Payment Risk and Bank Lending: Reassessing the Bundling of Payment Services and Credit Provision*

Ye Li† Yi Li‡

June 11, 2024

Abstract

Bundling credit provision and payment services creates liquidity mismatch for banks. While investing in illiquid loans, banks support payment activities by allowing depositors to freely transfer funds into and out of their accounts. Using payment data from Fedwire, we show that banks face sizeable liquidity risk due to depositors' payments. Payment liquidity risk is a form of funding risk inherent in the monetary role of deposits, yet it compromises the role of banks as lenders. An increase in payment risk is associated with a significant decline in lending. The effect is stronger for undercapitalized banks and when reserves are scarce.

Keywords: Payment, deposits, bank lending, reserves, funding stability, liquidity mismatch

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

---

*We are very grateful to helpful comments from Patrick Bolton, Philip Bond, Markus Brunnermeier, Isil Erel, Itay Goldstein, Florian Heider, Peter Hoffmann, Lei Li, Gordon Liao, Ouarda Merrouche, Steven Ongena, Christine Parlour, José-Luis Peydró, David Sraer, Dominik Supera, conference discussants and participants at at the Adam Smith Workshop at INSEAD, Barcelona School of Economics Summer Forum, European Finance Association, Northeastern University Finance Conference, OCC Research Symposium on Systemic Risk and Stress Testing in Banking, SFS Cavalcade North America, and seminar participants at Australian National University, Bank of Canada, Cheung Kong Graduate School of Business, Columbia Business School, European Finance Association (EFA), FDIC, Federal Reserve Board, Federal Reserve Bank of Chicago, Indiana University, Maastricht University, Monash University, Purdue University, University of Illinois Chicago, University of Illinois Urbana-Champaign, University of Liverpool, University of Notre Dame, University of Washington, and Washington University in St. Louis. The views expressed herein are those of the authors and do not necessarily reflect those of the Federal Reserve Board or its staff.

†University of Pennsylvania (Wharton) and University of Washington. E-mail: macrofin@wharton.upenn.edu

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

1 Introduction

The money view of banking emphasizes the role of deposits as means of payment, i.e., the liability side of bank balance sheet (e.g., Friedman and Schwartz, 1963). The credit view focuses instead on the asset side: loans are important sources of financing for firms and households (e.g., Bernanke, 1983). Banks have traditionally provided both payment services and credit.

Deposits circulate as means of payment. To ensure seamless operation of the payment systems, banks allow depositors to transfer funds freely into and out of their accounts. When a depositor sends money to depositors at a different bank, her bank loses reserves to the payee's bank under real-time gross settlement (RTGS). This loss of liquidity is costly, especially when frictions in the interbank market impede a redistribution of liquidity from banks with a surplus to those in a deficit.

While depositors' payments expose banks to liquidity shocks, loans are illiquid and cannot be readily sold to cover liquidity needs. Therefore, credit provision and payment services naturally conflict with each other. In this paper, we present the first evidence that banks reduce lending when they are exposed to greater payment liquidity risk. Our measure of payment liquidity risk is based on payment data from Fedwire, the primary payment settlement system in the U.S.

Previous studies on liquidity mismatch focused on bank runs and financial crises. In contrast, payment liquidity risk emerges in banks' day-to-day operations. The average weekly volume in Fedwire exceeds the U.S. GDP. In fact, even insured deposits bear payment liquidity risk. Depositors move funds out of their bank accounts not for fear of bank failure but to make payments.

Payment risk is a form of funding stability risk that is unique to banks and inherent in the monetary role of deposits. Deposits are often considered as stable sources of funding for banks. However, depositors' payment activities may generate significant liquidity risk. In recent years, payment volume has increased faster than deposits. From 2010 to 2019, customer-initiated transactions in Fedwire grew at an annualized rate of 8.8% for the median bank, compared to a 4.9%

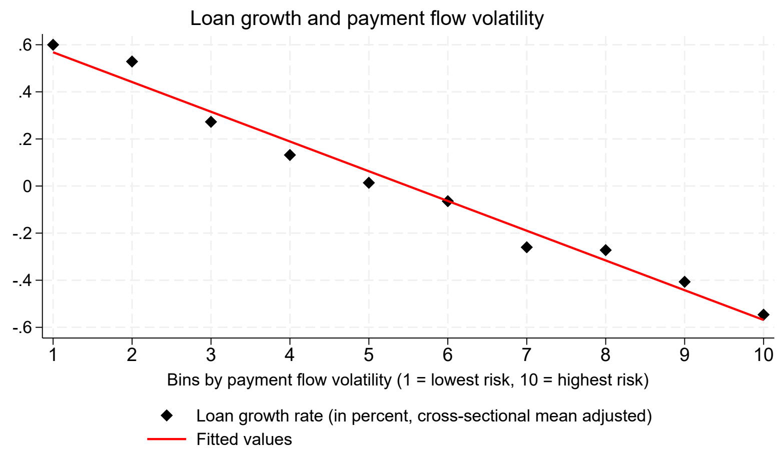


Figure 1: **Payment risk and loan growth.** This figure reproduces Figure 6A. We sort bank-quarter observations into 10 bins based on their previous-quarter payment flow volatility (defined in Section 3) with bin 1 representing the group with the lowest payment risk, and bin 10 the group with the highest 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.

annual increase in deposits. This disparity suggests an escalation in payment liquidity risk per dollar of deposits. Additionally, banks appear less prepared to manage such liquidity exposure; during the same period, the median bank's holdings of liquid assets grew by only 4.6% annually.[1]

In Figure 1, we illustrate our main result: banks that are more exposed to payment liquidity risk extend fewer loans. For a bank-quarter, we measure payment liquidity risk by the volatility of depositors' payment flows.[2] We then sort bank-quarter observations into deciles of payment liquidity risk; within each decile, we plot the average loan growth rate in the next quarter adjusted by the cross-sectional mean to eliminate potential effects of business cycles and seasonality.

The negative impact of payment risks on bank lending is robust after we control for various bank characteristics, bank type (regular banks, credit unions, and savings & loan banks), location,

[1]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.

[2]In the Fedwire payment records, we focus on depositor-initiated transactions that banks cannot control rather than bank-initiated transactions that involve banks buying and selling assets with reserves as means of payment.

and time fixed effects. An interquartile increase in payment risk is associated with a significant decline in quarterly loan growth rate by 0.6 percentage points. The magnitude is large in comparison with an average quarterly loan growth rate of 2% and a standard deviation of 6%.

To corroborate the economic mechanism, we consider an alternative and indirect measure of payment risk, namely the concentration (Herfindahl–Hirschman Index) of payment counterparty banks. Intuitively, if a bank's depositors make payments to (or receive payments from) depositors of only a few banks, the bank faces payment flows that can be easily affected by shocks specific to the payment needs of these banks' depositor clienteles; in contrast, such shocks tend to be diversified away when a bank's depositors transact with many banks' depositors. Using this alternative measure, we find an even stronger negative impact of payment liquidity risk on bank lending: an interquartile-range increase in counterparty concentration is associated with a decrease in loan growth rate by 1.3 percentage points, which is 22% of the standard deviation of loan growth rate.

Banks operate under distinct liquidity environments and regulatory requirements before and after the financial crisis. By conducting subsample analysis for the periods before and after the crisis, we show that payment risks are significant factors in banks' lending decisions during both periods, with a slightly more pronounced negative impact observed in the pre-crisis sample. Moreover, we demonstrate that our results remain consistent regardless of whether we include periods of global financial crisis or broadly defined economic downturns (e.g., the COVID-19 pandemic). Our findings suggest that the negative impact of payment liquidity risk on bank lending is consistently present and not driven by periods of extreme financial or economic conditions.

Loan growth can be driven by demand variation rather than banks' decisions on loan supply.[3] Including the interacting fixed effects of state and quarter alleviates the concern by controlling for time-varying economic conditions that drive loan demand in the bank headquarter state; nonethe-

[3]It is often challenging to control for loan demand when the goal is to identify the dynamics of credit supply (e.g., Khwaja and Mian, 2008; Puri et al., 2011; Jiménez et al., 2012, 2014; Becker and Ivashina, 2014).

less, this method does not apply to multi-state banks. To address this concern, we use information on bank branch locations from RateWatch to extract a subsample of single-state banks that constitute 87% of the observations. Our results in this subsample are consistent with the full-sample results in terms of both magnitude and statistical significance.

Small banks typically face more challenges than large banks when raising funds to meet liquidity needs. Moreover, as we find in our sample, large banks are less exposed to payment liquidity risk because, given a large depositor base, they internalize more payment flows (i.e., the recipients of depositors' payments are likely to be their own depositors). Consistent with these observations, we find that the negative impact of payment risk on bank lending is stronger for smaller banks.

We examine the impact of payment liquidity risk on different types of bank lending. For core loans (real estate, commercial and industrial, and consumer loans), the impact is almost identical to that on total loans. Moreover, we find a significant impact of payment liquidity risk on both long- and short-term lending, with a larger impact for loans with longer maturities. The negative impact of payment liquidity risk on loans with maturities exceeding five years is more than double that on all loans. This is consistent with our mechanism that emphasizes liquidity mismatch. For long-term loans, banks cannot expect repayments and the associated liquidity inflows in the near future. Moreover, these loans, due to their long duration, can be more sensitive to information on both interest-rate dynamics and default risk. Such information sensitivity may compromise secondary-market liquidity. Therefore, when extending loans with longer maturities, banks face more acute liquidity mismatch between loans and deposits that carry payment liquidity risk.

Several market-wide factors amplify the impact of payment risk on bank lending. Banks' concerns over payment liquidity risk should be alleviated when the costs of obtaining short-term funding are low and heightened when the funding markets are strained. We use the LIBOR–OIS spread as a proxy for funding stress and find its interaction with payment risk has a strong negative impact on loan growth.[4] For a bank with a median level of payment-flow volatility, a 50-basis-point increase in the LIBOR–OIS spread significantly reduces loan growth by 0.6 percentage points, representing 10% of the standard deviation of loan growth rate. Moreover, since the tightness of interbank funding market depends on the overall availability of reserves (Bianchi and Bigio, 2022), we use variations of the Treasury General Account (TGA) balance to proxy for reserve-supply shocks (Correa, Du, and Liao, 2020; Copeland, Duffie, and Yang, 2021), and we find that negative shocks to reserve availability amplify the negative effect of payment risk on bank lending.

We also consider how a bank's overall risk sensitivity affects the impact of payment risk on lending. Following Bolton et al. (2020), we use a bank's distance to breaching capital regulations to proxy for its risk sensitivity. Being close to regulatory thresholds amplifies the impact of payment risk in a nonlinear fashion: banks with capital below the cross-sectional 5th percentile exhibit a lending sensitivity to payment risk that is nearly twice that of banks above the 5th percentile.[5] Therefore, undercapitalized banks struggle to jointly provide credit and payment services.

Finally, we explore a mechanism through which banks mitigate payment liquidity risk. When a bank raises deposit rates, its depositor base is likely to expand, allowing more payment flows to be internalized and thus reducing payment risk. We find that banks facing greater payment risk set higher deposit rates across all types of deposit products, such as certificates of deposit, money market accounts, and savings accounts. Our findings uncover a new determinant of deposit rates.

Literature. Liquidity mismatch is a classic theme in the banking literature.[6] One strand of the empirical literature characterizes the illiquidity of loans.[7] The other strand of literature focuses

[4]From a different perspective, these findings indicate that the pass-through of interbank funding stress to credit supply, for example, as documented by Iyer et al. (2013), is strengthened when banks face more payment risk.

[5]It has been shown that capital requirements can reduce bank lending (e.g., Fraisse, Lé, and Thesmar, 2020). Our findings shed light on the mechanism: Capital requirements make banks more sensitive to payment risk.

[6]At the core of banking theory is intermediation between illiquid assets with liquid liabilities such as deposits (e.g., Bryant, 1980; Diamond and Dybvig, 1983; Calomiris and Kahn, 1991; Donaldson, Piacentino, and Thakor, 2018).

[7]Loutskina (2011) develops a measure of loan liquidity. Drucker and Puri (2008) find that covenants affect loan resalability. Banks can obtain liquidity by exiting a syndicate (Irani and Meisenzahl, 2017). Loan commitment adds to

on the liquidity risk of deposits, with an emphasis on bank runs and other distress scenarios when depositors exercise the right to withdraw.[8] Our paper differs in its focus on payment liquidity risk, a form of funding stability risk that is inherent in the role of deposits as means of payment. Our first contribution is to measure such risk. Quantifying funding risk is challenging. The Basel III definition of net stable funding ratio relies on rather ad hoc weights to funding sources.[9] Based on payment-flow data, our measures of payment risk are specific to a bank and its depositor clientele.[10]

Our main contribution is to demonstrate a negative impact of payment risk on bank lending. Deposits are often viewed as stable funding sources (e.g., Berlin and Mester, 1999; Hanson, Shleifer, Stein, and Vishny, 2015; Drechsler, Savov, and Schnabl, 2017, 2021; Li, Loutskina, and Strahan, 2019) and critical for financing loans (e.g., Gilje, Loutskina, and Strahan, 2016; Bustos, Garber, and Ponticelli, 2020; Carletti, De Marco, Ioannidou, and Sette, 2021); yet the role of deposits as means of payment exposes banks to liquidity risk, dampening lending. Our findings contribute to the literature on funding risk and bank lending (e.g., Khwaja and Mian, 2008; Paravisini, 2008; Loutskina and Strahan, 2009; Ivashina and Scharfstein, 2010; Cornett, McNutt, Strahan, and Tehranian, 2011; Schnabl, 2012; Iyer, Peydró, da-Rocha-Lopes, and Schoar, 2013; Dagher and Kazimov, 2015; Ivashina, Scharfstein, and Stein, 2015; Adelino and Ferreira, 2016; Benmelech, Meisenzahl, and Ramcharan, 2016; Acharya, Afonso, and Kovner, 2017; Kundu, Park, and Vats, 2021).

Another contribution of our paper is to bridge the literature on payment systems and the macro-finance literature. We show that liquidity churn in the payment system affects the macroeconomy through its impact on banks' credit supply. Our work builds upon the extensive literature on pay-

liquidity stress (Greenwald et al., 2020; Acharya et al., 2021; Kapan and Minoiu, 2021; Chodorow-Reich et al., 2022).

[8] An empirical literature studies deposit outflows at distressed banks or during runs (e.g., Gorton, 1988; Saunders and Wilson, 1996; Calomiris and Mason, 1997; Iyer and Puri, 2012; Acharya and Mora, 2015; Iyer et al., 2016; Egan et al., 2017; Martin et al., 2018; Brown et al., 2020; Chen et al., 2020; Jiang et al., 2023; Cipriani et al., 2024). A related literature studies the disciplinary effects of withdrawal on bankers (e.g., Park and Peristiani, 1998; Billett et al., 1998; Martinez Peria and Schmukler, 2001; Goldberg and Hudgins, 2002; Bennett et al., 2015; Ben-David et al., 2017).

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

[10] Our measure of payment liquidity risk can be embedded in broader frameworks of measuring bank liquidity mismatch (e.g., Berger and Bouwman, 2009; Brunnermeier et al., 2013; Bai et al., 2018).

ment systems that emphasizes banks' liquidity stress from payment settlement (e.g., Poole, 1968; Hamilton, 1996; McAndrews and Potter, 2002; Bech and Garratt, 2003; Ashcraft and Duffie, 2007; Bech, 2008; Kahn and Roberds, 2009; Afonso and Shin, 2011; Afonso, Kovner, and Schoar, 2011; Ashcraft, McAndrews, and Skeie, 2011; Bech, Martin, and McAndrews, 2012; Ihrig, 2019; Yang, 2020; Denbee, Julliard, Li, and Yuan, 2021; Afonso, Duffie, Rigon, and Shin, 2022). While the payment literature focuses on banks' decisions at high frequencies, such as intraday or daily reserve management and banks' discretion over intraday settlement timing, our paper explores the impact of payment liquidity risk on the quarterly growth of banks' loan books.

