dependent variable is defined as the spread of the 1-year CD rate (or money market account rate) minus the federal funds rate in quarter $t+1$ (in percent). The explanatory variables are defined the same as in equation (7), with $\mu_{state,t}$ and $\mu_{type,t}$ representing, respectively, State$\times$Quarter and Type$\times$Quarter fixed effects, and in stricter specifications, we add bank fixed effects (μ_i).[21]

We report the results in Table 5. To illustrate the robustness of our results, we use deposit spreads for two types of products: one-year CD (Columns 1–4) and money market account (Columns 5–8).[22] Deposit rates are obtained from the RateWatch survey data at branch-week level and aggregated to bank-quarter level. Across all specifications, our results are consistent: banks with greater payment risks set higher deposit rates. An interquartile-range increase in $Flow\ volatility$ is associated with an increase of 3 basis points in one-year CD spreads ($0.089 \times 0.36 = 0.03$), as seen in column (1) of Table 5, while an interquartile-range increase in $Counterparty\ HHI$ is associated with an increase of 6 basis points in one-year CD spreads ($0.132 \times 0.43 = 0.06$), as seen in column (3). Similar results are obtained for deposit spreads of money market accounts. As shown in the even-numbered columns, these results are generally robust to the inclusion of bank fixed effects. Figure C.3 in the appendix illustrates this relationship between payment risk and deposit spreads.

Overall, banks respond to payment risk on both sides of the balance sheet—by adjusting lending on the asset side and deposit rates on the liability side. Banks facing greater payment risk tend to offer higher deposit rates. This result aligns with Acharya and Mora (2015), who show that

[21]Note that the 1-year CD rates can be higher than the fed funds rate. The median spread is positive (see Table 1).

[22]RateWatch provides deposit rates for CDs of different maturities (3, 6, 12, 24, & 60 months) at the $10K tier and money market accounts at the $10K tier. We have chosen the most popular product from the CD category (one-year CD at the 10K tier) and the most popular product from the money market category (i.e., money market at the 10K tier).

Table 5: **Payment risk and deposit rates**

The sample is at the bank-quarter level and spans from 2000:Q1 to 2020:Q4, excluding the financial crisis from 2008:Q1 to 2009:Q2. The dependent variable is the spread of the deposit rate relative to target federal funds rate in quarter $t+1$, with columns (1)–(4) using one-year 10K CD rates and columns (5)–(8) using 10K money market rates. $Flow\ volatility$ is the standard deviation of a bank's daily excess payment flows, and $Counterparty\ HHI$ gauges the concentration levels of a bank's payment receivers and senders. Both measures are calculated from transaction-level Fedwire data in quarter t. Control variables are calculated as of quarter t and include $Loan\ growth$, $Deposit\ growth$, $Liquidity\ ratio$, $Loan\ ratio$, $Trading\ ratio$, $Capital\ ratio$, $Deposit\ ratio$, $Return\ on\ asset$, $\log(Size)$, squared $\log(Size)$, and $Number\ of\ states$, as defined in Table 2. Bank type includes: bank, credit union, and saving and loan bank. Standard errors are clustered at the bank and quarter levels, with corresponding t-values in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	Dependent variable: Deposit spread$_{t+1}$							
	1-year CD (10K)				**Money market (10K)**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Flow volatility	0.089***	0.027*			0.078***	0.027		
	(4.55)	(1.75)			(3.87)	(1.38)		
Counterparty HHI			0.132***	0.077***			0.113***	0.113***
			(4.90)	(3.01)			(3.97)	(3.37)
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State × Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Type × Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE		Yes		Yes		Yes		Yes
Adjusted R^2	0.808	0.875	0.808	0.875	0.930	0.953	0.930	0.953
N of Obs.	155633	155541	155633	155541	150851	150761	150851	150761

banks with greater liquidity risk raise deposit rates, though their focus is on a different source of liquidity risk and on the GFC period, whereas we focus on payment risk during normal times.

3.2 Controlling for loan demand

A potential endogeneity concern is that the observed loan volume reflects both loan supply (banks' lending decisions) and loan demand. While payment risk measures are constructed based on transaction-level Fedwire data and it is not evident whether these measures of depositors' pay-

Table 6: **Payment risk and loan growth: control for state-level loan demand**

The sample is at the bank-quarter level and spans from 2000:Q1 to 2020:Q4, excluding the financial crisis from 2008:Q1 to 2009:Q2 and containing only banks operating within a single state. The dependent variable is the loan growth rate in quarter $t+1$, winsorized at the top and bottom 0.5% levels. $Flow\ volatility$ is the standard deviation of a bank's daily payment flows, and $Counterparty\ HHI$ gauges the concentration levels of a bank's payment counterparties. Control variables are calculated as of quarter t and include $Loan\ growth$, $Deposit\ growth$, $Liquidity\ ratio$, $Loan\ ratio$, $Trading\ ratio$, $Capital\ ratio$, $Deposit\ ratio$, $Return\ on\ asset$, $\log(Size)$, and squared $\log(Size)$, as defined in Table 2. Bank type includes: bank, credit union, and saving and loan bank. Standard errors are clustered at the bank and quarter levels, with corresponding t-values in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Dependent variable: Loan growth rate$_{t+1}$				
	(1)	(2)	(3)	(4)
Flow volatility	-0.0145***	-0.0073***		
	(-6.76)	(-3.57)		
Counterparty HHI			-0.0239***	-0.0163***
			(-5.89)	(-3.89)
Bank controls	Yes	Yes	Yes	Yes
State × Quarter FE	Yes	Yes	Yes	Yes
Type × Quarter FE	Yes	Yes	Yes	Yes
Bank FE		Yes		Yes
Adjusted R^2	0.136	0.192	0.138	0.192
N of Obs.	135608	135514	135608	135514

ment activities would correlate with loan demand faced by bank i in quarter $t+1$, we nonetheless address this potential endogeneity concern through two exercises described below.

The State×Quarter two-way fixed effects in Table 2 control for time-varying economic conditions of the bank headquarter state, which include loan demand in that state. However, these two-way fixed effects do not fully control for variation in loan demand for multi-state banks that extend loans beyond their headquarter states. To address this concern, we exploit branch-level information from RateWatch to construct a subsample of single-state banks. We investigate whether our findings remain robust for these single-state banks that constitute 87% of total bank-quarter observations and report the regression results in Table 6. Across all specifications, our results are very close to those in Table 2, both in terms of magnitude and statistical significance.

Our analysis in Table 6 only covers single-state banks, and the State×Quarter fixed effects cannot absorb loan-demand variations at a more granular level. Our next approach allows us to include both single- and multi-state banks and control for time-varying loan demand at the county level. Using data from the Home Mortgage Disclosure Act (HMDA), which has the most comprehensive coverage of the U.S. mortgage market, we observe each bank's portfolio of mortgages across counties at the annual frequency, and by including County×Year two-way fixed effects in our regression, we control for county-level mortgage demand.[23] The regression specification follows our baseline analysis except that the estimation is done at annual frequency (the data frequency of HMDA) and loan growth is computed using banks' mortgage lending in HMDA.

Using our merged bank-year sample from 2013 to 2020, we run the following regression:

$$Loan\ growth_{i,c,t+1} = \alpha + \beta\, Payment\ risk_{i,t} + \gamma\, Controls_{i,t} + \mu_{c,t} + \mu_{type,t} + \mu_i + \epsilon_{i,t+1}. \quad (9)$$

Different from the regression given by equation (7) where the dependent variable is at bank-quarter level, the dependent variable in equation (9) is at bank-county-year level, and controlling for the County×Year two-way fixed effect $\mu_{c,t}$ effectively absorbs county-level variation in mortgage demand.[24] The rest of the explanatory variables are the same as in equation (7). We consider two versions of $Payment\ risk_{i,t}$, i.e., $Flow\ volatility_{i,t}$ and $Counterparty\ HHI_{i,t}$.[25]

We report regression results of equation (9) in Table 7. Column (1) shows that county-level mortgage lending growth rate is negatively associated with $Flow\ volatility$, significant at the 1%

[23] The data, filed by financial institutions (i.e., mortgage lenders), provides detailed loan-level information, including the loan applicant's basic demographic details and credit conditions, loan characteristics (such as amount, term, interest rates, and special features), property information (including value, location, etc.), and lender specifics. For our analysis, we aggregate these individual loans to the bank-county-year level based on lender identifier, Federal Information Processing Standard (FIPS) state and county code, and application year.

[24] As in our baseline analysis, the dependent variable is winsorized at the top and bottom 0.5% levels. To maintain enough observations at bank-county-year level, we require a bank to have issued at least eight mortgage in a county-year to be included in the sample. Our results remain similar if the threshold is modified, for example, to ten loans.

[25] In this bank-county-year sample, we use year-end values of payment risk measures.

Table 7: **Payment risk and loan growth: control for county-level mortgage demand**

The sample is constructed at the bank-county-year level, spanning from 2013 to 2020. The dependent variable is the year $t + 1$ mortgage loan growth rate for a given bank in a specific state-county, which is winsorized at the top and bottom 0.5% levels. For inclusion in the sample, a bank must have issued at least 8 mortgage loans within that county in the specified year. $Flow\ volatility$ is the standard deviation of a bank's daily payment flows, and $Counterparty\ HHI$ gauges the concentration levels of a bank's payment counterparties. Control variables are calculated as of the last quarter of year t and include $Loan\ growth$, $Deposit\ growth$, $Liquidity\ ratio$, $Loan\ ratio$, $Trading\ ratio$, $Capital\ ratio$, $Deposit\ ratio$, $Return\ on\ asset$, $\log(Size)$, squared $\log(Size)$, and $Number\ of\ states$, as defined in Table 2. Bank type includes: bank, credit union, and saving and loan bank. Standard errors are clustered at the state-county levels, with corresponding t-values in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Dependent variable: mortgate growth rate$_{t+1}$				
	(1)	(2)	(3)	(4)
Flow volatility	-0.161***	-0.389***		
	(-7.12)	(-7.36)		
Counterparty HHI			-0.041**	-0.301***
			(-2.11)	(-3.93)
Bank controls	Yes	Yes	Yes	Yes
State-County × Year FE	Yes	Yes	Yes	Yes
Type × Year FE	Yes	Yes	Yes	Yes
Bank FE		Yes		Yes
Adjusted R^2	0.044	0.070	0.043	0.069
N of Obs.	233651	233643	228923	228910

level. The result is economically significant as well. Specifically, an interquartile-range increase in $Flow\ volatility$ is associated with a decrease in mortgage loan growth rate by 6 percentage points ($0.36 \times (-0.16) = -6\%$), which equates to approximately 5% of the standard deviation of local mortgage growth rates.[26] Replacing $Flow\ volatility_{i,t}$ with $Counterparty\ HHI_{i,t}$, we obtain consistent regression results in columns (3)–(4) of Table 7. Overall, our findings indicate that a bank's county-level mortgage lending is negatively associated with the bank's payment risk exposure, significant both statistically and economically.

[26]The bank–county–year mortgage growth rate has a standard deviation of 114% and a mean of 16.4%.

4 Exploring the Mechanism Before and After the GFC

In this section, we show that in the pre-GFC era, the negative relationship between payment risk and bank lending primarily reflects cross-sectional heterogeneity across banks, suggesting a form of business specialization between facilitating payments (and bearing the associated payment risk) and extending credit. Importantly, after the GFC, liquidity conditions, such as tightness of the interbank market and shocks to reserves available in the banking system (i.e., variations in the Treasury General Account, TGA), became a key driver of the relationship between payment risk and bank lending, suggesting that the more than twentyfold increase in banks' reserve holdings after the GFC did not lead to liquidity abundance; instead, banks have become more alert to liquidity risk associated with depositors' payments. Moreover, we find strong evidence that regulatory pressure amplified the negative effect of payment risk on bank lending after the GFC, but not before.