Our findings echo the recent empirical studies on reserve scarcity. After the global financial crisis, banks' reserve holdings have increased through several channels (e.g., quantitative easing). Many hold the belief that banks are satiated with liquidity. To the contrary, evidence shows that reserves are not abundant, especially relative to liquidity risk associated with the rising level of deposits and tighter liquidity regulations (Correa, Du, and Liao, 2020; d'Avernas and Vandeweyer, 2021; Copeland, Duffie, and Yang, 2021; Afonso, Duffie, Rigon, and Shin, 2022; Yang, 2022; Acharya, Chauhan, Rajan, and Steffen, 2023; Lagos and Navarro, 2023; Lopez-Salido and Vissing-Jørgensen, 2023). Therefore, another contribution of our paper is to show that payment-driven reserve shocks affect bank lending. Moreover, we show that the stress in interbank reserve market and shocks to reserve supply amplify the dampening effect of payment risk on bank lending.[11]

Research on the synergy between bank lending and deposit-taking has a long tradition (e.g., Saidenberg and Strahan, 1999; Kashyap, Rajan, and Stein, 2002; Gatev and Strahan, 2006; Gatev, Schuermann, and Strahan, 2009; Acharya and Mora, 2015). Our findings point towards the tension between issuing monetary liabilities (deposits) and investing in illiquid loans. In recent years, non-

[11] Our results shed light on the connection between reserve supply and bank lending (Martin et al., 2016; Kandrac and Schlusche, 2021) and have implications on monetary policy transmission via adjusting reserves via open market operations or quantitative easing/tightening (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).

bank lenders have risen as fierce competitors against banks in loan markets.[12] In the payment area, competition from specialized payment service providers has intensified, enabled by rapidly changing technologies.[13] Even among banks, there is a trend towards specializing in credit provision or deposit-taking, partly driven by regulatory changes (Chen, Hanson, and Stein, 2017; Cortés, Demyanyk, Li, Loutskina, and Strahan, 2020; Gopal and Schnabl, 2022). Our paper contributes to the reassessment of traditional banking model that bundles credit and payment.

2 Hypotheses

In Section 2.1, we lay out the hypotheses and economic intuition. Section 2.2 presents a simple model that formalizes the hypotheses and motivates the measure of payment risk in Section 3.

2.1 Hypotheses

When depositors at different banks transact with one another, the payment sender's bank loses deposits on the liability side of its balance sheet and, to settle the transaction, transfers an equal amount of reserves to the payment recipient's banks, shrinking the asset side as well.[14] Losing liquidity is costly for banks. Reserves serve as precautionary savings and also help banks meet regulatory requirements on high-quality liquid assets (HQLA).[15] Interbank market may facilitate

[12] A growing literature studies non-bank lending (Irani and Meisenzahl, 2017; Buchak et al., 2018a,b; Tang, 2019; Vallée and Zeng, 2019; Davydiuk et al., 2020; de Roure et al., 2021; Chernenko et al., 2022). Earlier studies focus on non-bank lenders in syndicated loans (Jiang et al., 2010; Ivashina and Sun, 2011; Massoud et al., 2011; Nadauld and Weisbach, 2012; Lim et al., 2014). Berg et al. (2021) and Berg et al. (2022) review the recent developments.

[13] A literature studies new payment instruments (Duffie, 2019; Garratt and van Oordt, 2021; Brunnermeier and Payne, 2022; Chen and Jiang, 2022; Garratt et al., 2022; Kahn and van Oordt, 2022; Berg et al., 2023; Wang, 2023).

[14] Fedwire adopts real-time gross settlement (RTGS). RTGS and deferred net settlement (DNS) differ in the degrees of netting but, in both systems, banks ultimately settle payments with central bank reserves (Kahn and Roberds, 2015).

[15] A recent literature analyzes bank reserve management (e.g., Ihrig, 2019; Correa et al., 2020; d'Avernas and Vandeweyer, 2020). Reserves are the most liquid assets for banks. Bush et al. (2019) emphasize intraday liquidity benefits of reserves and point out that, in stress scenarios, even selling liquid assets such as Treasuries can be challenging.

risk sharing, as banks in a deficit may borrow from banks with a surplus (Bhattacharya and Gale, 1987). However, in reality, interbank reserve borrowing is costly, involving various frictions.[16]

Therefore, payment settlement can cause banks to lose liquidity. Payment liquidity risk is a unique form of funding risk for banks because deposits serve as means of payment among non-bank entities. We focus on the implications on bank lending. Loans are illiquid. When a bank faces liquidity shortage, loans cannot be readily sold or easily pledged as collateral for borrowing. Therefore, a bank that is more exposed to payment liquidity risk is expected to be more cautious in extending loans. Our primary goal in this paper is to test this hypothesis.

Hypothesis 1: *Payment liquidity risk has a negative impact on bank lending.*

If the interbank market is under stress, its risk-sharing role is compromised, and the negative impact of payment liquidity risk on bank lending is likely to be amplified. We measure the stress in the interbank market (Fed funds market) via the LIBOR-OIS spread. We also use variations in the Treasury General Account (TGA) as shocks to the reserve supply to banks (Correa, Du, and Liao, 2020; Copeland, Duffie, and Yang, 2021). As pointed out by Bianchi and Bigio (2022), reserve supply affects the functioning of interbank market. TGA variation has the advantage of being more exogenous to banks' lending decisions than interest-rate spreads. Moreover, undercapitalized banks tend to be more sensitive to risks, including payment risk. Following Bolton et al. (2020), we use a bank's distance to violating capital regulations as a proxy for risk sensitivity. We expect the negative impact of payment risk on bank lending to be stronger for undercapitalized banks.

Hypothesis 2: *The negative impact of payment risk on bank lending is stronger when there is stress in the interbank funding market and is stronger for undercapitalized banks.*

[16]A large literature has documented the costs and various frictions in interbank reserve markets (e.g., Furfine, 2000; Ashcraft and Bleakley, 2006; Cocco et al., 2009; Bech and Atalay, 2010; Wetherilt et al., 2010; Afonso et al., 2011; Angelini et al., 2011; Ashcraft et al., 2011; Iyer and Peydró, 2011; Acharya et al., 2012; Schnabl, 2012; Acharya and Merrouche, 2013; Kuo et al., 2013; Bianchi and Bigio, 2022; Gabrieli and Georg, 2014; Afonso and Lagos, 2015; Gofman, 2017; Blasques et al., 2018; Chapman et al., 2019; Craig and Ma, 2021).

A bank concerned with payment risk and reserve drain may raise deposit rates to attract deposits. Moreover, a higher deposit rate may grow the depositor base, so that when depositors make payments, the recipients are more likely to also hold an account at the same bank. By internalizing payment flows within its depositor base, a bank can mitigate the payment liquidity risk.

Hypothesis 3: *Banks with larger exposure to payment risk set higher deposit rates.*

2.2 Model

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.[17]

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

[17] 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.

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.[18] Specifically, depositor i's payment *outflow* is given by

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

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 $s'(r) > 0$.[19] We define $\widetilde{\Omega} \equiv \int_{i \in [0,\, 1]} \zeta(i) \widetilde{\omega}(i) di$, with zero mean and variance denoted by $\sigma^2 > 0$.[20] The bank faces a *net deposit outflow*,

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

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:

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

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

[18] In Figure 3, we show that deposits and gross payment volume closely comove over time.

[19] This specification of random payment-driven deposit flows and rate-sensitive flows follows Bolton et al. (2020).

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

impact on the overall interest expenses from the new and existing deposits.

The third and fourth terms in (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.[21] $L(\theta)$ 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 (3), represents an increasing and convex cost of borrowing cash in the interbank reserve market.[22] The convexity, as microfounded in Bigio and Sannikov (2019) and Parlour, Rajan, and Walden (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 (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, Kovner, and Schoar, 2011).[23] 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 (1) and (2), a higher Δy scales up p, resulting in more liquidity risk, through the second-order (last) term in (3), reducing

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

[22] Banks may borrow from the central bank, but in practice, they are discouraged from utilizing discount window and payment-system overdrafts (Copeland, Duffie, and Yang, 2021).

[23] Banks may borrow in other instruments but also face frictions (e.g., Pérignon, Thesmar, and Vuillemey, 2018).

the expected profits. The first-order condition for Δy implies an intuitive representation:

$$\Delta y = \frac{R-r}{\tau_2 \sigma^2} - d. \tag{4}$$

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.[24]

To demonstrate properties of the optimal deposit rate, we specify $s(r) = \lambda r$ where $\lambda > 0$. We impose two parameter conditions.[25] 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 (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., $\frac{d^2 \Delta y}{d(\sigma^2) d\tau_2} < 0$.

[24] 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.

[25] 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.

(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

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

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 (2), the net payment flow is

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

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

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

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.

Discussion: Payment flow predictability. Table C1 in the appendix 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.

3 Data and Variable Construction

We provide an overview of our data sources and sample construction, followed by a summary of the key statistics. We then explain the methodology for calculating our measures of payment risk.

3.1 Data sources and sample

We collect data from several sources. For interbank payment flows, we use Fedwire Funds confidential data on interbank transactions that span from 2000 to 2020. The Fedwire Funds Service is a real-time gross settlement (RTGS) system used by the Federal Reserve System to electronically settle U.S. dollar payments among banks; the system processes trillions of dollars daily. The Federal Reserve maintains accounts for both sender banks and receiver banks and settles individual transactions without netting.[26] The data include information such as the timestamp of each transaction, the identities of sender and receiver banks, payment amount, and transaction type. We focus on transactions instructed by customers (depositors), which are out of the banks' control and contribute to liquidity risk.[27] These customer-initiated transactions account for 88% of all transactions (in terms of number of transactions). If a bank performs customer-initiated payments of fewer than 10 business days in a quarter, we exclude that bank-quarter observation from our sample.

We merge Fedwire data with quarterly data from U.S. Call Report from 2000:Q1 to 2021:Q1 based on the Federal Reserve's internal identity system.[28] Call Report data include standard

[26]See Appendix B for detailed discussions on the Fedwire Funds System.

[27]We do not include bank-initiated transfer of funds or banks' purchases and sales of federal funds (reserves) as these are banks' voluntary spending of reserves rather than reserve loss due to depositors' payment outflow.

[28]As discussed in Section 3.2, 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.

balance-sheet items such as total assets, loan amounts (by type and maturity), deposit amounts, capital amounts, etc. Additionally, the data provide information on banks' income statements.

We acquire data on deposit rates and bank branch locations from RateWatch, which surveys deposit rates of new accounts for over 90,000 financial institution branches (including banks, thrifts, and credit unions) on a weekly basis.[29] The data contains deposit rates for various products, including CDs of different maturities at the $10K tier, money market accounts at different tiers (10K and 25K), and savings accounts at the $2.5K tier. We aggregate branch-level information to bank levels and merge the data with our Fedwire-Call Report merged data using the FDIC bank identifier.

Our final dataset includes 4,245 banks. Figure 2 shows that on average our sample covers 72% of banks in the Call Report universe for the period of 2000 to 2020 in terms of total assets. 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, while 10% comes from Tier-1 capital. 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. 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.

3.2 Payment liquidity risk

Payment and liquidity dynamics. When individuals or businesses make payments, banks debit their deposit accounts and transfer reserves to the payment recipients' banks. As the economy grows over time, payment volume grows accordingly, and the resultant interbank reserve churn intensifies. In Panel A of Figure 3, we plot the evolution of banks' quarterly transaction volume.

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

In any given quarter, we observe a cross section of banks and calculate the quarterly transaction volume for each bank. We show the median and interquartile range. From 2000 to 2020, payment volume has increased significantly alongside deposits (Panel B), and the growth of payment volume has outpaced that of deposits in the more recent years. By comparison, banks' holdings of liquid assets have grown at a slower pace. In Panel C, we plot the median liquidity holdings and the interquartile range for the cross section of banks.[30] At the beginning of 2000, the median was around $40 million dollars, and by the end of 2020, it had increased to $150 million. In contrast, the median payment volume has increased twenty-fold over the same period.

By granting depositors the flexibility to move money in and out of bank accounts, banks support the functioning of payment system but also expose themselves to liquidity risk. Banks hold liquid assets to buffer the uncertainty associated with payment-driven deposit flows (Afonso and Shin, 2011). The fact that payment volume has outgrown bank liquidity holdings suggests an increase over time in banks' exposure to liquidity risk in line with the observation in Acharya et al. (2023). In the recent decade, banks have held more reserves through several channels (e.g., quantitative easing) and increased their holdings of other liquid assets in compliance with the post-GFC regulations. Many hold the belief that banks are satiated with liquidity. To the contrary, evidence shows that liquidity shortages still happen in the banking system and affect different varieties of banking activities (Correa et al., 2020; Copeland et al., 2021; d'Avernas and Vandeweyer, 2021; Afonso et al., 2022; Bianchi and Bigio, 2022; Yang, 2022; Lagos and Navarro, 2023). Our focus is on the liquidity risk from depositors' payment activities and its impact on bank lending.

Measuring payment risk. For each bank in any given quarter, we use Fedwire data to construct a measure of payment risk based on our model in Section 2.2. The size of a bank's deposits determines the scale of payment activities while the direction of depositors' payment flows is

[30] 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.

uncertain.[31] Payment liquidity risk emerges from the imbalance between inflows and outflows and is measured by the volatility of net payment flow scaled by gross flow ($\widetilde{\Omega} = p/g$ in our model). For bank i in quarter t, we calculate the payment flow imbalance ratio for day d:

$$Flow\ imbalance\ ratio_{i,t,d} = \frac{Amount\ sent_{i,t,d} - Amount\ received_{i,t,d}}{Amount\ sent_{i,t,d} + Amount\ received_{i,t,d}}, \tag{8}$$

where $Amount\ sent_{i,t,d}$ is bank i's depositors' payment outflow and $Amount\ received_{i,t,d}$ is payment that bank i's depositors receive from depositors of other Fedwire member banks. By definition, $Flow\ imbalance\ ratio_{i,t,d}$ 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 (the two extreme forms of imbalance). Within quarter t for bank i, we define $Flow\ volatility_{i,t}$,

$$Flow\ volatility_{i,t} = S.D.(Flow\ imbalance\ ratio_{i,t,d}), \tag{9}$$

standard deviation of daily observations of $Flow\ imbalance\ ratio_{i,t,d}$ in quarter t. To have enough observations of $Flow\ imbalance\ ratio_{i,t,d}$ for calculating the standard deviation, we include banks that have payment sent or received on at least 10 business days in quarter t. In Appendix C.2, we consider alternative measures of payment risk and report results in Table C2 and C3.[32]

We also consider another indirect measure of payment risk, counterparty Herfindahl-Hirschman Index (counterparty HHI), which captures how concentrated a bank's payment counterparty banks are. Intuitively, when a bank's depositors conduct transactions with a very large set of counterparties, the idiosyncratic component of payment flow direction tends to be diversified away, resulting in less imbalance and a lower level of payment liquidity risk. While we do not observe depositors'

[31] Empirically, the gross payment flow is explained by seasonality with an R^2 of 92%, as shown in Table C1, and hence quite predictable while the net flow is not and thus contributes to the liquidity risk from depositors' payments.

[32] First, we consider scaling the daily net flow by average daily gross volume of the quarter (rather than daily gross volume in eq.(8)). Second, we construct measures of payment inflow risk and payment outflow risk separately.

payment counterparties that are depositors at other banks including businesses and households, we can observe the counterparties' banks. When a bank's depositors make payments to depositors at many different banks, it is reasonable to assume that the depositors have a diverse set of transaction counterparties. In contrast, when a bank has only a limited number of counterparty banks, its depositors are likely to transact with very few entities, so idiosyncratic shocks to the direction of payment flow may not wash out, resulting in significant liquidity risk for the bank.

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

$$Receiver\ HHI_{i,t,d} = \sum_{j \neq i} \left(\frac{Amount\ sent_{i,j,t,d}}{Amount\ sent_{i,t,d}} \right)^2, \tag{10}$$

where $Amount\ sent_{i,j,t,d}$ is defined as customer-instructed payment from bank i to bank 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 in a similar fashion:

$$Sender\ HHI_{i,t,d} = \sum_{j \neq i} \left(\frac{Amount\ received_{i,j,t,d}}{Amount\ received_{i,t,d}} \right)^2, \tag{11}$$

where $Amount\ received_{i,j,t,d}$ is defined as customer-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:

$$Counterparty\ HHI_{i,t} = (Receiver\ HHI_{i,t} + Sender\ HHI_{i,t})/2. \tag{12}$$

By definition, $Counterparty\ HHI_{i,t}$ is between zero and one.

In our empirical exercises, $Flow\ volatility_{i,t}$ is the primary measure of payment risk, and we estimate its effect on bank lending and deposit rate. We also present results based on the indirect measure, $Counterparty\ HHI_{i,t}$, to corroborate the mechanism. Both variables are constructed from Fedwire payment data and do not incorporate information on bank balance sheet or income statement, such as loan growth and deposit interest expenses, that may cause endogeneity concerns.

Figure 4 plots the frequency distributions of the two payment risk measures. These two measures bear substantial cross-sectional variation. Panel A of Table 1 shows that the interquartile range is 0.34 ($= 0.71-0.37$) for $Flow\ volatility$ and 0.44 ($= 0.75-0.31$) for $Counterparty\ HHI$. Banks differ in their exposure to payment liquidity risk. In Figure 5, we plot the average level of payment liquidity risks across different bank size groups (with size measured by total assets). A clear pattern emerges: Larger banks have smaller exposure to payment liquidity risks for both measures, $Flow\ volatility_{i,t}$ and $Counterparty\ HHI_{i,t}$. Intuitively, with a large depositor base, idiosyncratic shocks to depositors' payment flows tend to be diversified away. Panel B of Table 1 reports the correlations between payment risk measures and other bank characteristics.

4 Empirical Findings

We begin by examining the impact of payment liquidity risk on banks' lending decisions. We then show that such effects are strengthened by funding stress, shocks to reserve supply, and regulations on bank capital that amplify banks' risk sensitivity. Finally, we show that banks facing higher payment risks set higher deposit rates to attract deposits and stabilize their depositor base.

4.1 Payment risk and bank lending

The baseline results. In Panel A of Figure 6, we sort bank-quarter observations into ten bins based on the bank's *Flow volatility* from the previous quarter and, within each bin, calculate and plot the adjusted loan growth rate. To remove the time trend, exposure to macroeconomic cycles, and the mechanical effects of seasonality, we adjust the loan growth rate for a bank-quarter observation by subtracting the cross-sectional mean of that quarter. The figure reveals a robust negative relationship, in line with a negative impact of payment risk on bank lending in Hypothesis 1 in Section 2. In Panel B of Figure 6, we replace $Flow\ volatility$ with $Counterparty\ HHI$.

Next, we analyze how payment risk affects bank lending through the following regression where 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:

$$Loan\ growth_{i,t+1} = \alpha + \beta\, Flow\ volatility_{i,t} + \gamma\, Controls_{i,t} + \mu_{state} + \mu_{type} + \mu_t + \epsilon_{i,t+1}, \quad (13)$$

where the dependent variable, $Loan\ growth_{i,t+1}$ is defined as the loan growth rate of bank i over quarter $t+1$ and winsorized at the top and bottom 0.5% levels:

$$Loan\ growth_{i,t+1} = (Loan_{t+1} - Loan_t)/Loan_t. \quad (14)$$

We control for 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 on loan provision (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 fixed effects (μ_{state}, based on banks' headquarters), bank type fixed effects (μ_{type}), and time fixed effects (year-quarter, μ_t). Bank types include banks, credit unions, and savings & loan banks. Standard errors are clustered at the bank and quarter levels.

We report the regression results in Table 2. Column (1) shows that loan growth rate is negatively associated with payment-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 0.6 percentage points ($0.36 \times (-0.0174) = -0.6\%$). For comparison, the standard deviation of loan growth rate in our sample is 6 percentage points. To control for time-varying effects of bank type and location, in column (2) we include State×Quarter and Type×Quarter two-way fixed effects (thus absorbing μ_{state}, μ_{type}, and μ_t) and obtain similar results.

Next, we replace $Flow\ volatility_{i,t}$ with $Counterparty\ HHI_{i,t}$ in equation (13). With this indirect measure, we examine robustness of the relationship between payment risk and bank lending and also corroborate the underlying economic mechanism. A lower $Counterparty\ HHI_{i,t}$ indicates that bank i's depositors receive money from or send money to a more diversified set of banks and their depositors. Idiosyncratic shocks to payment flows tend to be smoothed out across these counterparty banks' clienteles. Therefore, bank i is less exposed to payment risk and willing to lend more. The results, presented in columns (3)–(4) of Table 2, confirm this conjecture. 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 $Flow\ volatility$. In particular, 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 ($0.43 \times (-0.0296) = -1.3\%$), which is equivalent to 21% of the standard deviation of loan growth rate.

Robustness for various time periods. Our baseline sample excludes the global financial crisis (GFC) from 2008:Q1 to 2009:Q2. As previously discussed, 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. Next, we show that our findings remain consistent across various time periods and economic cycles from 2000 to 2020.

Table 3's Columns (1)–(2) analyze the sample that excludes three recession phases as identified by NBER: the dot-com bubble burst (2001:Q2 to 2001:Q4), the GFC (2008:Q1 to 2009:Q2), and the COVID-19 pandemic (2020:Q1 to 2020:Q2). Conversely, the dataset for Columns (3)–(4) encompasses every quarter from 2000 to 2020, including the recession periods. The results from these two alternative samples align closely with those in Table 2, showing greater negative effects of payment risk on bank lending for the sample that encompasses recession periods.

Banks operate under distinct regulatory environments and liquidity requirements before and after the GFC. To demonstrate the consistency of our findings under these varied regulatory regimes, we conduct separate regressions for the periods before and after the crisis. Table 4 details this analysis: Columns (1)–(2) present the pre-crisis findings (data from 2000:Q1 to 2007:Q4), while Columns (3)–(4) outline the post-crisis findings (data from 2009:Q3 to 2020:Q4). Our analysis indicates that payment risks dampen bank lending during both the pre- and post-crisis periods, with a more pronounced negative impact observed in the pre-crisis sample.

Controlling for credit demand. An endogeneity concern is that the observed loan amount also depends on both loan supply (banks' decisions) and loan demand. $Flow\ volatility_{i,t}$ measures how volatile the payment-flow imbalance is, and $Counterparty\ HHI_{i,t}$ measures how concentrated transaction counterparties are. Both measures are purely extracted from Fedwire data. It is unclear how these measures of depositors' payments can be correlated with the demand for loans from bank i; nevertheless, to address the potential concern over endogeneity, we include the $State \times Quarter$ two-way fixed effects in Table 2 that control for economic conditions of the bank headquarter state, which may drive loan demand in that state.

Since 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, we exploit branch-level information from RateWatch and construct a subsample that contains only single-state banks. We investigate whether our findings remain robust for these single-state banks that constitute 87% of total bank-quarter observations. Across all specifications in Table 5, our results are very close to those in Table 2, both in terms of magnitude and statistical significance.

Results by bank size. In our baseline results in Table 2, we control for bank size. Next, we investigate the interaction between bank size and payment liquidity risk in affecting bank lending. Banks of different sizes behave differently, especially in how they manage liquidity risk exposure (Afonso, Kovner, and Schoar, 2011; Ashcraft, McAndrews, and Skeie, 2011). To investigate how payment risk impacts lending decisions across banks of different sizes, we categorize banks into three tiers based on their total assets each quarter. We then perform separate regression analyses for each of these size-based subsamples.

The regression results for these subsamples are presented in Table 6, where "bottom size tercile" represents the group of smallest banks and "top size tercile" represents the group of largest banks. For all three subsamples, the coefficients for $Flow\ volatility$ and $Counterparty\ HHI$ are negative and show high statistical significance, especially for the bottom and middle terciles. Additionally, we conduct the regression analysis again, excluding the four largest banks for each quarter, and find that these results are in line with our baseline findings. A key message is that smaller banks demonstrate the most pronounced negative impact of payment liquidity risk on lending. This aligns with the notion that larger banks typically have more options in managing their liquidity exposure and hence are less concerned with liquidity risk.

Results by loan types. To examine how payment risk impacts banks' decision to extend loans with different characteristics, we calculate loan growth rates for three distinct loan categories: core loans (including real estate loans, commercial and industrial loans, and consumer loans), loans with a maturity exceeding three years, and loans with a maturity beyond five years. We substitute the total loan growth rate with these specific category-specific growth rates as the dependent variables in our regression analysis. Table 7 reports the results. Columns (1)–(2) show that for core loans, the findings are similar to the baseline results seen in Table 2.

Columns (3)–(6) of Table 7 demonstrate that the estimated coefficients for payment risks remain negative and highly significant for loans of longer maturities. Interestingly, the magnitude increases by 30% to 50% for loans maturing beyond three years and more than doubles for those with maturity exceeding five years relative to our baseline results in Table 2. Moreover, the adjusted R^2 decreases notably in the analyses of long-term loans relative to that of the baseline analysis of all loans, suggesting that while the predictive power of payment risk remains strong, the power of explanatory variables collectively diminishes markedly (the explanatory power of other bank characteristics, i.e., the control variables, weakens for loans of longer maturities).

Our findings indicate that payment risk is particularly important for explaining banks' decisions on extending long-term loans. This is consistent with the timing in our model: At $t = 0$, the bank extends loans that mature at $t = 2$, so when it faces payment shocks at $t = 1$, it cannot rely on those loans to cover the liquidity loss as the loans have not been repaid and cannot be easily sold due to illiquidity. Loans of longer maturities tend to be less liquid as they are riskier and thus more information-sensitive (subject to stronger asymmetric information in the secondary market). Therefore, the mechanism in our model is expected to be more relevant for long-term loans.

4.2 The role of funding stress and regulatory constraints

Next, we test Hypothesis 2: The negative impact of payment risk on bank lending is stronger when there is stress in the interbank funding market and is stronger among undercapitalized banks.

Funding stress: LIBOR-OIS spread. When the depositors at one bank make payments to those at another bank, the payment senders' banks lose liquidity while the recipients' banks gain liquidity. Therefore, when the interbank funding market is well-functioning, banks in liquidity surplus can lend to those in deficit; banks mutually insure one another against payment liquidity risk (Bhattacharya and Gale, 1987). Funding market stress 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 model:

$$\begin{aligned} Loan\ growth_{i,t+1} =& \alpha + \beta_1\, \textbf{\textit{LIBOR-OIS spread}}_{t+1} \times Payment\ risk_{i,t} + \beta_2\, Payment\ risk_{i,t} \\ &+ \gamma\, Controls_{i,t} + \mu_{state,t} + \mu_{type,t} + \epsilon_{i,t+1}. \end{aligned} \tag{15}$$

$LIBOR\text{–}OIS\ spread_{t+1}$ represents the difference between the 1-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 (Taylor, 2009; Klingler and Syrstad, 2021). It spikes as funding conditions tighten. To better reflect the most extreme funding stress within a quarter, we utilize the 90th percentile of the daily LIBOR-OIS spreads observed within that quarter. In the regression, $Payment\ risk$ indicates either $Flow\ volatility$ or $Counterparty\ HHI$. Control variables are the same as in equation (13), with $\mu_{state,t}$ and $\mu_{type,t}$ representing State×Quarter and Type×Quarter fixed effects, respectively.[33]

We report the regression results (15) in Table 8. Column (1) shows that the interaction term between $Flow\ volatility$ and $LIBOR\text{–}OIS\ spread$ has a negative and significant coefficient, suggesting that the impact of $Flow\ volatility$ on bank lending is amplified when interbank funding cost is high. 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 0.6 percentage points ($-0.0224 \times 0.55 \times 0.5 = -0.00616$), which is 10% of standard deviation of the loan growth rate in our sample (0.06). In Column (2), we use $Counterparty\ HHI$

[33]Note that the variable $LIBOR\text{-}OIS\ spread$ is redundant with the inclusion of two-way fixed effects. Also, while not reported, our results are qualitatively similar in specifications with less strict fixed effects.

as a proxy for payment liquidity risk, and obtain similar results. We also use the 3-month LIBOR-OIS spread as an alternative measure to gauge funding stress and obtain similar results in Columns (3) and (4). In sum, funding stress amplifies the negative impact of payment risk on bank lending.

Funding stress: TGA variations. A concern over using interest rate spreads to proxy for funding stress is that such price variables are endogenously determined as banks may simultaneously decide on loan provision and participate in the funding markets. To address this concern, we consider a relatively more exogenous force that affects the liquidity availability in the banking sector. Following Correa, Du, and Liao (2020) and Copeland, Duffie, and Yang (2021), we use the variations of Treasury General Account (TGA) balance as shocks to reserve supply to banks. TGA is the account of the U.S. Treasury at the Federal Reserve, which serves as the primary operational account and is used to collect funds from the sales of Treasury debt and some tax receipts. An increase in TGA represents a decrease in available reserves within the banking system.[34] For example, when depositors pay taxes, banks lose reserves to TGA.[35]

In the regression specification given by equation (15), we replace $LIBOR\text{–}OIS\ spread$ with the TGA quarterly growth rate and estimate the regression

$$\begin{aligned} Loan\ growth_{i,t+1} =& \alpha + \beta_1\, TGA\ growth_{t+1} \times Payment\ risk_{i,t} + \beta_2\, Payment\ risk_{i,t} \\ &+ \gamma\, Controls_{i,t} + \mu_{state,t} + \mu_{type,t} + \epsilon_{i,t+1}, \end{aligned} \tag{16}$$

with other variables and fixed effects defined as in equation (15). Standard errors are clustered at the bank and quarter levels. We report the results in Table 9. Column (1) shows that the interaction term between $Flow\ volatility$ and $TGA\ growth$ has a negative and statistically significant coef-

[34] 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.

[35] The significant 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, Duffie, and Yang, 2021).

ficient. This suggests that the negative effect of $Flow\ volatility$ on bank lending is exacerbated when an increase in TGA drains reserves from the banking system. The economic magnitude is large. 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 decrease in loan growth by 0.7 percentage points ($-0.0113 \times 0.55 \times 1.2 = -0.7\%$). Column (2) reports the result using $Counterparty\ HHI$ as the payment risk measure. The results are consistent with those obtained with $Flow\ volatility$.