4.1 Impact of payment risk on lending before and after the GFC

In Table 8, we estimate our regression specified in equation (7) separately for the pre- and post-GFC periods (2000:Q1–2007:Q4 and 2009:Q3–2020:Q4). In Columns (1) and (3), where bank fixed effects are excluded, the coefficients on payment risk measures are significant and economically large in both periods. The magnitudes are slightly larger in the post-GFC period.

Banks' reserve holdings increased more than twentyfold after the GFC. However, reserve accumulation does not imply liquidity abundance, as banks' lowest comfortable level of reserves (LCLOR) has remained relatively high in the post-GFC period, according to the Senior Financial Officer Survey. While interbank payments are ultimately settled using reserves, what matters for banks' liquidity management is not reserves alone but the total stock of liquid assets available to cover payment outflows and other liquidity needs. Hence, the dramatic increase in reserve

Table 8: **Payment risk and bank lending: pre-GFC vs. post-GFC**

The samples for Panel A and B span from 2000:Q1 to 2007:Q4 and from 2009:Q3 to 2020:Q4, respectively. The dependent variable is the loan growth rate in quarter $t+1$, winsorized at the top and bottom 0.5% levels. $Flow\ volatility$ is the standard deviation of a bank's daily payment flows, and $Counterparty\ HHI$ gauges the concentration levels of a bank's payment counterparties. Control variables are calculated as of quarter t and include $Loan\ growth$, $Deposit\ growth$, $Liquidity\ ratio$, $Loan\ ratio$, $Trading\ ratio$, $Capital\ ratio$, $Deposit\ ratio$, $Return\ on\ asset$, $\log(Size)$, squared $\log(Size)$, and $Number\ of\ states$, as defined in Table 2. Bank type includes: bank, credit union, and saving and loan bank. Standard errors are clustered at the bank and quarter levels, with corresponding t-values in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Dependent variable: Loan growth rate$_{t+1}$				
Panel A: Pre-GFC				
	(1)	(2)	(3)	(4)
Flow volatility	-0.0142***	0.0003		
	(-6.94)	(0.11)		
Counterparty HHI			-0.0232***	-0.0018
			(-6.54)	(-0.31)
Bank controls	Yes	Yes	Yes	Yes
State × Quarter FE	Yes	Yes	Yes	Yes
Type × Quarter FE	Yes	Yes	Yes	Yes
Bank FE		Yes		Yes
Adjusted R^2	0.111	0.209	0.112	0.209
N of Obs.	58680	58581	58680	58581
Panel B: Post-GFC				
	(1)	(2)	(3)	(4)
Flow volatility	-0.0154***	-0.0054*		
	(-4.27)	(-1.85)		
Counterparty HHI			-0.0256***	-0.0166***
			(-4.51)	(-2.99)
Bank controls	Yes	Yes	Yes	Yes
State × Quarter FE	Yes	Yes	Yes	Yes
Type × Quarter FE	Yes	Yes	Yes	Yes
Bank FE		Yes		Yes
Adjusted R^2	0.121	0.190	0.123	0.190
N of Obs.	97786	97707	97786	97707

balances—largely a by-product of the Federal Reserve's balance sheet expansion through various policy initiatives—should not be mistaken for a fundamental strengthening of banks' liquidity positions. The focus should instead be on banks' overall liquidity buffers, which in fact have not increased significantly relative to deposits that carry the payment risk.

Figure 2 in Section 2 has shown an increase in money velocity: depositors' payments grew at an annualized rate of 8.8% for the median bank from 2010 to 2020, compared to a 4.9% annual increase in deposits and 4.6% annual increase in liquid assets. Therefore, even though liquid assets have increased in line with deposits, they may have not been enough relative to the payment volume because the money velocity—the ratio of payment volume to deposits—has increased. These observations may help explain why in Column (1) and (3) of Table 8, the post-GFC estimate of payment risk's effect on bank lending has not diminished compared to the pre-GFC estimate.

What also stands out is that in Columns (2) and (4) of Table 8, the inclusion of bank fixed effects erases the negative relationship between payment risk and bank lending in the pre-GFC sample, suggesting that this relationship is primarily driven by cross-sectional heterogeneity across banks. This pattern indicates a form of business model differentiation among banks before the GFC: the persistent cross-sectional differences in payment risk exposure have largely explained the variation in banks' loan provision, leaving little variation over time. In contrast, this is no longer the case in the post-GFC period—within-bank variation becomes economically meaningful, accounting for roughly one-third of the total effect of $Flow\ volatility$ and 65% for $Counterparty\ HHI$.

The impact of payment risk on bank lending can be identified via two sources of variation: cross-sectional heterogeneity across banks and within-bank variation over time. The latter becomes more prominent after the GFC, implying that banks actively adjust lending in response to changing payment risk. Next, we examine what factors drive banks' lending sensitivity to payment risk.

4.2 Aggregate liquidity conditions before and after the GFC

When the depositors at one bank make payments to those at another bank, the senders' banks lose liquidity while the recipients' banks gain liquidity. When the interbank market is well-functioning, banks in liquidity surplus can lend to those in deficit—that is, the interbank market effectively acts as a liquidity insurance mechanism for the banking system to hedge payment shocks (Bhattacharya and Gale, 1987). Stress in the interbank market compromises such risk-sharing mechanism, and in such scenarios, we expect the negative impact of payment risk on bank lending to be more pronounced. To test this hypothesis, we estimate the following regression:

$$\begin{aligned} Loan\ growth_{i,t+1} =& \alpha + \beta_1\, \textbf{\textit{LIBOR-OIS spread}}_{t+1} \times Payment\ risk_{i,t} + \beta_2\, Payment\ risk_{i,t} \\ &+ \gamma\, Controls_{i,t} + \mu_i + \mu_{state,t} + \mu_{type,t} + \epsilon_{i,t+1}. \end{aligned} \tag{10}$$

$LIBOR\text{–}OIS\ spread$ represents the difference between the 3-month London Interbank Offered Rate (LIBOR) and the Overnight Index Swap (OIS) rate for the same maturity period (expressed in percent). This spread is a commonly used indicator of funding stress (e.g., Taylor, 2009; Klingler and Syrstad, 2021). To better reflect the most acute funding stress within a quarter, we utilize the 90th percentile of the daily LIBOR-OIS spreads observed in a quarter. In the regression, $Payment\ risk$ indicates either $Flow\ volatility$ or $Counterparty\ HHI$. Control variables are the same as in equation (7), with $\mu_{state,t}$ and $\mu_{type,t}$ representing State×Quarter and Type×Quarter fixed effects, respectively. Note that the variable $LIBOR\text{-}OIS\ spread$ is redundant with the inclusion of these two-way fixed effects.[27] We control for bank fixed effects, μ_i, as our focus is on how a bank's response to payment risk variation depends on the aggregate liquidity condition.

We report the regression results (10) in Table 9. Column (1) shows that the interaction term

[27] While not reported, our results are qualitatively similar in specifications with less strict fixed effects.

Table 9: **Funding stress and the impact of payment risk: pre-GFC vs. post-GFC**

The bank-quarter sample spans 2000:Q1 to 2007:Q4 for Columns (1)–(2) and 2009:Q3 to 2020:Q4 for Columns (3)–(4). The dependent variable is the loan growth rate in quarter $t+1$, winsorized at the top and bottom 0.5% levels. $LIBOR\text{-}OIS\ spread$ is the spread between the 3-month London Interbank Offered Rate (LIBOR) and the overnight index swap (OIS) of the same maturity, expressed in percent and calculated as the 90th percentile level from daily observations in quarter $t+1$. Control variables are calculated as of quarter t and include $Loan\ growth$, $Deposit\ growth$, $Liquidity\ ratio$, $Loan\ ratio$, $Trading\ ratio$, $Capital\ ratio$, $Deposit\ ratio$, $Return\ on\ asset$, $\log(Size)$, squared $\log(Size)$, and $Number\ of\ states$, as defined in Table 2. Bank type includes: bank, credit union, and saving and loan bank. Standard errors are clustered at the bank and quarter levels, with corresponding t-values in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Dependent variable: Loan growth rate$_{t+1}$				
	Pre-GFC		**Post-GFC**	
	(1)	(2)	(3)	(4)
Flow volatility × LIBOR-OIS spread	-0.0144**		-0.0395***	
	(-2.57)		(-4.28)	
Counterparty HHI × LIBOR-OIS spread		-0.0160**		-0.0384***
		(-2.51)		(-4.01)
Flow volatility	0.0032		0.0062	
	(0.94)		(1.48)	
Counterparty HHI		0.0014		-0.0048
		(0.24)		(-0.88)
Bank controls	Yes	Yes	Yes	Yes
State × Quarter FE	Yes	Yes	Yes	Yes
Type × Quarter FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.209	0.209	0.190	0.191
N of Obs.	58581	58581	97707	97707

between $Flow\ volatility$ and $LIBOR\text{–}OIS\ spread$ has a negative and significant coefficient in the pre-GFC period, suggesting that the impact of $Flow\ volatility$ on bank lending is amplified by interbank market stress. The economic magnitude is large. For a bank with a median level of $Flow\ volatility$ (0.55), a 50-basis-point increase in $LIBOR\text{–}OIS\ spread$ is associated with a decrease in loan growth by 0.4 percentage points ($-0.0144 \times 0.55 \times 0.5 = -0.004$) that is 6.3% of standard deviation of the loan growth rate in our sample. In Column (2), we use $Counterparty\ HHI$ to measure payment risk, and obtain similar results. Importantly, even though Table 8 shows that the negative effect of payment risk on lending is mainly identified from cross-sectional heterogeneity before the GFC, adding the interaction between payment risk and $LIBOR–OIS\ spread$ picks up meaningful within-bank variation, which highlights the importance of examining the interbank market conditions.

In the post-GFC period, coefficients on the interaction terms in Columns (3) and (4) of Table 9 are more than twice as large as their pre-GFC counterparts. Regressing bank lending on payment risk provides a measure of banks' sensitivity to liquidity risk. The explanatory variable, constructed from Fedwire data, reflects only depositors' payments—liquidity shocks outside banks' control—and thus offers a relatively exogenous measure of liquidity exposure. The dependent variable captures banks' willingness to invest in illiquid assets (loans), which tends to decline as liquidity risk on the liability side increases. The results in Columns (3) and (4) show that an increase in the $LIBOR–OIS\ spread$ amplifies banks' sensitivity to payment risk much more after the GFC, suggesting that the banking system has become more vigilant and responsive to liquidity shocks.

While our results in Table 9 pertain to the costs of redistributing reserves across banks through the interbank market, our next analysis examines how shocks to the aggregate level of reserves in the banking system influences banks' responses to payment risk in their lending decisions.[28] Following Copeland et al. (2024) and Correa et al. (2025), we use the variations of Treasury General Account (TGA) balance as shocks to reserves supply. TGA is the account of the U.S. Treasury at the Federal Reserve, which collects funds from the sales of Treasury debt and tax receipts and covers fiscal spending. An increase in TGA represents a decrease in available reserves within the

[28]Bianchi and Bigio (2022) develop a model of bank liquidity management that emphasizes frictions in the interbank market for reserve borrowing and lending. They show that a reduction in reserve supply strains the interbank market. Therefore, TGA variation and LIBOR-OIS spread can be correlated, so the two exercises are closely related. The liquidity stress in short-term funding markets in September 2019 was attributed, in part, to reserve flows into the TGA (e.g., d'Avernas and Vandeweyer, 2020; Copeland et al., 2024).

banking system. For example, when depositors pay taxes to the government or when the government issues Treasury securities, the banking system loses reserves to TGA. In the regression specification given by equation (10), we replace $LIBOR\text{–}OIS\ spread$ with the TGA quarterly growth rate and estimate the regression

$$\begin{aligned} Loan\ growth_{i,t+1} =& \alpha + \beta_1\, TGA\ growth_{t+1} \times Payment\ risk_{i,t} + \beta_2\, Payment\ risk_{i,t} \\ & + \gamma\, Controls_{i,t} + \mu_i + \mu_{state,t} + \mu_{type,t} + \epsilon_{i,t+1}, \end{aligned} \tag{11}$$

with other variables and fixed effects defined as in equation (10).

The results in Table 10 reveal a striking contrast between the pre- and post-GFC periods. Before the GFC, TGA fluctuations had no discernible effect on banks' sensitivity to payment risk. In the post-GFC era, however, reserve drains resulting from TGA growth amplifies the negative impact of payment risk on bank lending. The economic magnitude is substantial. For a bank with a median level of $Flow\ volatility$ (0.55), a one–standard-deviation increase in the TGA growth rate (1.2) is associated with a 0.7 percentage point decline in loan growth ($-0.0122 \times 0.55 \times 1.2 = -0.8\%$).[29]

This pattern suggests an overall scarcity of liquidity in the post-GFC banking system despite a relatively high level of reserves: if liquidity were truly abundant, marginal variations in reserves caused by TGA fluctuations should have not materially altered banks' responses to liquidity (payment) risk in their lending decisions. These findings challenge the notion that the more than twentyfold increase in reserves after the GFC satiated the banking system with liquidity. As discussed earlier, the growth in banks' total liquid asset holdings—including reserves—has barely kept pace with that of deposits and has lagged behind the growth of depositors' payment volume. Furthermore, banks in the post-GFC era operate under tighter regulatory constraints and greater scrutiny,

[29] In our sample period, the standard deviation of TGA growth is 1.2 (in decimals), with a mean of 0.20.

Table 10: **Aggregate reserve shocks and the impact of payment risk: pre-GFC vs. post-GFC**

The bank-quarter sample spans from 2000:Q1 to 2007:Q4 for Columns (1)–(2) and 2009:Q3 to 2020:Q4 for Columns (3)–(4). The dependent variable is the loan growth rate in quarter $t+1$, winsorized at the top and bottom 0.5% levels. $TGA\ change$ is the quarterly growth rate of TGA based on average levels of the TGA within a quarter (in decimal), calculated as of quarter $t+1$. Control variables are calculated as of quarter t and include $Loan\ growth$, $Deposit\ growth$, $Liquidity\ ratio$, $Loan\ ratio$, $Trading\ ratio$, $Capital\ ratio$, $Deposit\ ratio$, $Return\ on\ asset$, $\log(Size)$, squared $\log(Size)$, and $Number\ of\ states$, as defined in Table 2. Bank type includes: bank, credit union, and saving and loan bank. Standard errors are clustered at the bank and quarter levels, with corresponding t-values in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Dependent variable: Loan growth rate$_{t+1}$				
	Pre-GFC		**Post-GFC**	
	(1)	(2)	(3)	(4)
Flow volatility × TGA Change	-0.0077		-0.0122*	
	(-0.39)		(-1.83)	
Counterparty HHI × TGA Change		-0.0032		-0.0135**
		(-0.16)		(-2.14)
Flow volatility	0.0003		-0.0036	
	(0.10)		(-1.20)	
Counterparty HHI		-0.0018		-0.0143***
		(-0.32)		(-2.86)
Bank controls	Yes	Yes	Yes	Yes
State × Quarter FE	Yes	Yes	Yes	Yes
Type × Quarter FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.209	0.209	0.190	0.190
N of Obs.	58581	58581	97707	97707

making them more reluctant to rely on intraday overdrafts in the payment system and much more conservative in managing liquidity risk. In the next subsection, we examine how such regulatory pressure amplifies the negative effect of payment risk on bank lending.

4.3 Regulatory pressure before and after the GFC

The U.S. banking system operated under a markedly tighter regulatory environment after the GFC. The post-crisis regulatory reforms were multi-faceted and varied by bank size, but a central focus was on strengthening bank capital. U.S. banks have long been subject to requirements on the ratio of Tier 1 capital to total consolidated assets (the U.S. Tier 1 leverage ratio). Institutions must maintain a minimum ratio of 4%, while those considered well-capitalized should meet a 5% minimum ratio.[30] As shown in Figure C.4, the Tier 1 leverage ratio exhibited a clear upward trend in the years following the GFC, reflecting banks' efforts to build stronger capital buffers over time. During the COVID-19 pandemic, U.S. banking regulators temporarily relaxed leverage regulations and reinstated them in April 2021 once the financial conditions stabilized. Such maneuver suggests that in spite of the capital build-up, the regulatory constraints are potentially binding for banks.

Next, we examine how regulatory pressure shapes the relationship between payment risk and bank lending and compare our results in the pre- and post-GFC samples. Specifically, following the theoretical prediction in Bolton et al. (2025), we test whether banks with lower regulatory capital exhibit greater sensitivity to fluctuations in deposits (represented by payment risk in our setting) when making lending decisions.[31]

We create a dummy variable ($Low\ regulatory\ capital$) for each bank-quarter that is equal to one if the bank's Tier 1 leverage ratio falls at or below the cross-sectional 5th percentile in that quarter. The variable aims to identify banks that are undercapitalized relative to their peers, because, first, the measure is robust to the changes in regulations over time, and second, it is often a bank's relative performance that tends to draw regulators' attention. We examine whether the negative impact of payment risk on bank lending is more pronounced for banks with low regulatory

[30] In July 2013, the U.S. bank agencies adopted the U.S. Basel III Final Rule, which requires that Advanced Approaches Banks (i.e., banks with more than $250 billion in total consolidated assets or more than $10 billion in foreign on-balance sheet exposure) maintain a supplementary leverage ratio (SLR) of at least 3%. In April 2014, the U.S. bank agencies adopted an additional supplementary leverage ratio, "Final Supplementary Leverage Ratio", which requires bank holding companies that have been identified as globally systemically important banks (G-SIBs) to maintain a supplementary leverage ratio of at least 5%. The final rule is effective on January 1, 2018.

[31] The model in Appendix B.2 reformulates the insight in a simpler framework that captures how we measure payment risk and unifies all the empirical hypotheses in this paper.

Table 11: **Bank capital and the impact of payment risk: pre-GFC vs. post-GFC**

The bank-quarter sample spans from 2000:Q1 to 2007:Q4 for Columns (1)–(2) and 2009:Q3 to 2020:Q4 for Columns (3)–(4). The dependent variable is the loan growth rate in quarter $t+1$, winsorized at the top and bottom 0.5% levels. $Low\ regulatory\ capital$ is a dummy variable that takes the value of 1 when a bank's regulatory leverage ratio is below the cross-sectional 5th percentile level in quarter t and zero otherwise. All U.S. banks are required to maintain a certain level of regulatory leverage ratio, defined as the ratio of a bank's Tier 1 capital to its total consolidated on-balance sheet assets. Control variables are calculated as of quarter t and include $Low\ regulatory\ capital$, $Loan\ growth$, $Deposit\ growth$, $Liquidity\ ratio$, $Loan\ ratio$, $Trading\ ratio$, $Capital\ ratio$, $Deposit\ ratio$, $Return\ on\ asset$, $\log(Size)$, squared $\log(Size)$, and $Number\ of\ states$, as defined in Table 2. Bank type includes: bank, credit union, and saving and loan bank. Standard errors are clustered at the bank and quarter levels, with corresponding t-values in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Dependent variable: Loan growth rate$_{t+1}$				
	Pre-GFC		**Post-GFC**	
	(1)	(2)	(3)	(4)
Flow volatility × Low regulatory capital	-0.0138		-0.0247***	
	(-1.38)		(-3.57)	
HHI × Low regulatory capital		-0.0051		-0.0245***
		(-0.61)		(-4.13)
Flow volatility	0.0007		-0.0041	
	(0.24)		(-1.42)	
Counterparty HHI		-0.0016		-0.0152***
		(-0.28)		(-2.73)
Bank controls	Yes	Yes	Yes	Yes
State × Quarter FE	Yes	Yes	Yes	Yes
Type × Quarter FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.209	0.209	0.190	0.190
N of Obs.	58581	58581	97707	97707

capital by estimating the following regression:

$$Loan\ growth_{i,t+1} = \alpha + \beta_1\, Low\ regulatory\ capital_{i,t} \times Payment\ risk_{i,t} + \beta_2\, Payment\ risk_{i,t} + \beta_3\, Low\ regulatory\ capital_{i,t} + \gamma \times Controls_{i,t} + \mu_i + \mu_{state,t} + \mu_{type,t} + \epsilon_{i,t+1}. \tag{12}$$

The results in Table 11 show that, in the post-GFC era, the interaction terms between the payment risk measures and *low regulatory capital* have negative and statistically significant coefficients. In other words, banks with capital ratios below the 5th percentile exhibit substantially greater lending sensitivity to payment risk than those above the threshold. By contrast, such regulatory pressure did not amplify the effect of payment risk on bank lending before the GFC. These findings suggest that banks' traditional business model of jointly providing payment services (and bearing the associated liquidity risk) and extending loans is under pressure amid more stringent regulatory environment. Our results shed light on the structural changes after the GFC, and in particular, the growth of nonbank lenders (e.g., Buchak et al., 2018; Chernenko et al., 2022; Gopal and Schnabl, 2022; Jiang, 2023; Davydiuk et al., 2024; Fleckenstein et al., 2025).

We next introduce more granular dummy variables to explore the nonlinear effect of regulatory capital on lending sensitivity to payment risk. Specifically, we create a dummy variable for banks whose Tier 1 leverage ratio is at or below the 1st percentile of cross-sectional distribution, another for banks that fall between the 1st to 5th percentile range, and a third for those in the 5th to 10th percentile bracket. We then use these dummy variables to run regressions similar to equation (12) and report results in Table 12.

Columns (1) and (2) of Table 12 confirm our findings in Table 11 that regulatory pressure did not amplify banks' sensitivity to payment risk before the GFC. In the post-GFC sample, however, the coefficients on the interaction between payment risk and the dummy for capital below the 1st percentile in Columns (3) and (4) are not only more statistically significant but also more than three times larger in magnitude than those for the interaction with the dummy for capital between the 1st and 5th percentiles. Furthermore, the interaction between payment risk and the dummy for capital between the 5th and 10th percentiles is statistically insignificant. Taken together, these results indicate that in the post-GFC era, banks with substantially lower regulatory capital relative to their peers experience a significantly stronger negative impact of payment risk on lending.