In addition to growth in the TGA (negative reserve-supply shock), the volatility of TGA can serve as an alternative measure of funding stress, as a more volatile TGA translates into a more volatile liquidity condition for the banking system. Each quarter, we calculate the standard deviation of weekly TGA levels (in trillion dollars) and use it as a proxy for the TGA volatility. We then replace $TGA\ growth$ with $TGA\ volatility$ in equation (16) and report the regression results in Columns (3)–(4) of Table 9. Column (3) shows that the interaction term between $Flow\ volatility$ and $TGA\ volatility$ has a negative and statistically significant coefficient. The economic magnitude is large. For example, for a bank with a median level of $Flow\ volatility$ (0.55), a one standard deviation increase in the TGA volatility (0.05) is associated with a decrease in loan growth by 0.3 percentage points ($-0.0983 \times 0.55 \times 0.05 = -0.3\%$). Column (4) provides further evidence of this relationship using $Counterparty\ HHI$ as a proxy of payment risk.

Risk sensitivity and regulatory capital. In our model, the optimal lending is akin to the optimal risky investment under a mean-variance preference, with τ_2, a proxy for funding stress playing a role similar to a risk aversion coefficient. A model that emphasizes a bank's overall risk sensitivity via a mean-variance objective function on earnings would deliver similar optimal lending, as risk in payment flows and costs of liquidity drain translate into risk in earnings. Next, we measure banks' risk sensitivity and test Hypothesis 2 with τ_2 taking the interpretation of risk sensitivity.

Bolton et al. (2020) show theoretically that a bank with less regulatory capital exhibits a high level of risk sensitivity. U.S. banks have long been subject to regulations on the ratio of Tier 1 capital to total consolidated assets, (the U.S. Tier 1 leverage ratio). Banks are required to maintain a minimum ratio of 4%, while those considered well-capitalized should meet a 5% minimum ratio.[36] As illustrated in Figure 7, there was an overall upward trend in the Tier 1 leverage ratio.

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 5th percentile in that quarter. The variable aims to identify banks that are undercapitalized relative to their peers rather than their own past levels of capitalization 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 for more risk-sensitive banks (with low regulatory capital), the negative impact of payment risk on bank lending is more pronounced by estimating the following model:

$$\begin{aligned} Loan\ growth_{i,t+1} = \alpha + \beta_1\, Low\ regulatory\ capital_{i,t} \times Payment\ risk_{i,t} + \beta_2\, Payment\ risk_{i,t} \\ + \beta_3\, Low\ regulatory\ capital_{i,t} + \gamma \times Controls_{i,t} + \mu_{state,t} + \mu_{type,t} + \epsilon_{i,t+1}. \end{aligned} \tag{17}$$

We report the regression results in Table 10. The interaction term between $Low\ regulatory\ capital$ and $Payment\ risk_{i,t}$ has a negative and statistically significant coefficient, indicating that payment risk has a greater negative impact on lending for banks with low regulatory capital. Specifically, Column (1) reveals that banks with capital below the 5th percentile exhibit a lending sensitivity to payment risk that is nearly twice as high compared to banks above the threshold.

We next introduce more granular dummy variables to explore the nonlinear effect of regulatory

[36] 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.

capital on lending sensitivity to payment risk.[37] Specifically, we create a dummy variable for banks whose Tier 1 leverage ratio is at or below the 1st percentile, 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 (17) and report results in Table 11. We observe that coefficient for the interaction between payment risk and the dummy for capital below the 1st percentile is not only more significant but also has more than three times the magnitude relative to the coefficient for interaction with the dummy for capital between the 1st and 5th percentiles. Moreover, the interaction between payment risk and the dummy for capital between the 5th and 10th percentiles is statistically insignificant. These results imply that as a bank's regulatory capital decreases, the negative impact of payment risk on bank lending strengthens.

4.3 Payment risk and deposit rates

We test Hypothesis 3 that banks mitigate their payment risk by raising deposit rates to attract deposit inflows and enlarge their depositor base. We start by plotting the deposit spread (relative to the Fed funds rate) averaged for each decile of banks sorted by payment risk in Figure 8. The results reveal a positive correlation between deposit rate and payment risk for both risk measures.

To formally test the hypothesis, we estimate the following regression model:

$$Deposit\ spread_{i,t+1} = \alpha + \beta \times Payment\ risk_{i,t} + \gamma \times Controls_{i,t} + \mu_{state,t} + \mu_{type,t} + \epsilon_{i,t+1}\,. \quad (18)$$

The dependent variable is defined as the spread of the deposit rate relative to the federal funds rate in quarter $t+1$ (in percent). $Payment\ risk$ indicates $Flow\ volatility$ or $Counterparty\ HHI$. Control variables are defined the same as in equation (13), with $\mu_{state,t}$ and $\mu_{type,t}$ representing, respectively, State$\times$Quarter and Type$\times$Quarter fixed effects.

[37] According to Bolton et al. (2020), under conditions of payment-flow volatility, a bank's risk aversion to lending increases convexly as it approaches the threshold of violating leverage requirements.

We report the results in Table 12. To illustrate the robustness of our results, we use deposit spreads for three different types of products: one-year CD (columns (1)–(2)), money market account (columns (3)–(4)), and saving account (columns (5)–(6)).[38] 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. Specifically, an interquartile-range increase in $Flow\ volatility$ is associated with an increase of 3 basis points in one-year CD spreads ($0.0875 \times 0.36 = 0.03$), as seen in column (1) of Table 12, while an interquartile-range increase in $Counterparty\ HHI$ is associated with an increase of 6 basis points in one-year CD spreads ($0.1287 \times 0.43 = 0.06$), as seen in column (2). Furthermore, similar results are obtained when utilizing deposit spreads of other products (columns (3)–(6)).

In sum, our results demonstrate that banks with greater payment risks set higher deposit rates across major deposit products, after controlling for various bank characteristics and fixed effects. This is consistent with the idea that banks with higher payment risks try to secure more stable funding by making their deposit rates more competitive. A higher deposit rate attracts deposit inflows that counterbalance outflows due to depositors' outgoing payments. A higher deposit rate also attracts new depositors. By enlarging the depositor base, a bank can internalize more payment flows, thus reducing payment liquidity risk: For a bank with a larger depositor base, the probability of depositors' payment recipients being also its own depositors increases. Overall, our findings suggest that banks manage their payment risks both on the asset side (through their lending decisions) and on the liability side of balance sheet (through the adjustments of deposit rates).

[38] RateWatch provides deposit rates for various products, including CDs of different maturities (3, 6, 12, 24, & 60 months) at the $10K tier, money market accounts at different tiers (2.5K, 10K and 25K), and savings at the $2.5K 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), as well as savings at the $2.5K tier.

5 Conclusion

Deposits circulate as means of payment and finance bank lending. The dual role of deposits generates liquidity mismatch: Depositors can move funds in and out of their accounts freely, which is key to seamless operation of the payment systems, while banks cannot easily sell loans to replenish liquidity when payment outflows drain reserves. Using granular payment data, we characterize a sizeable liquidity risk exposure that banks face due to depositors' payment activities. In contrast to existing studies on bank liquidity mismatch, our focus is not on distress scenarios such as bank runs or financial crises. Instead, we analyze the day-to-day operations of the payment system where the liquidity churn involves all banks and is relevant under all market conditions.

Payment risk is a form of funding stability risk that is unique to banks. Our analysis demonstrates the tension between the monetary and financing roles of deposits. Payment risk dampens bank lending, and the effect is stronger for undercapitalized banks and when funding stress is more pronounced. To manage payment risk, banks raise deposit rates to attract liquidity inflows.

Our findings highlight the challenges that banks face in combining credit provision and payment services. In the recent years, with the advent of technological innovations, specialized payment services providers and companies that focus on developing credit products have emerged and posed a challenge to the conventional banking model. To grasp the value propositions offered by the entrants that seek to unbundle and rebundle financial services, it is critical to identify the fault lines in the traditional financial system. Our paper takes an important step in this direction.

References

Acharya, V. and O. Merrouche (2013). Precautionary hoarding of liquidity and interbank markets: Evidence from the subprime crisis. *Review of Finance 17*(1), 107–160.

Acharya, V. V., G. Afonso, and A. Kovner (2017). How do global banks scramble for liquidity? evidence from the asset-backed commercial paper freeze of 2007. *Journal of Financial Intermediation 30*, 1–34.

Acharya, V. V., R. S. Chauhan, R. Rajan, and S. Steffen (2023). Liquidity dependence and the waxing and waning of central bank balance sheets. Working Paper 31050, National Bureau of Economic Research.

Acharya, V. V., I. Engle, Robert F, and S. Steffen (2021, March). Why did bank stocks crash during covid-19? Working Paper 28559, National Bureau of Economic Research.

Acharya, V. V., D. Gromb, and T. Yorulmazer (2012, April). Imperfect competition in the interbank market for liquidity as a rationale for central banking. *American Economic Journal: Macroeconomics 4*(2), 184–217.

Acharya, V. V. and N. Mora (2015). A crisis of banks as liquidity providers. *The Journal of Finance 70*(1), 1–43.

Adelino, M. and M. A. Ferreira (2016). Bank ratings and lending supply: Evidence from sovereign downgrades. *The Review of Financial Studies 29*(7), 1709–1746.

Afonso, G., D. Duffie, L. Rigon, and H. S. Shin (2022, December). How abundant are reserves? evidence from the wholesale payment system. Working Paper 30736, National Bureau of Economic Research.

Afonso, G., A. Kovner, and A. Schoar (2011). Stressed, not frozen: The federal funds market in the financial crisis. *The Journal of Finance 66*(4), 1109–1139.

Afonso, G. and R. Lagos (2015). Trade dynamics in the market for federal funds. *Econometrica 83*(1), 263–313.

Afonso, G. and H. S. Shin (2011). Precautionary demand and liquidity in payment systems. *Journal of Money, Credit and Banking 43*(s2), 589–619.

Angelini, P., A. Nobili, and C. Picillo (2011). The interbank market after august 2007: What has changed, and why? *Journal of Money, Credit and Banking 43*(5), 923–958.

Ashcraft, A. and C. H. Bleakley (2006). On the market discipline of informationally-opaque firms: Evidence from bank borrowers in the federal funds market. Staff Reports 257, Federal Reserve Bank of New York.

Ashcraft, A., J. McAndrews, and D. Skeie (2011). Precautionary reserves and the interbank market. *Journal of Money, Credit and Banking 43*(s2), 311–348.

Ashcraft, A. B. and D. Duffie (2007, May). Systemic illiquidity in the federal funds market. *American Economic Review 97*(2), 221–225.

Bai, J., A. Krishnamurthy, and C.-H. Weymuller (2018). Measuring liquidity mismatch in the banking sector. *The Journal of Finance 73*(1), 51–93.

Bech, M. (2008). Intraday liquidity management: A tale of games banks play. *Economic Policy Review 14*.

Bech, M. and E. Atalay (2010). The topology of the federal funds market. *Physica A: Statistical Mechanics and its Applications 389*(22), 5223–5246.

Bech, M., A. Martin, and J. McAndrews (2012). Settlement liquidity and monetary policy implementation–lessons from the financial crisis. *Economic Policy Review 18*(1).

Bech, M. L. and R. Garratt (2003). The intraday liquidity management game. *Journal of Economic Theory 109*(2), 198 – 219. Festschrift for Karl Shell.

Becker, B. and V. Ivashina (2014). Cyclicality of credit supply: Firm level evidence. *Journal of Monetary Economics 62*, 76–93.

Ben-David, I., A. Palvia, and C. Spatt (2017). Banks' internal capital markets and deposit rates. *Journal of Financial and Quantitative Analysis 52*(5), 1797–1826.

Benmelech, E., R. R. Meisenzahl, and R. Ramcharan (2016, 11). The Real Effects of Liquidity During the Financial Crisis: Evidence from Automobiles*. *The Quarterly Journal of Economics 132*(1), 317–365.

Bennett, R. L., V. Hwa, and M. L. Kwast (2015). Market discipline by bank creditors during the 2008–2010 crisis. *Journal of Financial Stability 20*(C), 51–69.

Berg, T., A. Fuster, and M. Puri (2022). Fintech lending. *Annual Review of Financial Economics 14*(1), 187–207.

Berg, T., J. Keil, F. Martini, and M. Puri (2023). Payment firms, cryptocurrencies, and CBDCs. Working paper, Duke University, Frankfurt School of Finance & Management, Goethe University, and Humboldt University of Berlin.

Berg, T., A. Saunders, and S. Steffen (2021). Trends in corporate borrowing. *Annual Review of Financial Economics 13*(1), 321–340.

Berger, A. N. and C. H. S. Bouwman (2009, 01). Bank Liquidity Creation. *The Review of Financial Studies 22*(9), 3779–3837.

Berlin, M. and L. J. Mester (1999). Deposits and Relationship Lending. *The Review of Financial Studies 12*(3), 579–607.

Bernanke, B. S. (1983). Nonmonetary effects of the financial crisis in the propagation of the great depression. *The American Economic Review 73*(3), 257–276.

Bernanke, B. S. and A. S. Blinder (1992). The Federal Funds Rate and the channels of monetary transmission. *The American Economic Review 82*(4), 901–921.

Bhattacharya, S. and D. Gale (1987). Preference shocks, liquidity, and central bank policy. In W. Barnett and K. Singleton (Eds.), *New approaches to monetary economics*. Cambridge, UK: Cambridge University Press.

Bianchi, J. and S. Bigio (2022). Banks, liquidity management, and monetary policy. *Econometrica 90*(1), 391–454.

Bigio, S. and Y. Sannikov (2019). A model of intermediation, money, interest, and prices. Working paper, Stanford and UCLA.

Billett, M. T., J. A. Garfinkel, and E. S. O'Neal (1998). The cost of market versus regulatory discipline in banking. *Journal of Financial Economics 48*(3), 333–358.

Blasques, F., F. Bräuning, and I. van Lelyveld (2018). A dynamic network model of the unsecured interbank lending market. *Journal of Economic Dynamics and Control 90*, 310–342.

Bolton, P., Y. Li, N. Wang, and J. Yang (2020). Dynamic banking and the value of deposits. Working Paper 28298, National Bureau of Economic Research.

Brown, M., B. Guin, and S. Morkoetter (2020). Deposit withdrawals from distressed banks: Client relationships matter. *Journal of Financial Stability 46*, 100707.

Brunnermeier, M., G. Gorton, and A. Krishnamurthy (2013, May). *Liquidity Mismatch Measurement*, pp. 99–112. University of Chicago Press.

Brunnermeier, M. and J. Payne (2022). Platforms, tokens, and interoperability. Working papers, Princeton University. Economics Department.

Bryant, J. (1980). A model of reserves, bank runs, and deposit insurance. *Journal of Banking & Finance 4*(4), 335–344.

Buchak, G., G. Matvos, T. Piskorski, and A. Seru (2018a). Beyond the balance sheet model of banking: Implications for bank regulation and monetary policy. Working Paper 25149, National Bureau of Economic Research.

Buchak, G., G. Matvos, T. Piskorski, and A. Seru (2018b). Fintech, regulatory arbitrage, and the rise of shadow banks. *Journal of Financial Economics 130*(3), 453–483.

Bush, R., A. Kirk, A. Martin, P. Weed, and P. Zobel (2019). Stressed outflows and the supply of central bank reserves. Liberty street economics, february 20, 2019, Federal Reserve Bank of New York.

Bustos, P., G. Garber, and J. Ponticelli (2020, 01). Capital Accumulation and Structural Transformation. *The Quarterly Journal of Economics 135*(2), 1037–1094.

Calomiris, C. W. and C. M. Kahn (1991). The role of demandable debt in structuring optimal banking arrangements. *The American Economic Review 81*(3), 497–513.

Calomiris, C. W. and J. R. Mason (1997). Contagion and bank failures during the great depression: The june 1932 chicago banking panic. *The American Economic Review 87*(5), 863–883.