Table 12: **The nonlinear effects of bank capital: pre-GFC vs. post-GFC**

The sample is at the bank-quarter level, spanning from 2000:Q1 to 2007:Q4 for Columns (1)–(2) and 2009:Q3 to 2020:Q4 for Columns (3)–(4). The dependent variable is the loan growth rate in quarter $t+1$, winsorized at the top and bottom 0.5% levels. $\mathbf{1}$(Regulatory capital $\leq$ 1pctl) is a dummy variable that takes the value of 1 when a bank's regulatory leverage ratio is below the cross-sectional 1st percentile level in quarter t and zero otherwise. $\mathbf{1}$(1pctl $<$ Regulatory capital $\leq$ 5pctl) and $\mathbf{1}$(5pctl $<$ Regulatory capital $\leq$ 10pctl) are similarly defined. Control variables are calculated as of quarter t and include regulatory capital dummies, $Loan\ growth$, $Deposit\ growth$, $Liquidity\ ratio$, $Loan\ ratio$, $Trading\ ratio$, $Capital\ ratio$, $Deposit\ ratio$, $Return\ on\ asset$, $\log(Size)$, squared $\log(Size)$, and $Number\ of\ states$, as defined in Table 2. Bank type includes: bank, credit union, and saving and loan bank. Standard errors are clustered at the bank and quarter levels, with corresponding t-values in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Dependent variable: Loan growth rate$_{t+1}$				
	Pre-GFC		**Post-GFC**	
	(1)	(2)	(3)	(4)
Flow volatility $\times\mathbf{1}$(Regulatory capital $\leq$ 1pctl)	-0.0346		-0.0591***	
	(-1.35)		(-3.75)	
Flow volatility $\times\mathbf{1}$(1pctl $<$ Regulatory capital $\leq$ 5pctl)	-0.0132		-0.0170**	
	(-1.22)		(-2.50)	
Flow volatility $\times\mathbf{1}$(5pctl $<$ Regulatory capital $\leq$ 10pctl)	-0.0045		0.0025	
	(-0.55)		(0.55)	
Counterparty HHI $\times\mathbf{1}$(Regulatory capital $\leq$ 1pctl)		-0.0067		-0.0646***
		(-0.27)		(-4.03)
Counterparty HHI $\times\mathbf{1}$(1pctl $<$ Regulatory capital $\leq$ 5pctl)		-0.0077		-0.0182***
		(-0.87)		(-2.93)
Counterparty HHI $\times\mathbf{1}$(5pctl $<$ Regulatory capital $\leq$ 10pctl)		-0.0061		0.0002
		(-0.76)		(0.05)
Flow volatility	0.0009		-0.0040	
	(0.32)		(-1.36)	
Counterparty HHI		-0.0012		-0.0151**
		(-0.20)		(-2.68)
Bank controls	Yes	Yes	Yes	Yes
State $\times$ Quarter FE	Yes	Yes	Yes	Yes
Type $\times$ Quarter FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.209	0.209	0.190	0.191
N of Obs.	58581	58581	97707	97707

Overall, our findings in this section reveal a stark contrast between the pre- and post-GFC eras. Before the GFC, the negative relationship between payment risk and bank lending was primarily driven by cross-sectional differences across banks. In the post-GFC period, however, the relationship also reflects within-bank variation, with the relationship strength depending on aggregate liquidity conditions and regulatory pressure. These results suggest that the U.S. banking system has become more sensitive to liquidity risk in the post-GFC era, likely due to tighter liquidity and regulations within the overall financial system. Throughout this section, we present results separately for the pre- and post-GFC samples, while the corresponding full-sample results are reported in Tables C.3, C.4, C.5, and C.6 in the appendix.

5 Conclusion

This paper examines how banks' exposure to payment risk—arising from the monetary function of deposits—shapes their lending decisions and reveals a fundamental trade-off between their roles as money and credit suppliers. Using confidential Fedwire settlement data, we measure banks' payment risk through the volatility of daily payment imbalances and counterparty concentration. Our empirical findings demonstrate that banks facing greater payment risk systematically extend fewer loans, a relationship that is economically substantial and robust across multiple specifications and identification strategies. This negative association reflects banks' rational response to liquidity risk: when depositors' payment flows are less stable, banks refrain from investing in illiquid assets (loans), taking into account the asset-liability liquidity mismatch.

A striking finding emerges when comparing the pre- and post-GFC periods: despite a substantial increase in banks' reserves after the crisis, banks' sensitivity to payment risk actually strengthened. Before the GFC, the payment-credit tension primarily reflected cross-sectional differences in banks' business models and depositor clienteles, with limited within-bank time variation. After the GFC, however, within-bank variations over time became important, driven by aggregate liquidity conditions, including interbank market tightness and TGA flows, and regulatory pressure.

Our results contribute to the growing literature on post-GFC liquidity paradoxes and shed light on several ongoing structural changes in the financial system. The persistent and even intensifying sensitivity to payment risk—despite massive central bank balance sheet expansion—suggests that banks remain fundamentally liquidity-constrained and has likely contributed to the gradual shift of credit intermediation away from traditional banks that bundle payment and credit.

Understanding the payment-credit trade-off banks face also has important implications for banking regulation and oversight. Current frameworks, such as the net stable funding ratio, rely on stylized assumptions about deposit stability that may not fully capture the heterogeneity in payment risk documented here. Our approach, grounded in payment settlement data, offers a more bottom-up measurement of banks' funding risk that is unique to the monetary role of deposits. As payment system design and the landscape of credit supply continue to evolve, it is important to incorporate payment-based metrics of bank funding risks into policy frameworks.

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Appendix A Institutional Background and Data Sources

A.1 U.S. Payment Systems

The Fedwire Funds Service is the primary payment system in the United States for large-value transactions. This real-time gross settlement system allows participants to initiate funds transfers that are instantaneous, final, and irrevocable, once processed. The service is provided and operated by the Federal Reserve Banks and is open to any financial institution that holds an account with a Federal Reserve Bank, such as Federal Reserve member banks, non-member depository institutions, and certain other organizations like U.S. branches and agencies of foreign banks.

The Fedwire Funds Service is a transfer service. Participants originate funds transfers by instructing a Federal Reserve Bank to debit funds from its own (reserve) account and credit funds to the account of another participant. To make transfers, the following information is submitted to the Federal Reserve via Fedwire: the receiving bank's routing number, account number, name, and dollar amount being transferred. Each transaction is processed individually and settled upon receipt. Participants may originate funds transfers online, by initiating a secure electronic message, or offline, via telephone procedures.

Participants can use it to send or receive payments for their own accounts or on behalf of corporate or individual clients, to settle commercial payments, to settle positions with other financial institutions or clearing arrangements, to submit federal tax payments, or to buy and sell federal funds. Households, businesses, and government agencies rely on Fedwire for mission-critical, same-day transactions. In the paper, we focus on Fedwire fund transfers made on behalf of banks' corporate or individual clients (i.e., reserve transfers that result from the depositors' payment instructions), which make up about 80% of total transactions in terms of transaction numbers.

The Fedwire Funds Service business day begins at 9:00 p.m. EST (eastern standard time) on the preceding calendar day and ends at 7:00 p.m. EST, Monday through Friday, excluding designated holidays. For example, the Fedwire Funds Service opens on Monday at 9:00 p.m. on the preceding Sunday. The deadline for initiating transfers for the benefit of a third party (such as a bank's customer) is 6:00 p.m. EST each business day. Under certain circumstances, Fedwire Funds Service operating hours may be extended by the Federal Reserve Banks.

To facilitate the smooth operation of the Fedwire Funds Service, the Federal Reserve Banks offer intraday credit, in the form of daylight overdrafts, to financially healthy Fedwire participants with regular access to the discount window. Before the GFC, many Fedwire Funds Service participants use daylight credit to facilitate payments throughout the operating day, and such usage declines substantially after the GFC. The Federal Reserve Policy on Payment System Risk prescribes daylight credit limits, which can constrain some Fedwire Funds Service participants' payment operations. Each participant is aware of these constraints and is responsible for managing its account throughout the day. Specifically, a Fedwire participant's maximum dollar amount of daylight overdrafts that it may incur is referred as the net debit cap. A participant is by default assigned either an exempt-from-filing category (incurring daylight overdrafts no more than $10 million or 20 percent of their capital measure) or a zero-cap category (incurring no overdrafts). To apply for higher daylight overdrafts, Fedwire participants need to submit to its Reserve Bank at least once a year a copy of its board of directors' resolution.

In 2020, approximately 5,000 participants initiate funds transfers over the Fedwire Funds Service, and the Fedwire Funds Service processed an average daily volume of 727,313 payments, with an average daily value of approximately $3.3 trillion.[32] The distribution of these payments is highly skewed, with a median value of $24,500 and an average value of approximately $4.6 million. In particular, only about 7 percent of Fedwire fund transfers are for more than $1 million.

The other important interbank payment system for large-value transactions in the U.S. is the Clearing House Interbank Payments System (CHIPS), which is a private clearing house for transactions between banks. In 2020, CHIPS processed an average daily volume of 462,798 payments, with an average daily value of approximately $1.7 trillion, about half of the daily value processed by Fedwire.[33] There are three key differences between CHIPS and Fedwire Funds Service. First, CHIPS is privately owned by The Clearing House Payments Company LLC, while Fedwire is operated by the Federal Reserve. Second, CHIPS has only 43 member participants as of 2020, compared with thousands of banking institutions making and receiving funds via Fedwire. Third, CHIPS is not a real-time gross settlement system like Fedwire, but a netting engine that uses bilateral and multi-lateral netting to consolidate pending payments into single transactions. Compared to the Fedwire Funds Service, the low institution coverage of CHIPS and its netting feature make it less desirable to be the test field of the effects of payment liquidity risks on the bank lending.

A.2 HMDA and Merge with Call Report

The Home Mortgage Disclosure Act (HMDA) was enacted by Congress in 1975 and implemented through the Federal Reserve Board's Regulation C. This regulation mandates that lending institutions report public mortgage loan data. It covers a wide range of financial institutions including banks, savings associations, credit unions, and other mortgage lending entities.

The data reported under HMDA is detailed at the mortgage loan level and includes diverse information segments. It collects demographic information about the loan applicant, such as ethnicity, race, age, gender, and socioeconomic data including income, debt-to-income ratio, and credit scores. Additionally, the data encompasses specifics about the loan itself, such as the amount, term, interest rates, purpose, collateral, and special features. Details about the housing property, including its value, type, number of units, and location, are also provided. Information about the lender is reported as well, including identity and the use of Automated Underwriting Systems (AUS). This comprehensive data collection aims to provide transparency, monitor fairness in mortgage lending, and help regulatory bodies oversee and enforce anti-discrimination laws.

Starting from 2018, the Legal Entity Identifier (LEI), sourced from a Global LEI Foundation

[32] Please refer to Fedwire Funds Service Annual Statistics.

[33] Please refer to CHIPS Annual Statistics.

(GLEIF) operating unit, serves as the consistent and unique identifier for all lenders filing HMDA forms. Additionally, the National Information Center (NIC) provides a mapping between the LEI and the RSSD ID (the standard bank identifier in CALL Reports) for both active and closed banks, effectively linking HMDA and CALL Report from 2018 onward.

For the years 2017 and earlier, HMDA lenders did not use a consistent identifier. Instead, they reported various types of identifiers known as $Respondent\ ID$, determined by their supervisory or regulatory agency, referred to as $Agency\ Code$. These agencies include the Office of the Comptroller of the Currency (OCC), Federal Reserve System (FRS), Federal Deposit Insurance Corporation (FDIC), Office of Thrift Supervision (OTS), National Credit Union Administration (NCUA), Department of Housing and Urban Development (HUD), Private Mortgage Insurance Companies (PMIC), and Consumer Financial Protection Bureau (CFPB). Depending on the agency, lenders would report their $Respondent\ ID$ as an OCC charter number, FDIC certificate number, NCUA charter number, NIC RSSD, or federal tax ID. The OCC, FDIC, NCUA, and RSSD identifiers all employ a sequential integer system for ID assignment, where identifiers begin at 1 and increase incrementally by 1 as new institutions are registered. This system can potentially lead to duplicate IDs among HMDA filers. To ensure each identifier is unique within a given year, it is necessary to concatenate an institution's $Agency\ Code$ with its $Respondent\ ID$.

Additional complications with pre-2018 HMDA identifiers arise because a bank might report different types of IDs in different years, as it is under the supervision of multiple agencies. For instance, Bank of America holds multiple identifiers: an RSSD ID of 480228, an OCC charter number of 13044, an FDIC certificate number of 3510, and a special identifier for the CFPB. Prior to 2018, it could potentially report any of these IDs in its HMDA filings, creating challenges in consistently tracking a bank's lending activity over time.

In 2018, when HMDA transitioned from reporting multiple IDs to the uniform identifier of LEI, the CFPB provided a one-time mapping of 2017 Agency Codes and Respondent IDs to their new institution identifiers, LEI. This mapping offers an almost perfect identification of lenders in the 2017 HMDA data. However, the effectiveness of this mapping decreases as we look further back in time. For instance, in 2010, about 24% of observations are matched with the LEI of the mortgage lender, and in 2000, only about 2% are matched. To ensure a relatively balanced sample, we impose a requirement that at least 80% of loan-level observations must be matched with the lender's LEI. This criterion allows us to use HMDA data starting from 2013.

With 100% of LEI information available for 2018 and onwards, and over 80% of LEI data populated using the aforementioned approach for the period from 2013 to 2017, we merge the HMDA data with CALL Report data. Over 30% of observations in the HMDA data are matched to banks reported in the CALL Report, with a consistent matching rate across different years. This matching rate is partially driven by the fact that many mortgage lenders are not FDIC-insured banks. Since the matching process is conducted at the bank level, the total amount of mortgage loans issued by a given bank in a specific county within a given year remains unaffected by the unmatched observations. Therefore, our merged sample of HMDA and CALL Report data provides a relatively complete record of local mortgage loan activities over time for the matched banks.

Table B.1: **Predictability of payment activities: gross volume vs. net flow**

The sample comprises a fully expanded dataset at the bank-business day level, including days with zero payment volumes, spanning from January 2000 to December 2020 and excluding the financial crisis period from 2008:Q1 to 2009:Q2. The dependent variable for columns (1) and (2) is the daily gross payment volume for a given bank (i.e., the total of payments received and payments sent) and is measured in thousands of dollars. For columns (3) and (4), the dependent variable is the daily net payment flow for a given bank, defined as the difference between payments received and payments sent, also measured in thousands of dollars. The variable $Beginning\ of\ Month$ is a dummy variable assigned a value of one for the first three business days of each month and zero otherwise. Similarly, $End\ of\ Month$ is a dummy variable that takes a value of one for the last three business days of each month and zero otherwise. Standard errors are clustered at the bank and quarter levels, with corresponding t-values in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	Gross Volume (in $K)		**Net Flow (in $K)**	
	(1)	(2)	(3)	(4)
Beginning of Month	38871**	38803**	434	445
	(2.24)	(2.19)	(0.09)	(0.09)
End of Month	71251***	71182**	-2280	-2269
	(2.65)	(2.60)	(-0.88)	(-0.88)
Bank FE	Yes	Yes	Yes	Yes
Quarter FE		Yes		Yes
Adjusted R^2	0.918	0.918	0.091	0.091
N of Obs.	9800162	9800162	9800162	9800162

Appendix B Modeling Payment Risk

B.1 Gross payment volume seasonality

In Table B.1, we report results on a simple seasonality-based analysis of payment flow predictability. In Column (1) and (2), we regress a bank's daily gross payment volume on the dummy for the beginning of the month (first three business days) and the dummy for the end of the month (last three business days) without and with quarter fixed effects, respectively (bank fixed effects are included in both specifications). The R^2 is 91.8%, indicating that banks can comfortably predict the gross payment volume using seasonality. In contrast, the same seasonality model does not explain well the daily net payment flow as shown in Column (3) and (4). Therefore, in our model, we do not emphasize the randomness in gross volume but focus instead of the risk in net payment flow (i.e., the imbalance between inflows and outflows); accordingly, in our measure of payment risk, we use the daily gross flow as the scaling factor for $Flow\ imbalance_{i,t,d}$ and then calculate its standard deviation to obtain $Flow\ volatility_{i,t}$, our primary measure of payment liquidity risk.

B.2 A simple model of payment risk and bank lending

We formalize the hypotheses in a stylized model of a bank that finances lending with deposits. The bank has a unit mass of depositors. On the asset side of its balance sheet, there are reserves, loans, and other assets (e.g., securities), denoted by m, y, and a, respectively, and on the liability side, it has existing deposit liabilities, d, and equity capital, e. The bank chooses Δy, the amount of new loans financed by deposits. The bank may lend beyond Δy with funds from other sources (e.g., bond and equity issuance), but given our emphasis on liquidity mismatch in financing loans with deposits, we focus on characterizing the optimal Δy. The timing is as follows. The bank chooses Δy and deposit rate, denoted by r, at $t = 0$. At $t = 1$, depositors make payments, which we will discuss shortly. At $t = 2$, the bank receives loan repayments and repays the depositors.

At $t = 0$, aggregating across depositors, we have $\int_{i\in[0,1]} \Delta d(i)di = \Delta y$, i.e., the bank's source of funds (the newly raised deposits), is equal to the use of funds (loans). By financing new loans with deposits, the bank earns a net interest margin equal to $(R - r)\Delta y$, where R is the loan rate.[34]

Depositor i's share of total deposits is denoted by $\zeta(i)$. The depositor uses her bank account to receive and send payments. A large amount of deposits may indicate that depositor i has large payment needs and will send out more deposits. A large amount of deposits may also indicate that depositor i will receive large payment inflows, because her deposits may have accumulated from past inflows, such as business revenues and payroll, that may persist into the future. Therefore, we assume that a depositor's payment volume is proportional to her deposit amount but the direction is uncertain.[35] Specifically, depositor i's payment *outflow* is given by

$$p(i) \equiv (d + \Delta y)\,\zeta(i)\psi\widetilde{\omega}(i), \tag{B.1}$$

Depositor i holds $\zeta(i)$ fraction of total deposits $d + \Delta y$, and ψ is the scaling parameter that links deposit amount to payment amount. $\widetilde{\omega}(i)$ determines the payment direction, drawn from $\{-1, 1\}$ with a zero mean and variance denoted by $\sigma(i)^2$. $\widetilde{\omega}(i) = 1$ is for outflow and $\widetilde{\omega}(i) = -1$ for inflow.

Finally, when the bank raises the deposit rate, r, depositors hold more deposits. This component of deposit flow is denoted by $s(r)$ with $s'(r) > 0$.[36] We define $\widetilde{\Omega} \equiv \int_{i\in[0,1]} \zeta(i)\widetilde{\omega}(i)di$, with zero mean and variance denoted by $\sigma^2 > 0$.[37] The bank faces a *net deposit outflow*,

$$p - s(r) = \int_{i\in[0,1]} p(i)di - s(r) = (d + \Delta y)\,\psi\widetilde{\Omega} - s(r)\,, \tag{B.2}$$

[34]Assuming a constant loan rate is without loss of generality as long as the loan default risk is not correlated with shocks to depositors' payment flows (which are the focus of our model). We interpret R as the risk-adjusted return that already accounts for the systematic risk in loan returns. The systematic risk factors are priced by bank shareholders' stochastic discount factor (SDF), and the SDF does not load shocks to bank depositors' payment flows.

[35]In Figure 2, we show that deposits and gross payment volume closely comove over time.

[36]This specification of random payment-driven deposit flows and rate-sensitive flows follows Bolton et al. (2025).

[37]The payment direction shock, $\widetilde{\omega}(i)$, can be correlated across depositors so the randomness may not average out.

where the aggregated net payment outflow, denoted by p, is given by $(d + \Delta y)\,\psi\widetilde{\Omega}$.

At $t = 0$, the bank chooses Δy, the amount of new loans financed by deposits, and r, the deposit rate to maximize the expected profits, taking into account the payment risk in p:

$$\max_{\Delta y,\, r} \mathbb{E}\left[(R-r)\Delta y - rd - \tau_1\left(p - s(r) - m - L(\theta)\right) - \frac{\tau_2}{2}\left(p - s(r) - m - L(\theta)\right)^2\right], \quad \text{(B.3)}$$

The first term represents the net interest margin from financing new loans with deposits. The second term is the interest expense from the existing deposits. When choosing r, the bank considers impact on the overall interest expenses from the new and existing deposits.

The third and fourth terms in (B.3) represent the cost of liquidity loss. When the bank faces a net deposit outflow, $p - s(r)$, it covers it using reserves (cash), m, and can obtain liquidity, $L(\theta)$, by pledging other assets as collateral, such as the existing loans, y, and securities, a, i.e., $\theta = \{y, a\}$ representing the bank's asset portfolio.[38] $L(\theta)$ may also represent the resale value of these assets.

When $p - s(r) - m - L(\theta) > 0$, the bank experiences liquidity shortfall. The quadratic form, given by the third and fourth term in (B.3), represents an increasing and convex cost of borrowing cash in the interbank reserve market.[39] The convexity, as microfounded in Bigio and Sannikov (2019) and Parlour et al. (2020), can be motivated by frictions in the OTC interbank market for reserve borrowing and lending (Afonso and Lagos, 2015). When $p - s(r) - m - L(\theta) < 0$, this quadratic form represents a concave return on lending reserves in the interbank market. The concavity can also be motivated by attrition due to frictions in the interbank reserve market.

To sharpen the empirical predictions, we clarify the interpretations of the coefficients, τ_1 and τ_2, in the quadratic form of liquidity cost in (B.3). The parameter τ_1 is a baseline cost of borrowing or a baseline return on lending reserves. Our focus is on τ_2 which captures frictions and tightness of the interbank reserve market and tends to increase when the interbank market and broader financial system are under stress (e.g., Afonso et al., 2011).[40] Moreover, as we will show shortly, τ_2 plays a role akin to that of a risk aversion coefficient in the portfolio theory. Therefore, an undercapitalized bank tends to be more sensitive to payment risk that imputes risk in earnings.

Next, we solve the optimal Δy and r (see Appendix A for derivation details). A higher Δy allows the bank to earn more net interest margin. However, as shown in (B.1) and (B.2), a higher Δy scales up p, resulting in more liquidity risk, through the second-order (last) term in (B.3), reducing the expected profits. The first-order condition for Δy implies an intuitive representation:

$$\Delta y = \frac{R - r}{\tau_2 \sigma^2} - d. \quad \text{(B.4)}$$

[38] $L(\theta)$ is the funds raised after accounting for financing costs, and the lenders may impose haircuts (not all assets are perfectly pledgeable), so $L(\theta) < y + a$.

[39] Banks may borrow from the central bank, but in practice, they are discouraged from utilizing discount window and payment-system overdrafts (Copeland et al., 2024).

[40] Banks may borrow in other instruments but also face frictions (e.g., Pérignon et al., 2018).