Carletti, E., F. De Marco, V. Ioannidou, and E. Sette (2021). Banks as patient lenders: Evidence from a tax reform. *Journal of Financial Economics 141*(1), 6–26.

Chakraborty, I., I. Goldstein, and A. MacKinlay (2020). Monetary stimulus and bank lending. *Journal of Financial Economics 136*(1), 189–218.

Chapman, J., M. Gofman, and S. Jafri (2019). High-frequency analysis of financial stability. Working paper, Bank of Canada and University of Rochester.

Chen, B. S., S. G. Hanson, and J. C. Stein (2017). The decline of big-bank lending to small business: Dynamic impacts on local credit and labor markets. Working Paper 23843, National Bureau of Economic Research.

Chen, Q., I. Goldstein, Z. Huang, and R. Vashishtha (2020, September). Liquidity transformation and fragility in the us banking sector. Working Paper 27815, National Bureau of Economic Research.

Chen, Z. and Z. Jiang (2022). The liquidity premium of digital payment vehicle. Working paper, Peking University and Kellogg School of Management.

Chernenko, S., I. Erel, and R. Prilmeier (2022, 03). Why Do Firms Borrow Directly from Nonbanks? *The Review of Financial Studies 35*(11), 4902–4947.

Chodorow-Reich, G., O. Darmouni, S. Luck, and M. Plosser (2022). Bank liquidity provision across the firm size distribution. *Journal of Financial Economics 144*(3), 908–932.

Cipriani, M., T. M. Eisenbach, and A. Kovner (2024). Tracing bank runs in real time. Staff Reports 1104, Federal Reserve Bank of New York.

Cocco, J. F., F. J. Gomes, and N. C. Martins (2009). Lending relationships in the interbank market. *Journal of Financial Intermediation 18*(1), 24–48.

Copeland, A., D. Duffie, and Y. Yang (2021). Reserves were not so ample after all. Staff Reports 974, Federal Reserve Bank of New York.

Cornett, M. M., J. J. McNutt, P. E. Strahan, and H. Tehranian (2011). Liquidity risk management and credit supply in the financial crisis. *Journal of Financial Economics 101*(2), 297–312.

Correa, R., W. Du, and G. Y. Liao (2020). U.S. banks and global liquidity. Working Paper 27491, National Bureau of Economic Research.

Cortés, K. R., Y. Demyanyk, L. Li, E. Loutskina, and P. E. Strahan (2020). Stress tests and small business lending. *Journal of Financial Economics 136*(1), 260–279.

Craig, B. and Y. Ma (2021). Intermediation in the interbank lending market. *Journal of Financial Economics*.

Dagher, J. and K. Kazimov (2015). Banks' liability structure and mortgage lending during the financial crisis. *Journal of Financial Economics 116*(3), 565–582.

d'Avernas, A. and Q. Vandeweyer (2020). Intraday liquidity and money market dislocations. Working paper, Stockholm School of Economics and University of Chicago Booth School of Business.

d'Avernas, A. and Q. Vandeweyer (2021). Intraday liquidity and money market dislocations. Working paper, Stockholm School of Economics and University of Chicago Booth School of Business.

Davydiuk, T., T. Marchuk, and S. Rosen (2020). Direct lenders in the U.S. middle market. Working paper, BI Norwegian Business School, Carnegie Mellon University, and Temple University.

de Roure, C., L. Pelizzon, and A. Thakor (2021, 12). P2P Lenders versus Banks: Cream Skimming or Bottom Fishing? *The Review of Corporate Finance Studies 11*(2), 213–262.

Denbee, E., C. Julliard, Y. Li, and K. Yuan (2021). Network risk and key players: A structural analysis of interbank liquidity. *Journal of Financial Economics 141*(3), 831–859.

Diamond, D. W. and P. H. Dybvig (1983). Bank runs, deposit insurance, and liquidity. *Journal of Political Economy 91*(3), 401–419.

Donaldson, J. R., G. Piacentino, and A. Thakor (2018). Warehouse banking. *Journal of Financial Economics 129*(2), 250 – 267.

Drechsler, I., A. Savov, and P. Schnabl (2017). The deposits channel of monetary policy. *Quarterly Journal of Economics 132*(4), 1819–1876.

Drechsler, I., A. Savov, and P. Schnabl (2021). Banking on deposits: Maturity transformation without interest rate risk. *The Journal of Finance 76*(3), 1091–1143.

Drucker, S. and M. Puri (2008, 07). On Loan Sales, Loan Contracting, and Lending Relationships. *The Review of Financial Studies 22*(7), 2835–2872.

Duffie, D. (2019). Digital currencies and fast payment systems: Disruption is coming. Working paper, Stanford University.

Egan, M., A. Hortaçsu, and G. Matvos (2017, January). Deposit competition and financial fragility: Evidence from the us banking sector. *American Economic Review 107*(1), 169–216.

Fraisse, H., M. Lé, and D. Thesmar (2020). The real effects of bank capital requirements. *Management Science 66*(1), 5–23.

Friedman, M. and A. J. Schwartz (1963). *A Monetary History of the United States, 1867-1960*. Princeton, N.J.: Princeton University Press.

Furfine, C. H. (2000). Interbank payments and the daily federal funds rate. *Journal of Monetary Economics 46*(2), 535 – 553.

Gabrieli, S. and C.-P. Georg (2014). A network view on interbank market freezes. Discussion Papers 44/2014, Deutsche Bundesbank.

Garratt, R. J. and M. R. C. van Oordt (2021). Privacy as a public good: A case for electronic cash. *Journal of Political Economy 129*(7), 2157–2180.

Garratt, R. J., J. Yu, and H. Zhu (2022, October). The Case for Convenience: How CBDC Design Choices Impact Monetary Policy Pass-Through. BIS Working Papers 1046, Bank for International Settlements.

Gatev, E., T. Schuermann, and P. E. Strahan (2009). Managing bank liquidity risk: How deposit-loan synergies vary with market conditions. *Review of Financial Studies 22*(3), 995–1020.

Gatev, E. and P. E. Strahan (2006). Banks' advantage in hedging liquidity risk: Theory and evidence from the commercial paper market. *The Journal of Finance 61*(2), 867–892.

Gilje, E. P., E. Loutskina, and P. E. Strahan (2016). Exporting liquidity: Branch banking and financial integration. *The Journal of Finance 71*(3), 1159–1184.

Gofman, M. (2017). Efficiency and stability of a financial architecture with too-interconnected-to-fail institutions. *Journal of Financial Economics 124*(1), 113–146.

Goldberg, L. G. and S. C. Hudgins (2002, February). Depositor discipline and changing strategies for regulating thrift institutions. *Journal of Financial Economics 63*(2), 263–274.

Gopal, M. and P. Schnabl (2022, 06). The Rise of Finance Companies and FinTech Lenders in Small Business Lending. *The Review of Financial Studies 35*(11), 4859–4901.

Gorton, G. (1988). Banking panics and business cycles. *Oxford Economic Papers 40*(4), 751–781.

Greenwald, D. L., J. Krainer, and P. Paul (2020, July). The Credit Line Channel. Working Paper Series 2020-26, Federal Reserve Bank of San Francisco.

Hamilton, J. D. (1996). The daily market for federal funds. *Journal of Political Economy 104*(1), 26–56.

Hanson, S., A. Shleifer, J. C. Stein, and R. W. Vishny (2015). Banks as patient fixed-income investors. *Journal of Financial Economics 117*(3), 449–469.

Ihrig, J. (2019). Banks' demand for reserves in the face of liquidity regulations. On the economy blog, march 5, 2019, Federal Reserve Bank of St. Louis.

Irani, R. M. and R. R. Meisenzahl (2017, 03). Loan Sales and Bank Liquidity Management: Evidence from a U.S. Credit Register. *The Review of Financial Studies 30*(10), 3455–3501.

Ivashina, V. and D. Scharfstein (2010). Bank lending during the financial crisis of 2008. *Journal of Financial Economics 97*(3), 319–338. The 2007-8 financial crisis: Lessons from corporate finance.

Ivashina, V., D. S. Scharfstein, and J. C. Stein (2015). Dollar funding and the lending behavior of global banks. *The Quarterly Journal of Economics 130*(3), 1241–1282.

Ivashina, V. and Z. Sun (2011). Institutional demand pressure and the cost of corporate loans. *Journal of Financial Economics 99*(3), 500–522.

Iyer, R. and J.-L. Peydró (2011). Interbank Contagion at Work: Evidence from a Natural Experiment. *The Review of Financial Studies 24*(4), 1337–1377.

Iyer, R., J.-L. Peydró, S. da-Rocha-Lopes, and A. Schoar (2013, 10). Interbank Liquidity Crunch and the Firm Credit Crunch: Evidence from the 2007–2009 Crisis. *The Review of Financial Studies 27*(1), 347–372.

Iyer, R. and M. Puri (2012, June). Understanding bank runs: The importance of depositor-bank relationships and networks. *American Economic Review 102*(4), 1414–45.

Iyer, R., M. Puri, and N. Ryan (2016). A tale of two runs: Depositor responses to bank solvency risk. *The Journal of Finance 71*(6), 2687–2726.

Jiang, E. X., G. Matvos, T. Piskorski, and A. Seru (2023). Monetary tightening and u.s. bank fragility in 2023: Mark-to-market losses and uninsured depositor runs? Working paper, Columbia University, Northwestern University, Stanford University, and University of Southern California.

Jiang, W., K. Li, and P. Shao (2010, 08). When Shareholders Are Creditors: Effects of the Simultaneous Holding of Equity and Debt by Non-commercial Banking Institutions. *The Review of Financial Studies 23*(10), 3595–3637.

Jiménez, G., S. Ongena, J.-L. Peydró, and J. Saurina (2012, May). Credit supply and monetary policy: Identifying the bank balance-sheet channel with loan applications. *American Economic Review 102*(5), 2301–26.

Jiménez, G., S. Ongena, J.-L. Peydró, and J. Saurina (2014). Hazardous times for monetary policy: What do twenty-three million bank loans say about the effects of monetary policy on credit risk-taking? *Econometrica 82*(2), 463–505.

Kahn, C. M. and W. Roberds (2009). Why pay? an introduction to payments economics. *Journal of Financial Intermediation 18*(1), 1–23.

Kahn, C. M. and W. Roberds (2015, 06). Payment System Settlement and Bank Incentives. *The Review of Financial Studies 11*(4), 845–870.

Kahn, C. M. and M. R. van Oordt (2022, November). The Demand for Programmable Payments. Tinbergen Institute Discussion Papers 22-076/IV, Tinbergen Institute.

Kandrac, J. and B. Schlusche (2021). Quantitative easing and bank risk taking: Evidence from lending. *Journal of Money, Credit and Banking 53*(4), 635–676.

Kapan, T. and C. Minoiu (2021). Liquidity insurance vs. credit provision: Evidence from the covid-19 crisis. Working paper, Federal Reserve Bank of Atlanta and International Monetary Fund.

Kashyap, A. K., R. Rajan, and J. C. Stein (2002). Banks as liquidity providers: An explanation for the coexistence of lending and deposit-taking. *The Journal of Finance 57*(1), 33–73.

Kashyap, A. K. and J. C. Stein (2000, June). What do a million observations on banks say about the transmission of monetary policy? *American Economic Review 90*(3), 407–428.

Khwaja, A. I. and A. Mian (2008, September). Tracing the impact of bank liquidity shocks: Evidence from an emerging market. *American Economic Review 98*(4), 1413–42.

Kishan, R. P. and T. P. Opiela (2000). Bank size, bank capital, and the bank lending channel. *Journal of Money, Credit and Banking 32*(1), 121–141.

Klingler, S. and O. Syrstad (2021). Life after libor. *Journal of Financial Economics 141*(2), 783–801.

Kundu, S., S. Park, and N. Vats (2021). The geography of bank deposits and the origins of aggregate fluctuations. Working paper, UCLA, UNSW, and Washington University in Saint Louis.

Kuo, D., D. R. Skeie, J. I. Vickery, and T. Youle (2013). Identifying term interbank loans from fedwire payments data. Staff Reports 603, Federal Reserve Bank of New York.

Lagos, R. and G. Navarro (2023, June). Monetary policy operations: Theory, evidence, and tools for quantitative analysis. Working Paper 31370, National Bureau of Economic Research.

Li, L., E. Loutskina, and P. E. Strahan (2019, August). Deposit market power, funding stability and long-term credit. Working Paper 26163, National Bureau of Economic Research.

Lim, J., B. A. Minton, and M. S. Weisbach (2014). Syndicated loan spreads and the composition of the syndicate. *Journal of Financial Economics 111*(1), 45–69.

Lopez-Salido, D. and A. Vissing-Jørgensen (2023). Reserve demand, interest rate control, and quantitative tightening. Working paper, Board of Governors of the Federal Reserve System.

Loutskina, E. (2011). The role of securitization in bank liquidity and funding management. *Journal of Financial Economics 100*(3), 663–684.

Loutskina, E. and P. E. Strahan (2009). Securitization and the declining impact of bank finance on loan supply: Evidence from mortgage originations. *The Journal of Finance 64*(2), 861–889.

Luck, S. and T. Zimmermann (2020). Employment effects of unconventional monetary policy: Evidence from qe. *Journal of Financial Economics 135*(3), 678–703.

Martin, A., J. McAndrews, and D. Skeie (2016). Bank lending in times of large bank reserves. *International Journal of Central Banking 12*(4), 193–222.

Martin, C., M. Puri, and A. Ufier (2018, May). Deposit inflows and outflows in failing banks: The role of deposit insurance. Working Paper 24589, National Bureau of Economic Research.

Martinez Peria, M. and S. Schmukler (2001). Do depositors punish banks for bad behavior? market discipline, deposit insurance, and banking crises. *Journal of Finance 56*(3), 1029–1051.

Massoud, N., D. Nandy, A. Saunders, and K. Song (2011). Do hedge funds trade on private information? evidence from syndicated lending and short-selling. *Journal of Financial Economics 99*(3), 477–499.

McAndrews, J. and S. Potter (2002). Liquidity effects of the events of september 11, 2001. *Economic Policy Review 8*.

Nadauld, T. D. and M. S. Weisbach (2012). Did securitization affect the cost of corporate debt? *Journal of Financial Economics 105*(2), 332–352.

Paravisini, D. (2008). Local bank financial constraints and firm access to external finance. *The Journal of Finance 63*(5), 2161–2193.

Park, S. and S. Peristiani (1998). Market discipline by thrift depositors. *Journal of Money, Credit and Banking 30*(3), 347–64.

Parlour, C. A., U. Rajan, and J. Walden (2020). Payment system externalities and the role of central bank digital currency. *Journal of Finance forthcoming*.

Pérignon, C., D. Thesmar, and G. Vuillemey (2018). Wholesale funding dry-ups. *The Journal of Finance 73*(2), 575–617.

Peydró, J.-L., A. Polo, and E. Sette (2021). Monetary policy at work: Security and credit application registers evidence. *Journal of Financial Economics 140*(3), 789–814.

Poole, W. (1968). Commercial bank reserve management in a stochastic model: Implications for monetary policy. *The Journal of Finance 23*(5), 769–791.

Puri, M., J. Rocholl, and S. Steffen (2011). Global retail lending in the aftermath of the us financial crisis: Distinguishing between supply and demand effects. *Journal of Financial Economics 100*(3), 556–578.

Rodnyansky, A. and O. M. Darmouni (2017). The effects of quantitative easing on bank lending behavior. *The Review of Financial Studies 30*(11), 3858–3887.