Given the net interest margin, $R - r$, a higher level of payment risk, σ^2, leads to less lending. Also note that the existing deposit liabilities already imply a liquidity drain, which discourages the bank from taking on more payment risk by financing loans with new deposits. In our empirical model, we include the deposits-to-total asset ratio ("deposit ratio") as a control variable in the loan growth regression and find a negative coefficient consistent with such *payment risk overhang* effects.[41]

To demonstrate properties of the optimal deposit rate, we specify $s(r) = \lambda r$ where $\lambda > 0$. We impose two parameter conditions.[42] The first condition, $\lambda \tau_2 \sigma > 1$, requires the marginal benefit of raising deposit rate to preserve liquidity is sufficiently large. On the left side, the marginal increase of deposits is multiplied by a "payment risk premium", $\tau_2 \sigma$ where τ_2 is the convexity parameter of liquidity cost in the objective function (B.3) and σ is the size of payment risk. The second condition, $R/\sigma > \tau_1$, requires lending to be sufficiently profitable on a risk-adjusted basis. The left side is the loan rate scaled by payment risk. The right side is the linear coefficient of liquidity cost. In Appendix A, we derive the following results that correspond to the three hypotheses.

Proposition 1 The optimal Δy and r are functions of payment risk, σ^2, and bank balance-sheet condition (m, y, a, d, and e). Δy and r have the following properties:

(1) The optimal Δy is decreasing in payment risk, σ^2, i.e., $\frac{d\Delta y}{d(\sigma^2)} < 0$.

(2) The sensitivity of bank lending to payment risk is amplified by a higher τ_2, i.e., $\frac{d^2 \Delta y}{d(\sigma^2) d\tau_2} < 0$.

(3) The optimal r is increasing in payment risk, σ^2, i.e., $\frac{dr}{d(\sigma^2)} > 0$.

When testing these hypotheses, we observe loan growth from Call Report and deposit rates from RateWatch, and we obtain proxy for τ_2 following the literature. For payment risk, σ, the volatility of $\widetilde{\Omega}$, our model offers guidance on measurement. The gross payment volume is given by

$$g = \int_{i \in [0,1]} \zeta(i)(d + \Delta y)\psi |\widetilde{\omega}(i)| di = \int_{i \in [0,1]} \zeta(i)(d + \Delta y)\psi di = (d + \Delta y)\psi, \tag{B.5}$$

where we take absolute value of the payment direction shock, $\widetilde{\omega}(i) \in \{-1, 1\}$, and use $\int_{i \in [0,1]} \zeta(i) di = 1$ (as a reminder, $\zeta(i)$ is depositor i's share of total deposits). As in (B.2), the net payment flow is

$$p = (d + \Delta y)\psi \widetilde{\Omega}. \tag{B.6}$$

[41] The amount of existing loans, y, does not affect Δy. Our model does not feature loan risk and only emphasizes deposit risk related to payment. If the loan return is risky, the risk overhang effects will apply to existing loans as well as deposits. In our empirical model, we include the loans-to-total asset ratio ("loan ratio") as a control variable.

[42] We also assume that the bank generates positive profits even in the worst scenario of payment outflow, i.e., $\widetilde{\Omega} = 1$, so that insolvency is not a concern and depositors do not have incentive to run on the bank. Our focus is on characterizing a bank's choice of Δy in normal times rather than crises or bank runs.

Therefore, taking the ratio of net to gross payment flow, we can compute $\widetilde{\Omega}$:

$$\frac{p}{g} = \frac{(d + \Delta y)\psi\widetilde{\Omega}}{(d + \Delta y)\psi} = \widetilde{\Omega}. \tag{B.7}$$

In our empirical exercise, we obtain daily gross and net payment flows, i.e., g and p, from Fedwire and calculate the standard deviation of g/p, which maps to the payment risk, σ.

Table B.1 shows that gross payment flow is strongly predictable. It peaks near the beginning and end of a month. These seasonality indicators generate a R^2 of 92%; in contrast, the R^2 for explaining net payment flow is only 9%. Thus, when modeling payment risk, our focus is not on the highly predictable gross payment volume but rather on the imbalance of payment flows, that is a bank's net liquidity loss per unit of gross volume, $p/g = \widetilde{\Omega}$. When inflows and outflows perfectly net out, $p = 0$, there is no payment risk no matter how large the gross volume is. Our model captures the fact that the imbalance of payment flow originates from payment direction shock $\widetilde{\omega}(i)$ at the individual depositor level and such shocks then aggregate to $\widetilde{\Omega}$ at the bank level, resulting in payment liquidity risk.

B.3 Proof of Proposition 1

Under $\widetilde{\omega} \sim \mathcal{N}(\mu, \sigma^2)$, the bank's objective function can be written as

$$\begin{aligned}&(R - r)\Delta y - rd - \tau_1 \mu\,(d + \Delta y) + \tau_1\,(m + L(\theta)) + \tau_1 s(r)\\&- \frac{\tau_2}{2}\sigma^2\,(d + \Delta y)^2 - \frac{\tau_2}{2}\,(\mu\,(d + \Delta y) - (m + L(\theta)) - s(r))^2\end{aligned}$$

We derive the F.O.C. for r,

$$-\Delta y - d + \tau_1 s'(r) + \tau_2\,(\mu\,(d + \Delta y) - (m + L(\theta)) - s(r))\,s'(r) = 0, \tag{B.8}$$

which can be written as

$$-\frac{\Delta y + d}{s'(r)} - \tau_2\,(m + L(\theta)) - \tau_2 s(r) + \tau_1 + \tau_2\mu\,(d + \Delta y) = 0. \tag{B.9}$$

Using the F.O.C. for Δy,

$$R - r - \tau_1\mu - \tau_2\sigma^2(d + \Delta y) - \tau_2\,(\mu\,(d + \Delta y) - (m + L(\theta)) - s(r))\,\mu = 0 \tag{B.10}$$

we obtain

$$\Delta y = \frac{R - r - \tau_1\mu}{\tau_2\,(\sigma^2 + \mu^2)} + \frac{\mu\,(m + L(\theta)) + \mu s(r)}{(\sigma^2 + \mu^2)} - d. \tag{B.11}$$

Let $s'(r) = \lambda$. The F.O.C. for r can be written as

$$s(r) = \left(\mu - \frac{1}{\tau_2 \lambda}\right)(d + \Delta y) + \frac{\tau_1}{\tau_2} - (m + L(\theta)). \tag{B.12}$$

Substituting the expression of $s(r)$ into the F.O.C. for Δy, we have

$$\Delta y = \frac{R - r}{\tau_2 \sigma^2 + \frac{\mu}{\lambda}} - d. \tag{B.13}$$

Substituting the solution into the F.O.C. for r, we obtain

$$s(r) = \left(\mu - \frac{1}{\tau_2 \lambda}\right)\left(\frac{R - r}{\tau_2 \sigma^2 + \frac{\mu}{\lambda}}\right) + \frac{\tau_1}{\tau_2} - (m + L(\theta)). \tag{B.14}$$

Let μ be zero because for any $i \in [0,\, 1]$, $\mathbb{E}[\widetilde{\omega}(i)] = 0$. We have

$$\Delta y = \frac{R - r}{\tau_2 \sigma^2} - d, \tag{B.15}$$

and

$$s(r) + \left(\frac{R - r}{\tau_2^2 \sigma^2 \lambda}\right) = \frac{\tau_1}{\tau_2} - (m + L(\theta)). \tag{B.16}$$

Replacing $s(r)$ with λr, we obtain

$$r = \frac{-R + \lambda \tau_1 \tau_2 \sigma^2 - \lambda \tau_2^2 \sigma^2 (m + L(\theta))}{\lambda^2 \tau_2^2 \sigma^2 - 1} \tag{B.17}$$

Taking the derivative with respect to σ^2, we obtain

$$\frac{dr}{d\sigma^2} = \lambda \tau_2 \frac{\lambda \tau_2 R - \tau_1 + \tau_2 (m + L(\theta))}{(\lambda^2 \tau_2^2 \sigma^2 - 1)^2} \tag{B.18}$$

Note that we have

$$R - r = \lambda \tau_2 \sigma^2 \frac{\lambda \tau_2 R - \tau_1 + \tau_2 (m + L(\theta))}{\lambda^2 \tau_2^2 \sigma^2 - 1} > 0. \tag{B.19}$$

Therefore, we have

$$\frac{dr}{d\sigma^2} = \left(\frac{R - r}{\sigma^2}\right) \frac{1}{\lambda^2 \tau_2^2 \sigma^2 - 1}. \tag{B.20}$$

We have $\lambda^2\tau_2^2\sigma^2 - 1 > 0$ under the parameter condition (1), $\lambda\tau_2\sigma > 1$. Note that $R - r > 0$ in (B.19) because, under parameter condition (2), $R/\sigma > \tau_1$, we have $\lambda\tau_2 R - \tau_1 > \lambda\tau_2\sigma\tau_1 - \tau_1 = (\lambda\tau_2\sigma - 1)\tau_1$, which is positive under the parameter condition (1), $\lambda\tau_2\sigma > 1$. Therefore, $\frac{dr}{d\sigma^2} > 0$. From (B.15), an increase in σ^2 reduces Δy by increasing r and σ^2. Moreover, in the solutions of Δy and r, σ^2 always appears with τ_2 in the form of $\tau_2\sigma^2$. Therefore, τ_2 amplifies the impact of σ^2 in both Δy and r. We can fully solve Δy by substituting out $R - r$ in (B.15) using (B.19):

$$\Delta y = \lambda \frac{\lambda\tau_2 R - \tau_1 + \tau_2\left(m + L(\theta)\right)}{\lambda^2\tau_2^2\sigma^2 - 1} - d. \tag{B.21}$$

Appendix C Additional Results

C.1 Additional figures

Figure C.1: **Data merge: Fedwire, RateWatch, and Call Report**

This figure shows the time series of total bank assets, separately for banks covered by Call Report and banks in our matched sample, where banks have merged information from the following three data sources: Fedwire (containing transaction-level payment information), RateWatch (deposit rate and bank location information), and Call report (bank balance sheet and income statement information). The sample period spans 21 years from 2000:Q1 to 2020:Q4.

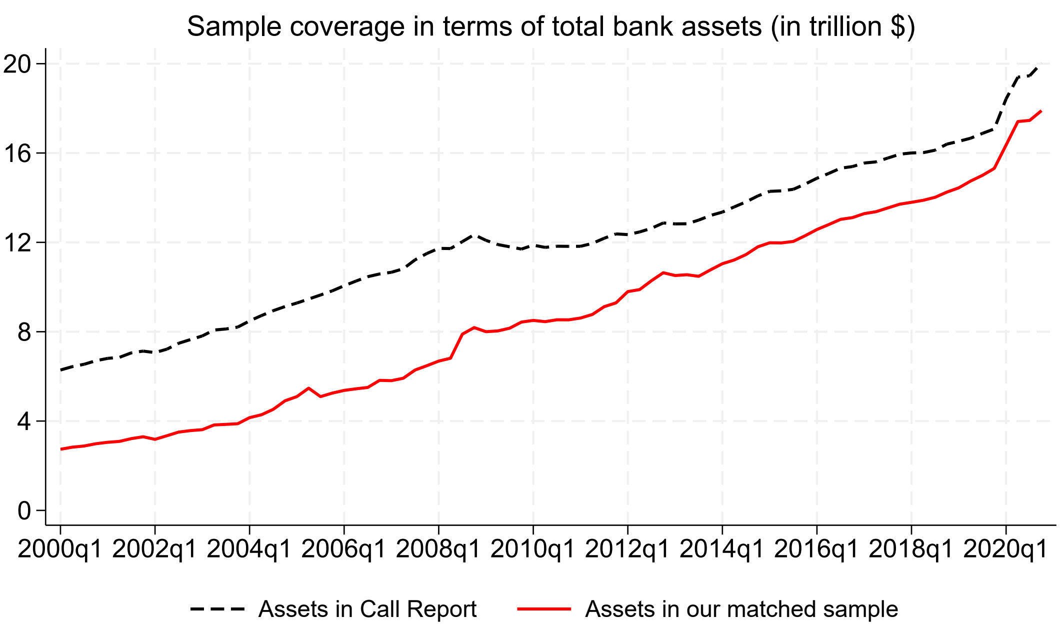
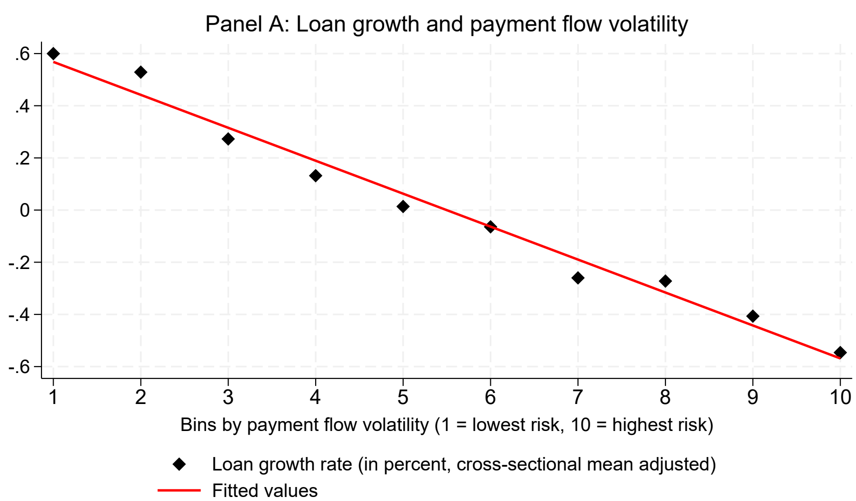


Figure C.2: **Payment risk and loan growth**

This figure illustrates the relationship between banks' loan growth rates and their payment risk measures. Specifically, we sort banks into 10 bins based on their previous-quarter payment risk measures: $Flow\ volatility$ (Panel A) and $Counterparty\ HHI$ (Panel B), with bin 1 representing the group with the lowest payment risk, and bin 10 the group with the highest payment risk. We then compute the average loan growth rate (with the cross-sectional mean subtracted) for each bin and mark their values with black diamonds. The sample is at the bank-quarter level and spans from 2000:Q1 to 2020:Q4, excluding the GFC from 2008:Q1 to 2009:Q2.



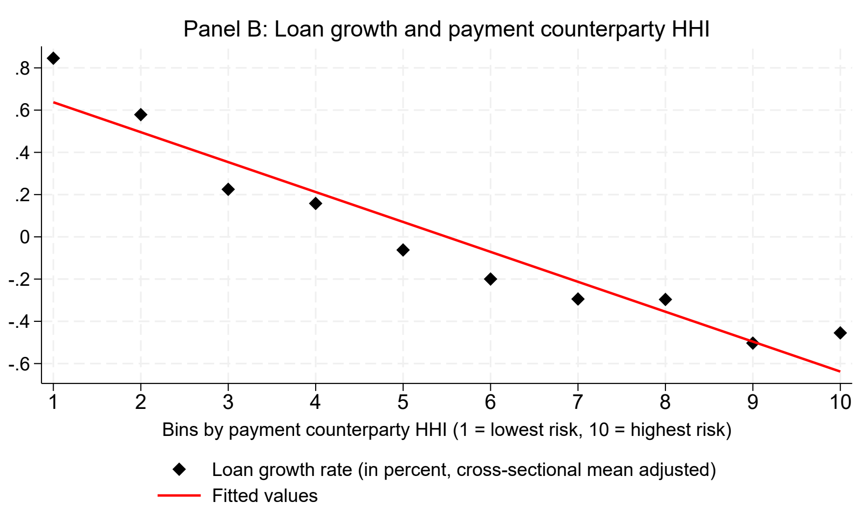
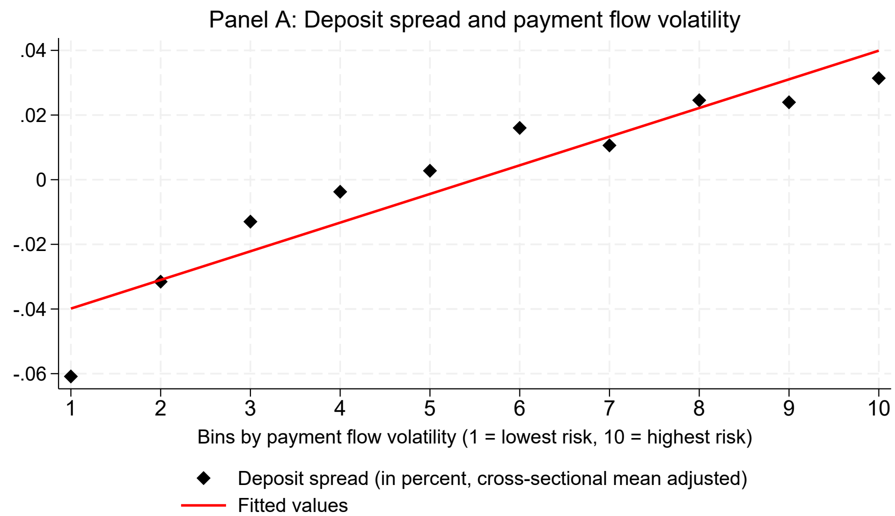


Figure C.3: **Payment risk and deposit rate**

This figure illustrates the relationship between banks' deposit spreads, i.e., deposit rate minus the Fed Funds rate (in percent) and their payment risk measures. We sort banks into 10 bins based on their previous-quarter payment risk measures: $Flow\ volatility$ (Panel A) and $Counterparty\ HHI$ (Panel B), with bin 1 representing the group with the lowest payment risk, and bin 10 the group with the highest payment risk. We then calculate the average deposit rate (based on the one-year 10K CD, adjusted for the cross-sectional mean) for each risk bin and mark their values with black diamonds. The sample is at the bank-quarter level and spans from 2000:Q1 to 2020:Q4, excluding the financial crisis from 2008:Q1 to 2009:Q2.



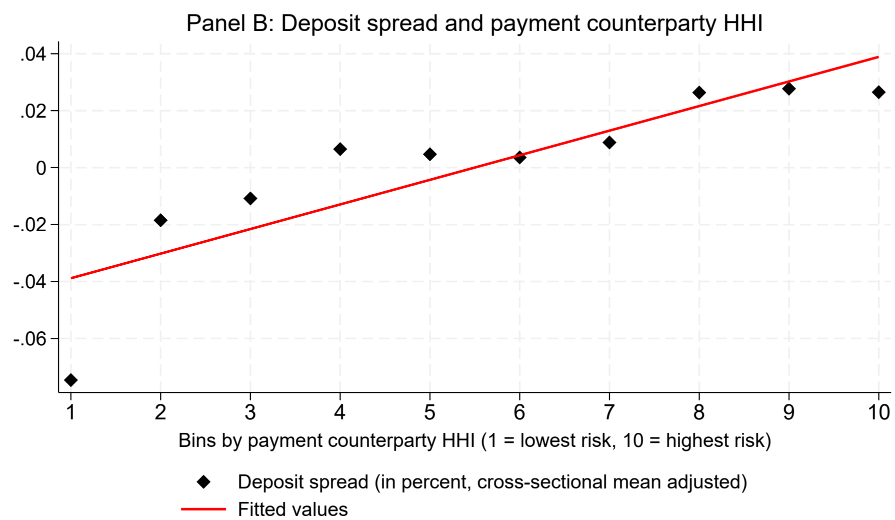
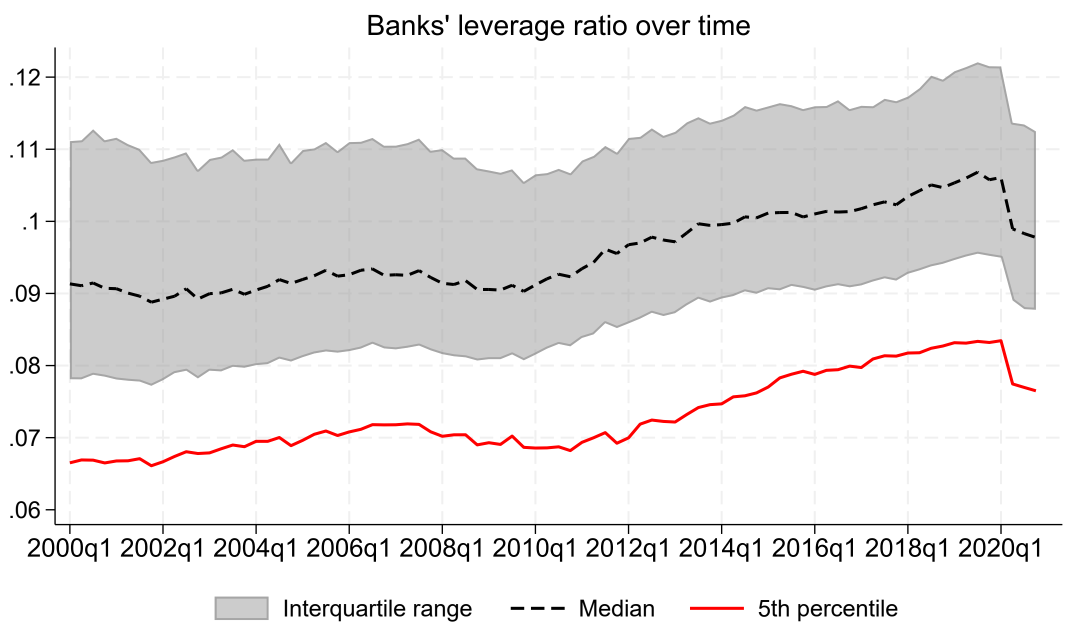


Figure C.4: **The evolution of Tier 1 leverage ratios**

This figure shows the distribution of banks' Tier 1 leverage ratios over time. Tier 1 leverage ratio is defined as the ratio of a bank's Tier 1 capital to its total consolidated on-balance sheet assets. In general, a bank needs to maintain a Tier-1 leverage ratio of at least 5% to be considered well-capitalized. The sample is at the bank-quarter level and spans from 2000:Q1 to 2020:Q4.