Saidenberg, M. R. and P. E. Strahan (1999). Are banks still important for financing large businesses? *Current Issues in Economics and Finance 5*(Jul), 12.

Saunders, A. and B. Wilson (1996). Contagious bank runs: Evidence from the 1929-1933 period. *Journal of Financial Intermediation 5*(4), 409–423.

Schnabl, P. (2012). The international transmission of bank liquidity shocks: Evidence from an emerging market. *The Journal of Finance 67*(3), 897–932.

Tang, H. (2019, 04). Peer-to-Peer Lenders Versus Banks: Substitutes or Complements? *The Review of Financial Studies 32*(5), 1900–1938.

Taylor, J. (2009). The financial crisis and the policy responses: An empirical analysis of what went wrong. NBER Working Papers 14631, National Bureau of Economic Research, Inc.

Vallée, B. and Y. Zeng (2019). Marketplace Lending: A New Banking Paradigm? *The Review of Financial Studies 32*(5), 1939–1982.

Wang, L. (2023). Payment network competition. Working paper, Stanford University.

Wetherilt, A., P. Zimmerman, and K. Soramäki (2010). The sterling unsecured loan market during 2006-08: insights from network theory. Bank of England working papers 398, Bank of England.

Yang, Y. (2020). Funding rate spikes: How the fed's balance sheet impacts monetary policy transmission. Working paper, Stanford University.

Yang, Y. (2022). What quantity of reserves is sufficient? Working paper, Stanford University.

Figure 2: **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.

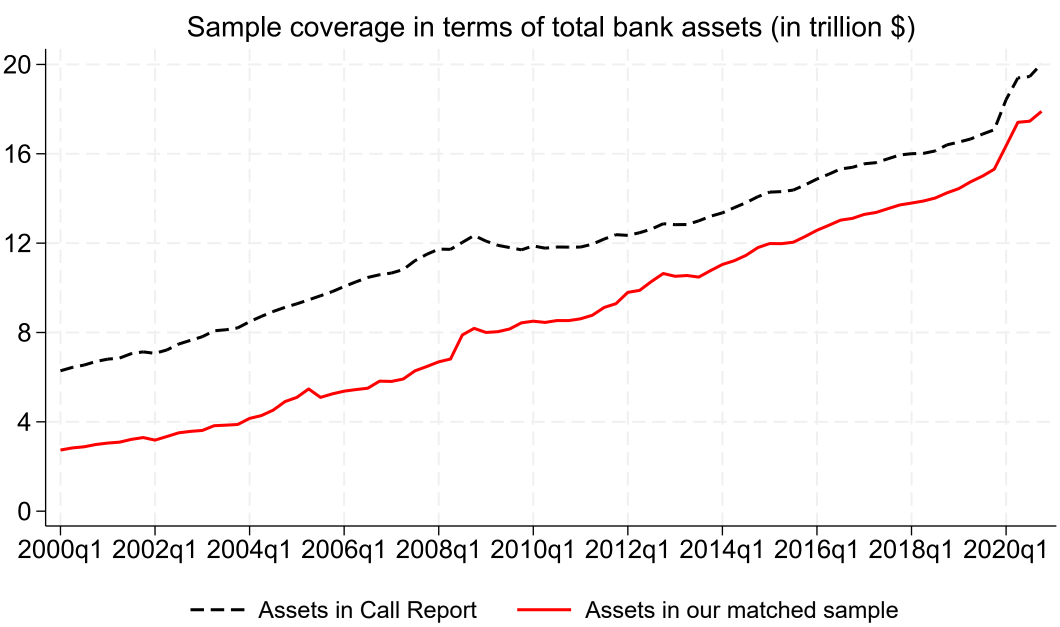


Figure 3: **The evolution of payment activities, deposits, and bank liquidity**

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 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.

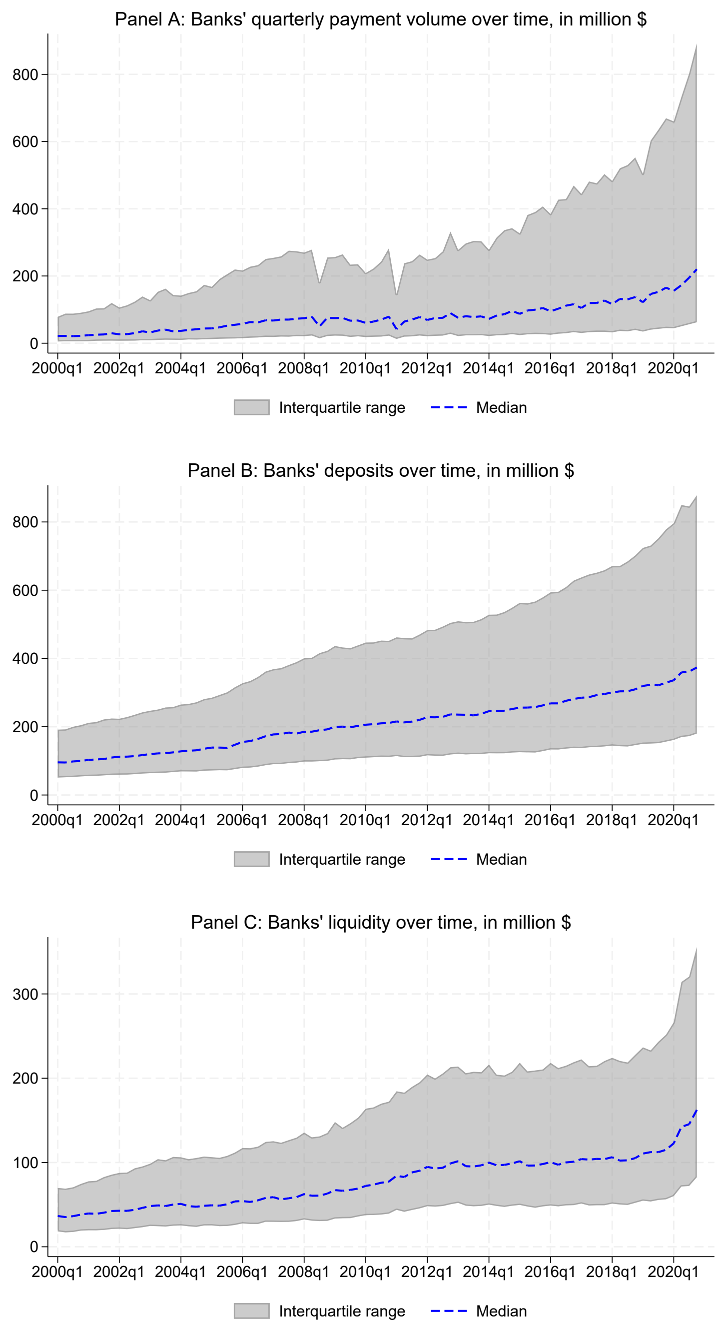


Figure 4: **The distributions of payment risk measures**

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 (9), and $Counterparty\ HHI$ is defined as in equation (12). 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.

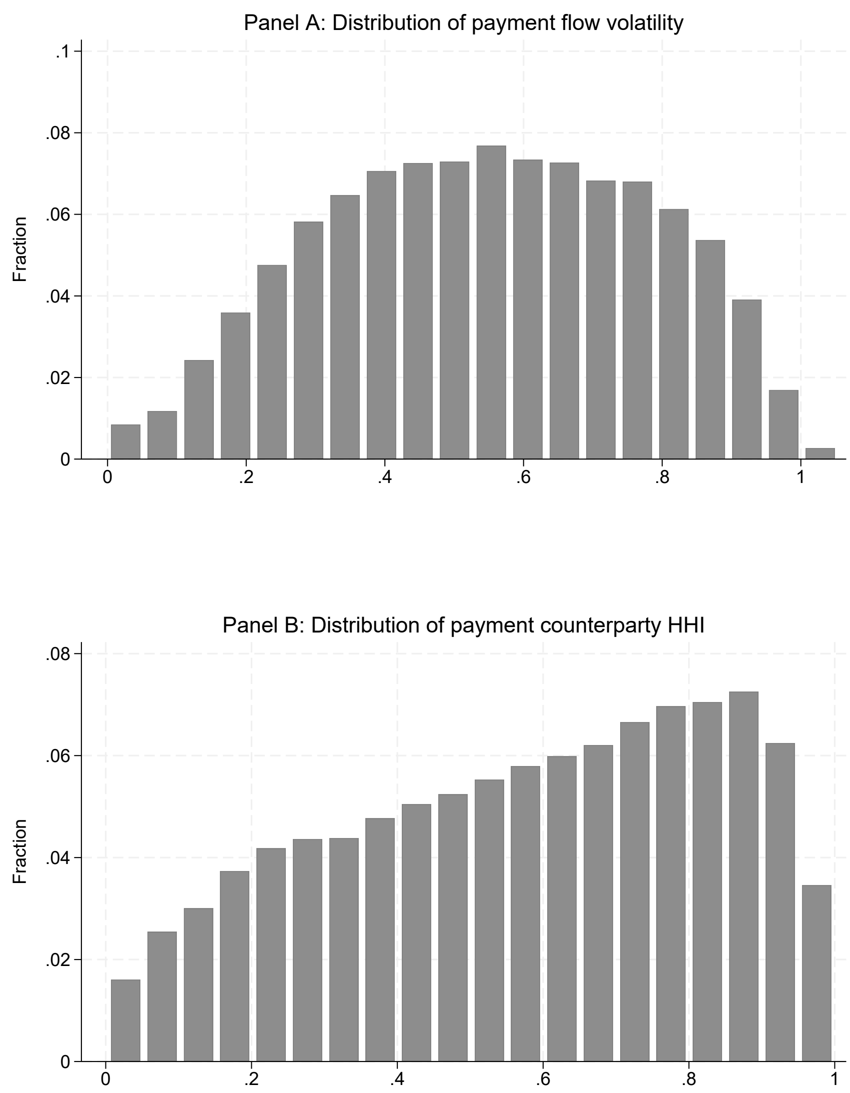
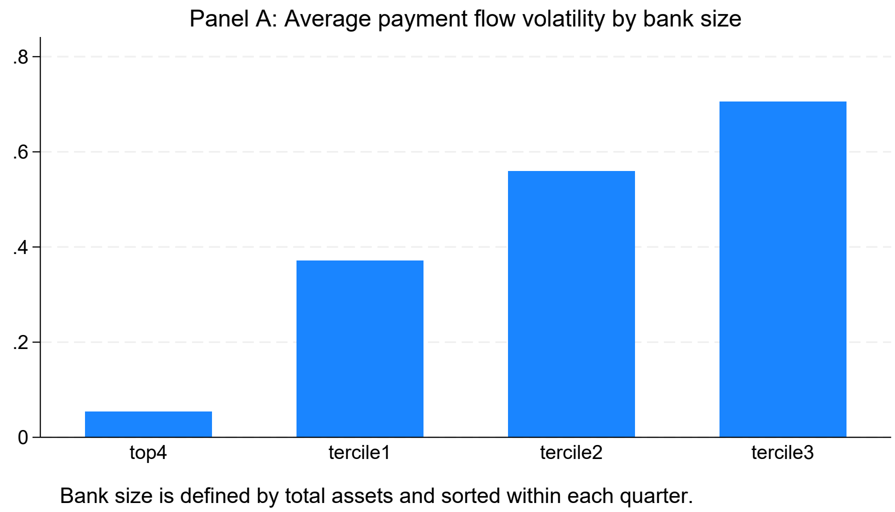


Figure 5: **Payment risk by bank size**

This figure displays the average level of payment risks across different bank size groups, categorized by total assets and sorted quarterly. In Panel A, payment risk is assessed using payment-flow volatility, while in Panel B, it is evaluated based on the counterparty HHI. The "Top4" group includes the four largest banks, "Tercile1" represents banks in the top third of the size distribution, "Tercile2" includes those in the middle third, and "Tercile3" comprises banks in the bottom third. 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.



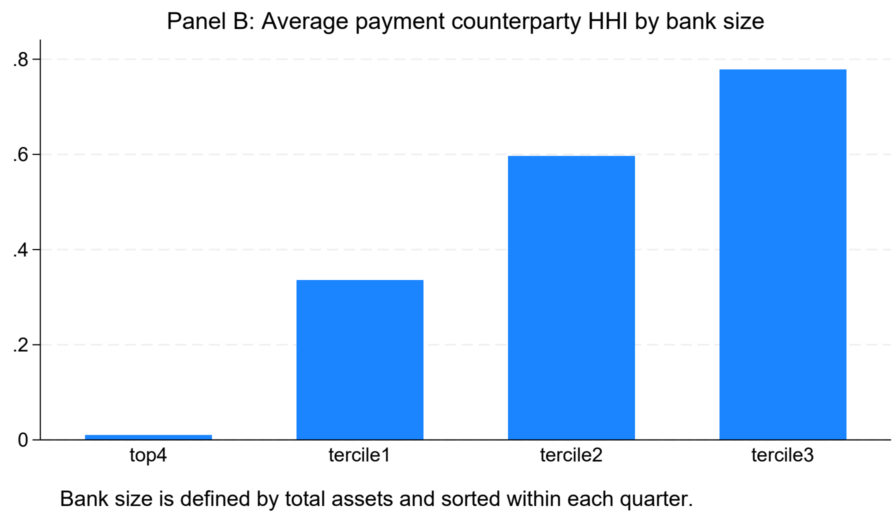
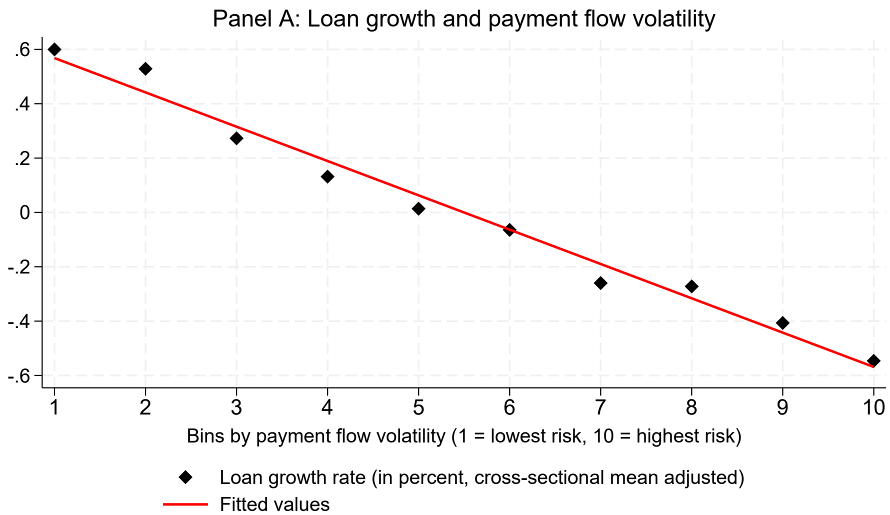


Figure 6: **Payment risk and loan growth**

This figure illustrates the relationship between banks' loan growth rates (in percent, adjusted for the cross-sectional mean) 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 calculate the average loan growth rate (with the cross-sectional mean subtracted) for each payment 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.