C.2 Additional tables

Table C.1: **Payment risk and bank lending: loan ratio as the dependent variable**

The sample is at the bank-quarter level from 2000:Q1 to 2020:Q4, excluding the financial crisis from 2008:Q1 to 2009:Q2. The dependent variable is loan-to-asset ratio in quarter $t+1$, winsorized at the top and bottom 0.5% levels. $Flow\ volatility$ is the standard deviation of a bank's daily payment flows, and $Counterparty\ HHI$ gauges the concentration levels of a bank's payment counterparties. Control variables are calculated as of quarter t and include $Liquidity\ ratio$, $Trading\ ratio$, $Capital\ ratio$, $Deposit\ ratio$, $Return\ on\ asset$, $\log(Size)$, squared $\log(Size)$, and $Number\ of\ states$, as defined in Table 2. Bank type includes: bank, credit union, and saving and loan bank. Standard errors are clustered at the bank and quarter levels, with corresponding t-values in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Dependent variable: Loan ratio$_{t+1}$				
	(1)	(2)	(3)	(4)
Flow volatility	-0.0412***	-0.0141***		
	(-6.08)	(-3.81)		
Counterparty HHI			-0.0610***	-0.0272***
			(-5.70)	(-3.68)
Bank controls	Yes	Yes	Yes	Yes
State × Quarter FE	Yes	Yes	Yes	Yes
Type × Quarter FE	Yes	Yes	Yes	Yes
Bank FE		Yes		Yes
Adjusted R^2	0.724	0.909	0.725	0.909
N of Obs.	156498	156400	156498	156400

Table C.2: **Payment risk and bank lending: including recessions vs. excluding recessions**

The sample for Panel A spans from 2000:Q1 to 2020:Q4, excluding three economic recession periods defined by NBER: 2001:Q2 to 2001:Q4, 2008:Q1 to 2009:Q2, and 2020:Q1 to 2020:Q2. The sample for Panel B spans from 2000:Q1 to 2020:Q4. The dependent variable is the loan growth rate in quarter $t+1$, winsorized at the top and bottom 0.5% levels. $Flow\ volatility$ is the standard deviation of a bank's daily payment flows, and $Counterparty\ HHI$ gauges the concentration levels of a bank's payment counterparties. Control variables are calculated as of quarter t and include $Loan\ growth$, $Deposit\ growth$, $Liquidity\ ratio$, $Loan\ ratio$, $Trading\ ratio$, $Capital\ ratio$, $Deposit\ ratio$, $Return\ on\ asset$, $\log(Size)$, squared $\log(Size)$, and $Number\ of\ states$, as defined in Table 2. Bank type includes: bank, credit union, and saving and loan bank. Standard errors are clustered at the bank and quarter levels, with corresponding t-values in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Dependent variable: Loan growth rate$_{t+1}$				
Panel A: Excluding recessions				
	(1)	(2)	(3)	(4)
Flow volatility	-0.0138***	-0.0056***		
	(-8.53)	(-2.85)		
Counterparty HHI			-0.0226***	-0.0135***
			(-8.24)	(-3.53)
Bank controls	Yes	Yes	Yes	Yes
State × Quarter FE	Yes	Yes	Yes	Yes
Type × Quarter FE	Yes	Yes	Yes	Yes
Bank FE		Yes		Yes
Adjusted R^2	0.088	0.142	0.089	0.143
N of Obs.	146400	146299	146400	146299
Panel B: Entire sample (2000:Q1 to 2020:Q4)				
	(1)	(2)	(3)	(4)
Flow volatility	-0.0156***	-0.0072***		
	(-7.51)	(-3.62)		
Counterparty HHI			-0.0252***	-0.0151***
			(-6.71)	(-3.80)
Bank controls	Yes	Yes	Yes	Yes
State × Quarter FE	Yes	Yes	Yes	Yes
Type × Quarter FE	Yes	Yes	Yes	Yes
Bank FE		Yes		Yes
Adjusted R^2	0.115	0.169	0.116	0.169
N of Obs.	167037	166945	167037	166945

Table C.3: **Funding stress and the impact of payment risk (full sample)**

The sample is at the bank-quarter level and spans from 2000:Q1 to 2020:Q4, excluding the financial crisis from 2008:Q1 to 2009:Q2. The dependent variable is the loan growth rate in quarter $t+1$, winsorized at the top and bottom 0.5% levels. $LIBOR\text{-}OIS\ spread$ is the spread between the 3-month London Interbank Offered Rate (LIBOR) and the overnight index swap (OIS) of the same maturity, expressed in percent and calculated as the 90th percentile level from daily observations in quarter $t+1$. $Flow\ volatility$ is the standard deviation of a bank's daily excess payment flows, and $Counterparty\ HHI$ gauges the concentration levels of a bank's payment receivers and senders. Both measures are calculated from transaction-level Fedwire data in quarter t. Control variables are calculated as of quarter t and include $Loan\ growth$, $Deposit\ growth$, $Liquidity\ ratio$, $Loan\ ratio$, $Trading\ ratio$, $Capital\ ratio$, $Deposit\ ratio$, $Return\ on\ asset$, $\log(Size)$, squared $\log(Size)$, and $Number\ of\ states$, as defined in Table 2. Bank type includes: bank, credit union, and saving and loan bank. Standard errors are clustered at the bank and quarter levels, with corresponding t-values in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Dependent variable: Loan growth rate$_{t+1}$		
	(1)	(2)
Flow volatility × LIBOR-OIS spread	-0.0224***	
	(-2.90)	
Counterparty HHI × LIBOR-OIS spread		-0.0236***
		(-2.97)
Flow volatility	-0.0012	
	(-0.48)	
Counterparty HHI		-0.0093**
		(-2.40)
Bank controls	Yes	Yes
State × Quarter FE	Yes	Yes
Type × Quarter FE	Yes	Yes
Bank FE	Yes	Yes
Adjusted R^2	0.169	0.169
N of Obs.	156368	156368

Table C.4: **Reserve shocks and the impact of payment risk (full sample)**

The sample is at the bank-quarter level and spans from 2000:Q1 to 2020:Q4, excluding the financial crisis from 2008:Q1 to 2009:Q2. The dependent variable is the loan growth rate in quarter $t + 1$, winsorized at the top and bottom 0.5% levels. $TGA\ change$ is the quarterly growth rate of Treasury General Account (TGA) based on average levels of the TGA within a quarter (in decimal), calculated as of quarter $t + 1$. $Flow\ volatility$ is the standard deviation of a bank's daily excess payment flows, and $Counterparty\ HHI$ gauges the concentration levels of a bank's payment receivers and senders. Both measures are calculated from transaction-level Fedwire data in quarter t. Control variables are calculated as of quarter t and include $Loan\ growth$, $Deposit\ growth$, $Liquidity\ ratio$, $Loan\ ratio$, $Trading\ ratio$, $Capital\ ratio$, $Deposit\ ratio$, $Return\ on\ asset$, $\log(Size)$, squared $\log(Size)$, and $Number\ of\ states$, as defined in Table 2. Bank type includes: bank, credit union, and saving and loan bank. Standard errors are clustered at the bank and quarter levels, with corresponding t-values in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Dependent variable: Loan growth rate$_{t+1}$		
	(1)	(2)
Flow volatility × TGA Change	-0.0102*	
	(-1.81)	
Counterparty HHI × TGA Change		-0.0111**
		(-2.04)
Flow volatility	-0.0060***	
	(-2.98)	
Counterparty HHI		-0.0143***
		(-3.73)
Bank controls	Yes	Yes
State × Quarter FE	Yes	Yes
Type × Quarter FE	Yes	Yes
Bank FE	Yes	Yes
Adjusted R^2	0.169	0.169
N of Obs.	156368	156368

Table C.5: **Bank capital and the impact of payment risk (full sample)**

The sample is at the bank-quarter level and spans from 2000:Q1 to 2020:Q4, excluding the financial crisis from 2008:Q1 to 2009:Q2. The dependent variable is the loan growth rate in quarter $t+1$, winsorized at the top and bottom 0.5% levels. $Low\ regulatory\ capital$ is a dummy variable that takes the value of 1 when a bank's regulatory leverage ratio is below the cross-sectional 5th percentile level in quarter t and zero otherwise. All U.S. banks are required to maintain a certain level of regulatory leverage ratio, defined as the ratio of a bank's Tier 1 capital to its average total consolidated on-balance sheet assets. $Flow\ volatility$ is the standard deviation of a bank's daily excess payment flows, and $Counterparty\ HHI$ gauges the concentration levels of a bank's payment receivers and senders. Both measures are calculated from transaction-level Fedwire data in quarter t. Control variables are calculated as of quarter t and include $Low\ regulatory\ capital$, $Loan\ growth$, $Deposit\ growth$, $Liquidity\ ratio$, $Loan\ ratio$, $Trading\ ratio$, $Capital\ ratio$, $Deposit\ ratio$, $Return\ on\ asset$, $\log(Size)$, squared $\log(Size)$, and $Number\ of\ states$, as defined in Table 2. Bank type includes: bank, credit union, and saving and loan bank. Standard errors are clustered at the bank and quarter levels, with corresponding t-values in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Dependent variable: Loan growth rate$_{t+1}$		
	(1)	(2)
Flow volatility × Low regulatory capital	-0.0218***	
	(-3.72)	
HHI × Low regulatory capital		-0.0183***
		(-3.74)
Flow volatility	-0.0058***	
	(-2.83)	
Counterparty HHI		-0.0148***
		(-3.61)
Bank controls	Yes	Yes
State × Quarter FE	Yes	Yes
Type × Quarter FE	Yes	Yes
Bank FE	Yes	Yes
Adjusted R^2	0.169	0.169
N of Obs.	156368	156368

Table C.6: **Bank capital and the impact of payment risk: the nonlinear effects (full sample)**

The sample is at the bank-quarter level and spans from 2000:Q1 to 2020:Q4, excluding the financial crisis from 2008:Q1 to 2009:Q2. The dependent variable is the loan growth rate in quarter $t+1$, winsorized at the top and bottom 0.5% levels. $\mathbf{1}$(Regulatory capital $\leq$ 1pctl) is a dummy variable that takes the value of 1 when a bank's regulatory leverage ratio is below the cross-sectional 1st percentile level in quarter t and zero otherwise. $\mathbf{1}$(1pctl $<$ Regulatory capital $\leq$ 5pctl) and $\mathbf{1}$(5pctl $<$ Regulatory capital $\leq$ 10pctl) are similarly defined. Control variables are calculated as of quarter t and include regulatory capital dummies, $Loan\ growth$, $Deposit\ growth$, $Liquidity\ ratio$, $Loan\ ratio$, $Trading\ ratio$, $Capital\ ratio$, $Deposit\ ratio$, $Return\ on\ asset$, $\log(Size)$, squared $\log(Size)$, and $Number\ of\ states$, as defined in Table 2. Bank type includes: bank, credit union, and saving and loan bank. Standard errors are clustered at the bank and quarter levels, with corresponding t-values in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Dependent variable: Loan growth rate$_{t+1}$		
	(1)	(2)
Flow volatility $\times\mathbf{1}$(Regulatory capital $\leq$ 1pctl)	-0.0506***	
	(-3.72)	
Flow volatility $\times\mathbf{1}$(1pctl $<$ Regulatory capital $\leq$ 5pctl)	-0.0148***	
	(-2.70)	
Flow volatility $\times\mathbf{1}$(5pctl $<$ Regulatory capital $\leq$ 10pctl)	0.0024	
	(0.64)	
Counterparty HHI $\times\mathbf{1}$(Regulatory capital $\leq$ 1pctl)		-0.0457***
		(-3.63)
Counterparty HHI $\times\mathbf{1}$(1pctl $<$ Regulatory capital $\leq$ 5pctl)		-0.0130***
		(-2.74)
Counterparty HHI $\times\mathbf{1}$(5pctl $<$ Regulatory capital $\leq$ 10pctl)		0.0007
		(0.21)
Flow volatility	-0.0059***	
	(-2.85)	
Counterparty HHI		-0.0149***
		(-3.61)
Bank controls	Yes	Yes
State $\times$ Quarter FE	Yes	Yes
Type $\times$ Quarter FE	Yes	Yes
Bank FE	Yes	Yes
Adjusted R^2	0.169	0.169
N of Obs.	156368	156368