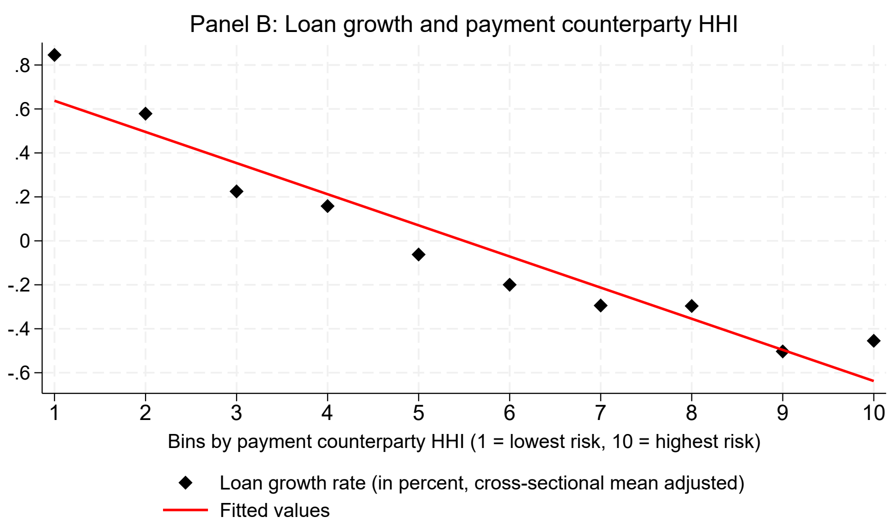


Figure 7: **The evolution of Tier 1 leverage ratios**

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.

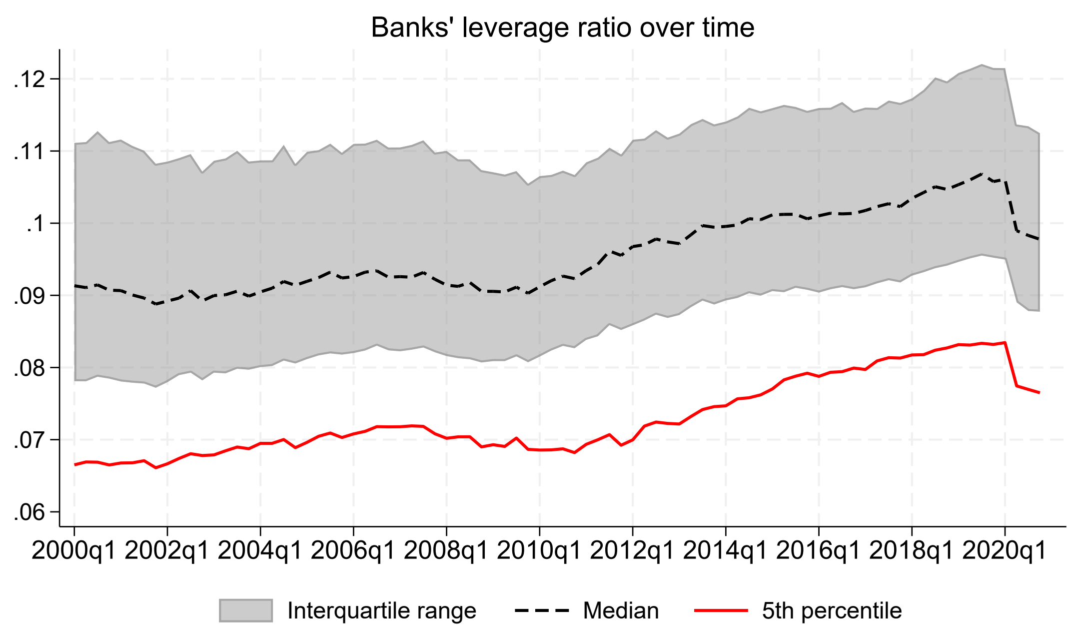


Figure 8: **Payment risk and deposit rate**

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.

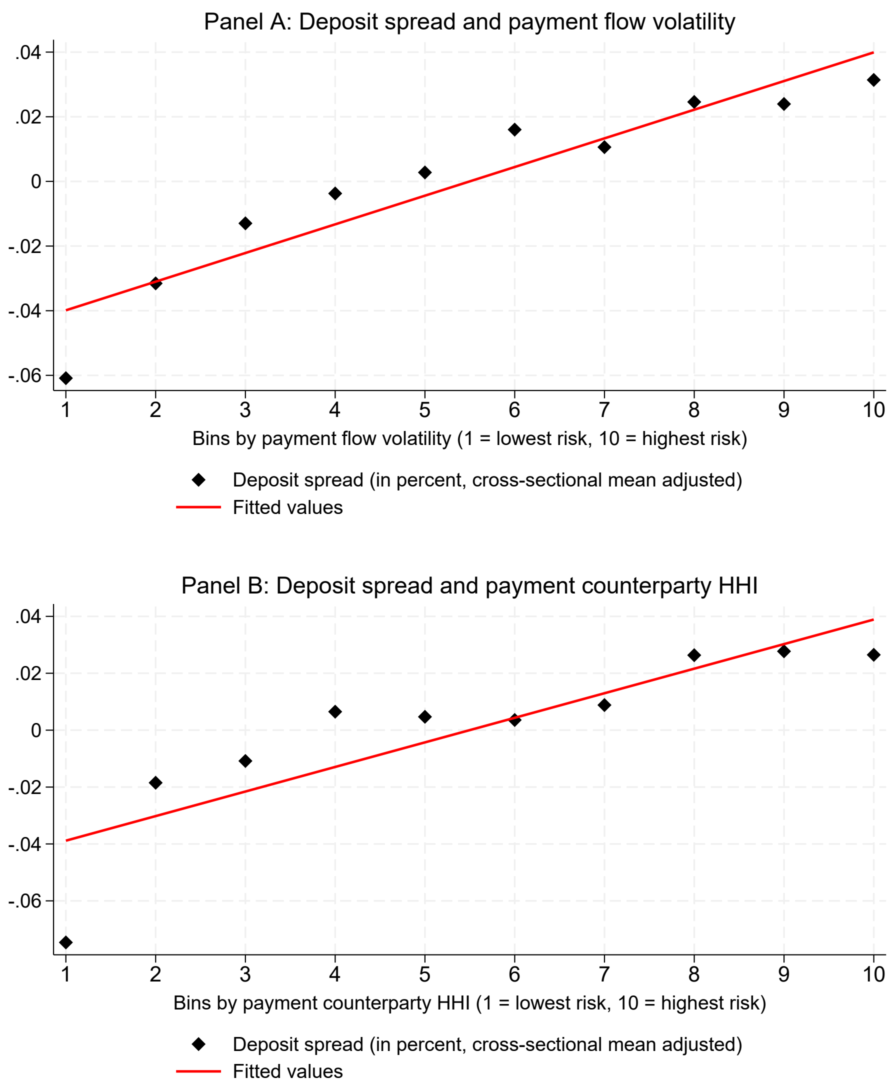


Table 1: **Summary statistics**

Panel A provides summary statistics for 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 $Asset$), $Deposit\ ratio$ (non-transaction 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. $Loan\ growth\ rate$ 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 net payment flows (scaled by gross payment volume)in a quarter, and $Counterparty\ HHI$ gauges the concentration levels of a bank's payment receivers and senders. Both measures are calculated from transaction-level Fedwire data. Panel B reports the correlation between banks' payment risk measures and other bank characteristics.

Panel A: Summary statistics for bank characteristics, deposit rates, and payment risk measures

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
loan growth rate	156588	0.02	0.06	-0.01	0.01	0.04
spread of 10K 1-year CD	155754	-0.06	0.74	-0.51	0.11	0.40
spread of 10K money market	150988	-0.91	1.29	-1.67	-0.30	0.01
spread of 2.5K saving	155082	-1.08	1.45	-1.87	-0.38	-0.03
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

Panel B: Correlations between payment risk measures and bank characteristics

	Flow volatility	**Counterparty HHI**
Asset	-0.14	-0.15
Liquidity ratio	0.18	0.21
Loan ratio	-0.17	-0.21
Trading ratio	-0.14	-0.15
Capital ratio	0.20	0.19
Deposit ratio	-0.19	-0.23
Return on asset	-0.08	-0.08
Number of states	-0.26	-0.28

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

The bank-quarter 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. $Flow\ volatility$ is the standard deviation of a bank's daily net payment flows scaled by gross payment volume, and $Counterparty\ HHI$ gauges the concentration levels of a bank's payment counterparties. Both measures are calculated from transaction-level Fedwire data in quarter t. Control variables are calculated from Call Report data as of quarter t. $Liquidity\ ratio$, $Loan\ ratio$, $Trading\ ratio$, $Capital\ ratio$, $Deposit\ ratio$, and $Return\ on\ asset$ are defined as in Table 1, 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 as a depository institution, 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	-0.0174***	-0.0173***		
	(-7.15)	(-7.07)		
Counterparty HHI			-0.0296***	-0.0292***
			(-7.08)	(-6.77)
Liquidity ratio	0.0109***	0.0106***	0.0111***	0.0106***
	(2.78)	(2.71)	(2.83)	(2.72)
Loan ratio	0.0162***	0.0177***	0.0138***	0.0152***
	(3.65)	(3.99)	(3.10)	(3.45)
Trading ratio	-0.3043	-0.2776	-0.2543	-0.2276
	(-1.01)	(-0.90)	(-0.86)	(-0.75)
Capital ratio	0.1542***	0.1567***	0.1573***	0.1600***
	(5.75)	(5.69)	(5.92)	(5.87)
Deposit ratio	-0.0024	-0.0013	-0.0017	-0.0006
	(-0.88)	(-0.50)	(-0.64)	(-0.22)
Return on asset	-0.7795**	-0.9031**	-0.7634**	-0.8896**
	(-2.06)	(-2.38)	(-2.03)	(-2.36)
log(Size)	0.0059	0.0057	-0.0025	-0.0028
	(1.48)	(1.47)	(-0.63)	(-0.72)
$(\log(\text{Size}))^2$	-0.0002	-0.0002	-0.0000	-0.0000
	(-1.57)	(-1.56)	(-0.15)	(-0.06)
Number of states	0.0013***	0.0014***	0.0014***	0.0014***
	(4.05)	(3.89)	(4.23)	(4.04)
State FE	Yes		Yes	
Type FE	Yes		Yes	
Quarter FE	Yes		Yes	
State $\times$ Quarter FE		Yes		Yes
Type $\times$ Quarter FE		Yes		Yes
Adjusted R^2	0.074	0.091	0.076	0.093
N of Obs.	156588	156498	156588	156498

Table 3: **Payment risk and bank lending: Robustness for various time periods**

The sample for Columns (1)–(2) 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 Columns (3)–(4) 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 net payment flows scaled by gross payment volume, and $Counterparty\ HHI$ gauges the concentration levels of a bank's payment counterparties. Both measures are calculated from transaction-level Fedwire data in quarter t. Control variables are calculated as of quarter t and include $Liquidity\ ratio$, $Loan\ ratio$, $Trading\ ratio$, $Capital\ ratio$, $Deposit\ ratio$, $Return\ on\ asset$, $\log(Size)$, 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$_{t+1}$				
	Excluding recessions (defined in description)		**Entire sample (2000:Q1 to 2020:Q4)**	
	(1)	(2)	(3)	(4)
Flow volatility	-0.0153***		-0.0176***	
	(-8.06)		(-7.49)	
Counterparty HHI		-0.0254***		-0.0287***
		(-8.11)		(-6.96)
Bank controls	Yes	Yes	Yes	Yes
State $\times$ Quarter FE	Yes	Yes	Yes	Yes
Type $\times$ Quarter FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.065	0.066	0.088	0.090
N of Obs.	146427	146427	167070	167070

Table 4: **Payment risk and bank lending: Comparing pre-crisis vs. post-crisis**

The sample for Columns (1)–(2) spans from 2000:Q1 to 2007:Q4. The sample for Columns (3)–(4) spans from 2009:Q3 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 net payment flows scaled by gross payment volume, and $Counterparty\ HHI$ gauges the concentration levels of a bank's payment counterparties. Both measures are calculated from transaction-level Fedwire data in quarter t. Control variables are calculated as of quarter t and include $Liquidity\ ratio$, $Loan\ ratio$, $Trading\ ratio$, $Capital\ ratio$, $Deposit\ ratio$, $Return\ on\ asset$, $\log(Size)$, 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-crisis (2000:Q1 to 2007:Q4)		**Post-crisis (2009:Q3 to 2020:Q4)**	
	(1)	(2)	(3)	(4)
Flow volatility	-0.0174***		-0.0154***	
	(-6.57)		(-4.11)	
Counterparty HHI		-0.0287***		-0.0267***
		(-6.37)		(-4.49)
Bank controls	Yes	Yes	Yes	Yes
State × Quarter FE	Yes	Yes	Yes	Yes
Type × Quarter FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.076	0.077	0.108	0.110
N of Obs.	58708	58708	97790	97790

Table 5: **Payment risk and loan growth: Controlling for loan demand**

The bank-quarter sample 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 net payment flows scaled by gross payment volume, and $Counterparty\ HHI$ gauges the concentration levels of a bank's payment counterparties. Both measures are calculated from transaction-level Fedwire data in quarter t. Control variables are calculated as of quarter t and include $Liquidity\ ratio$, $Loan\ ratio$, $Trading\ ratio$, $Capital\ ratio$, $Deposit\ ratio$, $Return\ on\ asset$, $\log(Size)$, 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)
Flow volatility	-0.0165***	
	(-6.84)	
Counterparty HHI		-0.0275***
		(-6.18)
Bank controls	Yes	Yes
State × Quarter FE	Yes	Yes
Type × Quarter FE	Yes	Yes
Adjusted R^2	0.102	0.104
N of Obs.	135632	135632

Table 6: **Payment risk and loan growth: Results by bank size**

The bank-quarter sample spans from 2000:Q1 to 2020:Q4, excluding the financial crisis from 2008:Q1 to 2009:Q2. Columns (1)–(6) use the subsamples sorted in each quarter based on bank size (total assets), and Columns (7)–(8) use the sample excluding the largest four banks in each quarter. 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 net payment flows scaled by gross payment volume, and $Counterparty\ HHI$ gauges the concentration levels of a bank's payment counterparties. Both measures are calculated from transaction-level Fedwire data in quarter t. Control variables are calculated as of quarter t and include $Liquidity\ ratio$, $Loan\ ratio$, $Trading\ ratio$, $Capital\ ratio$, $Deposit\ ratio$, $Return\ on\ asset$, $\log(Size)$, 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$_{t+1}$							
	Bottom size tercile		**Middle size tercile**		**Top size tercile**		**Excluding top 4 banks**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Flow volatility	-0.0156***		-0.0140***		-0.0047		-0.0173***	
	(-5.08)		(-5.26)		(-1.36)		(-7.07)	
Counterparty HHI		-0.0332***		-0.0241***		-0.0126***		-0.0293***
		(-4.55)		(-5.44)		(-3.03)		(-6.80)
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
Adjusted R^2	0.134	0.135	0.098	0.100	0.071	0.072	0.092	0.093
N of Obs.	51908	51908	51873	51873	51950	51950	156186	156186

Table 7: **Payment risk and loan growth: Results by loan type**

The bank-quarter 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, with Columns (1)–(2) based on core loans (real estate, commercial and industrial, and consumer loans), Columns (3)–(4) on loans with maturity over three years, and Columns (5)–(6) on loans with maturity over five years. $Flow\ volatility$ is the standard deviation of a bank's daily net payment flows scaled by gross payment volume, and $Counterparty\ HHI$ gauges the concentration levels of a bank's payment counterparties. Both measures are calculated from transaction-level Fedwire data in quarter t. Control variables are calculated as of quarter t and include $Liquidity\ ratio$, $Loan\ ratio$, $Trading\ ratio$, $Capital\ ratio$, $Deposit\ ratio$, $Return\ on\ asset$, $\log(Size)$, 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$_{t+1}$					
	Core loan		**Over-3-year loan**		**Over-5-year loan**	
	(1)	(2)	(3)	(4)	(5)	(6)
Flow volatility	-0.0177***		-0.0227***		-0.0372***	
	(-7.02)		(-7.79)		(-4.51)	
Counterparty HHI		-0.0291***		-0.0432***		-0.0702***
		(-6.56)		(-9.45)		(-7.61)
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes
State × Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Type × Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.075	0.076	0.037	0.038	0.010	0.011
N of Obs.	156498	156498	154760	154760	154351	154351

Table 8: **Funding stress and the impact of payment risk on bank lending**

The bank-quarter 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. $LIBOR-OIS\ spread$ is the spread between the 1(3)-month London Interbank Offered Rate (LIBOR) and the overnight index swap (OIS) of the same maturity (in percent) and calculated at the 90th percentile level from daily observations in quarter $t+1$. $Flow\ volatility$ is the standard deviation of a bank's daily net payment flows scaled by gross payment volume, and $Counterparty\ HHI$ gauges the concentration levels of a bank's payment counterparties. Both measures are calculated from transaction-level Fedwire data in quarter t. Control variables are calculated as of quarter t and include $Liquidity\ ratio$, $Loan\ ratio$, $Trading\ ratio$, $Capital\ ratio$, $Deposit\ ratio$, $Return\ on\ asset$, $\log(Size)$, 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)
Flow volatility × 1-month LIBOR-OIS spread	-0.0224*			
	(-1.70)			
Counterparty HHI × 1-month LIBOR-OIS spread		-0.0250*		
		(-1.88)		
Flow volatility × 3-month LIBOR-OIS spread			-0.0218***	
			(-2.72)	
Counterparty HHI × 3-month LIBOR-OIS spread				-0.0230***
				(-2.91)
Flow volatility	-0.0139***		-0.0118***	
	(-6.24)		(-5.09)	
Counterparty HHI		-0.0255***		-0.0229***
		(-7.29)		(-6.46)
Bank controls	Yes	Yes	Yes	Yes
State × Quarter FE	Yes	Yes	Yes	Yes
Type × Quarter FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.091	0.093	0.091	0.093
N of Obs.	156498	156498	156498	156498

Table 9: **Reserve supply shocks and the impact of payment risk on bank lending**

The bank-quarter 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. $TGA\ growth$ is the quarterly growth rate of Treasury General Account (TGA) based on average levels of the TGA within a quarter (in decimal), and $TGA\ volatility$ is the standard deviation of weekly TGA levels (in trillion dollars) within a quarter, both calculated as of quarter $t+1$. $Flow\ volatility$ is the standard deviation of a bank's daily net payment flows scaled by gross payment volume, and $Counterparty\ HHI$ gauges the concentration levels of a bank's payment counterparties. Both measures are calculated from transaction-level Fedwire data in quarter t. Control variables are calculated as of quarter t and include $Liquidity\ ratio$, $Loan\ ratio$, $Trading\ ratio$, $Capital\ ratio$, $Deposit\ ratio$, $Return\ on\ asset$, $\log(Size)$, 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)
Flow volatility × TGA Growth	-0.0113**			
	(-2.20)			
Counterparty HHI × TGA Growth		-0.0126**		
		(-2.54)		
Flow volatility × TGA Volatility			-0.0983***	
			(-2.82)	
Counterparty HHI × TGA Volatility				-0.0955**
				(-2.56)
Flow volatility	-0.0164***		-0.0145***	
	(-7.48)		(-6.79)	
HHI		-0.0278***		-0.0255***
		(-7.28)		(-6.94)
Bank controls	Yes	Yes	Yes	Yes
State × Quarter FE	Yes	Yes	Yes	Yes
Type × Quarter FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.091	0.093	0.091	0.093
N of Obs.	156498	156498	156498	156498

Table 10: **Bank capital and the impact of payment risk on bank lending**

The bank-quarter 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. $Low\ regulatory\ capital$ 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 net payment flows scaled by gross payment volume, and $Counterparty\ HHI$ gauges the concentration levels of a bank's payment counterparties. Both measures are calculated from transaction-level Fedwire data in quarter t. Control variables are calculated as of quarter t and include $Liquidity\ ratio$, $Loan\ ratio$, $Trading\ ratio$, $Capital\ ratio$, $Deposit\ ratio$, $Return\ on\ asset$, $\log(Size)$, 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	-0.0158***	
	(-3.48)	
HHI × Low regulatory capital		-0.0138***
		(-3.59)
Flow volatility	-0.0167***	
	(-6.79)	
Counterparty HHI		-0.0287***
		(-6.69)
Low regulatory capital	0.0045	0.0033
	(1.54)	(1.26)
Bank controls	Yes	Yes
State × Quarter FE	Yes	Yes
Type × Quarter FE	Yes	Yes
Adjusted R^2	0.091	0.093
N of Obs.	156498	156498

Table 11: **Payment risk and bank lending: The nonlinear effects of bank capital**

The bank-quarter 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. $\mathbf{1}$(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. $Flow\ volatility$ is the standard deviation of a bank's daily net payment flows scaled by gross payment volume, and $Counterparty\ HHI$ gauges the concentration levels of a bank's payment counterparties. Both measures are calculated from transaction-level Fedwire data in quarter t. Control variables are calculated as of quarter t and include $Liquidity\ ratio$, $Loan\ ratio$, $Trading\ ratio$, $Capital\ ratio$, $Deposit\ ratio$, $Return\ on\ asset$, $\log(Size)$, 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)	-0.0322***	
	(-3.07)	
Flow volatility $\times\mathbf{1}$(1pctl $<$ Regulatory capital $\leq$ 5pctl)	-0.0100**	
	(-2.28)	
Flow volatility $\times\mathbf{1}$(5pctl $<$ Regulatory capital $\leq$ 10pctl)	0.0063*	
	(1.82)	
Counterparty HHI $\times\mathbf{1}$(Regulatory capital $\leq$ 1pctl)		-0.0313***
		(-3.26)
Counterparty HHI $\times\mathbf{1}$(1pctl $<$ Regulatory capital $\leq$ 5pctl)		-0.0083**
		(-2.18)
Counterparty HHI $\times\mathbf{1}$(5pctl $<$ Regulatory capital $\leq$ 10pctl)		0.0039
		(1.30)
Flow volatility	-0.0171***	
	(-6.83)	
Counterparty HHI		-0.0290***
		(-6.70)
$\mathbf{1}$(Regulatory capital $\leq$ 1pctl)	0.0034	0.0034
	(0.52)	(0.51)
$\mathbf{1}$(1pctl $<$ Regulatory capital $\leq$ 5pctl)	0.0040	0.0030
	(1.38)	(1.11)
$\mathbf{1}$(5pctl $<$ Regulatory capital $\leq$ 10pctl)	-0.0002	0.0010
	(-0.07)	(0.52)
Bank controls	Yes	Yes
State $\times$ Quarter FE	Yes	Yes
Type $\times$ Quarter FE	Yes	Yes
Adjusted R^2	0.091	0.093
N of Obs.	156498	156498

Table 12: **Payment risk and deposit rate**

The bank-quarter sample 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)–(2) using one-year 10K CD rates, columns (3)–(4) using 10K money market rates, and columns (5)–(6) using 2.5K saving rates. $Flow\ volatility$ is the standard deviation of a bank's daily net payment flows scaled by gross payment volume, and $Counterparty\ HHI$ gauges the concentration levels of a bank's payment counterparties. Both measures are calculated from transaction-level Fedwire data in quarter t. Control variables are calculated as of quarter t and include $Liquidity\ ratio$, $Loan\ ratio$, $Trading\ ratio$, $Capital\ ratio$, $Deposit\ ratio$, $Return\ on\ asset$, $\log(Size)$, 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)**		**Saving (2.5K)**	
	(1)	(2)	(3)	(4)	(5)	(6)
Flow volatility	0.0875***		0.0766***		0.1068***	
	(4.47)		(3.80)		(5.90)	
Counterparty HHI		0.1287***		0.1096***		0.1643***
		(4.77)		(3.84)		(6.29)
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes
State $\times$ Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Type $\times$ Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.807	0.807	0.930	0.930	0.969	0.969
N of Obs.	155665	155665	150882	150882	154983	154983

Internet Appendix

Appendix A Proof of Proposition 1

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

$$(R-r)\Delta y - rd - \tau_1\mu\left(d+\Delta y\right) + \tau_1\left(m + L(\theta)\right) + \tau_1 s(r)$$
$$-\frac{\tau_2}{2}\sigma^2\left(d+\Delta y\right)^2 - \frac{\tau_2}{2}\left(\mu\left(d+\Delta y\right) - \left(m+L(\theta)\right) - s(r)\right)^2$$

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

$$-\Delta y - d + \tau_1 s'(r) + \tau_2\left(\mu\left(d+\Delta y\right) - \left(m+L(\theta)\right) - s(r)\right)s'(r) = 0, \tag{19}$$

which can be written as

$$-\frac{\Delta y + d}{s'(r)} - \tau_2\left(m + L(\theta)\right) - \tau_2 s(r) + \tau_1 + \tau_2\mu\left(d+\Delta y\right) = 0. \tag{20}$$

Using the F.O.C. for Δy,

$$R - r - \tau_1\mu - \tau_2\sigma^2(d+\Delta y) - \tau_2\left(\mu\left(d+\Delta y\right) - \left(m+L(\theta)\right) - s(r)\right)\mu = 0 \tag{21}$$

we obtain

$$\Delta y = \frac{R - r - \tau_1\mu}{\tau_2\left(\sigma^2+\mu^2\right)} + \frac{\mu\left(m+L(\theta)\right) + \mu s(r)}{\left(\sigma^2+\mu^2\right)} - d. \tag{22}$$

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

$$s(r) = \left(\mu - \frac{1}{\tau_2\lambda}\right)\left(d+\Delta y\right) + \frac{\tau_1}{\tau_2} - \left(m + L(\theta)\right). \tag{23}$$

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

$$\Delta y = \frac{R-r}{\tau_2\sigma^2 + \frac{\mu}{\lambda}} - d. \tag{24}$$

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

$$s(r) = \left(\mu - \frac{1}{\tau_2\lambda}\right)\left(\frac{R-r}{\tau_2\sigma^2+\frac{\mu}{\lambda}}\right) + \frac{\tau_1}{\tau_2} - \left(m + L(\theta)\right). \tag{25}$$

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

$$\Delta y = \frac{R - r}{\tau_2 \sigma^2} - d, \tag{26}$$

and

$$s(r) + \left(\frac{R - r}{\tau_2^2 \sigma^2 \lambda} \right) = \frac{\tau_1}{\tau_2} - (m + L(\theta)). \tag{27}$$

Replacing $s(r)$ with λr, we obtain

$$r = \frac{-R + \lambda \tau_1 \tau_2 \sigma^2 - \lambda \tau_2^2 \sigma^2 (m + L(\theta))}{\lambda^2 \tau_2^2 \sigma^2 - 1} \tag{28}$$

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

$$\frac{dr}{d\sigma^2} = \lambda \tau_2 \frac{\lambda \tau_2 R - \tau_1 + \tau_2 (m + L(\theta))}{(\lambda^2 \tau_2^2 \sigma^2 - 1)^2} \tag{29}$$

Note that we have

$$R - r = \lambda \tau_2 \sigma^2 \frac{\lambda \tau_2 R - \tau_1 + \tau_2 (m + L(\theta))}{\lambda^2 \tau_2^2 \sigma^2 - 1} > 0. \tag{30}$$

Therefore, we have

$$\frac{dr}{d\sigma^2} = \left(\frac{R - r}{\sigma^2} \right) \frac{1}{\lambda^2 \tau_2^2 \sigma^2 - 1}. \tag{31}$$

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 (30) 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 (26), 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 (26) using (30):

$$\Delta y = \lambda \frac{\lambda \tau_2 R - \tau_1 + \tau_2 (m + L(\theta))}{\lambda^2 \tau_2^2 \sigma^2 - 1} - d. \tag{32}$$

Appendix B 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. Wire transfers sent via Fedwire are completed instantly. 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. Many Fedwire Funds Service participants use daylight credit to facilitate payments throughout the operating day. Nevertheless, 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.[39] 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.[40] 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.

Table C1: **Predictability of payment activities: gross volume vs. net flow**

The sample comprises observations 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 (i.e., the total value 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, 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 C Additional Results

C.1 Gross payment volume seasonality

In Table C1, 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 comfortable 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

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

[40]Please refer to CHIPS Annual Statistics.

Table C2: **Payment risk and bank lending: Alternative payment risk measure**

The sample for Column (1) spans from 2000:Q1 to 2020:Q4, excluding the financial crisis from 2008:Q1 to 2009:Q2. The sample for Column (2) is from 2000:Q1 to 2007:Q4, and the sample for Column (3) is from 2009:Q3 to 2020:Q4. The dependent variable is the loan growth rate in quarter $t+1$, winsorized at the top and bottom 0.5% levels. Alternative payment risk measure is defined as the standard deviation of daily net payment flow (scaled by average payment volume within the quarter) for a given bank in quarter t. Control variables are calculated as of quarter t and include $Liquidity\ ratio$, $Loan\ ratio$, $Trading\ ratio$, $Capital\ ratio$, $Deposit\ ratio$, $Return\ on\ asset$, $\log(Size)$, 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$_{t+1}$			
	Overall (1)	**Pre-crisis** (2)	**Post-crisis** (3)
Alternative payment risk	-0.0028***	-0.0030***	-0.0023**
	(-4.81)	(-4.28)	(-2.66)
Bank controls	Yes	Yes	Yes
State × Quarter FE	Yes	Yes	Yes
Type × Quarter FE	Yes	Yes	Yes
Adjusted R^2	0.089	0.075	0.107
N of Obs.	156498	58708	97790

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 $Flow\ imbalance\ ratio_{i,t,d}$ and then calculate its standard deviation to obtain $Flow\ volatility_{i,t}$, our primary measure of payment liquidity risk.

C.2 Alternative payment risk measures

In calculating the first measure of payment risk, $Flow\ volatility_{i,t}$ for bank i in quarter t, we divide daily net payment flow by daily gross payment volume to obtain $Flow\ imbalance\ ratio_{i,t,d}$ for day d in quarter t, followed by calculating the standard deviation of $Flow\ imbalance\ ratio_{i,t,d}$ within quarter t. This method follows our model where payment risk emerges from the imbalance between inflows and outflows (i.e., the net payment flow) while the gross volume is known (Table C1 shows that daily gross volume is highly predictable). Next, we consider an alternative measure. The daily gross volume in the denominator is replaced the average daily gross volume of the quarter, that is

$Flow\ imbalance\ ratio_{i,t,d}$ has the same denominator for days in a quarter.[41]

Table C2 displays regression results based on this alternative measures. Column (1) provides results from the baseline sample, while Columns (2) and (3) focus on the pre-GFC and post-GFC samples, respectively. The findings based on this alternative measure of payment risk align with the baseline results. Specifically, Column (1) reveals a negative correlation between loan growth and payment risk, with statistical significance at the 1% level. The economic magnitude is also large: an interquartile-range increase in this alternative measure is associated with a 0.25 percentage point decrease in loan growth rate, calculated as $0.89 \times (-0.0028) = -0.25\%$.

Next, we consider another set of alternative payment risk measures. In our baseline measure, we use the standard deviation of $Flow\ imbalance\ ratio_{i,t,d}$. The first set differentiates days with positive and negative net payment flows. Specifically, we calculate separately the standard deviation of $Flow\ imbalance\ ratio_{i,t,d}$ for days with $Flow\ imbalance\ ratio_{i,t,d} > 0$ and standard deviation of $Flow\ imbalance\ ratio_{i,t,d}$ for days with $Flow\ imbalance\ ratio_{i,t,d} < 0$. In Column (1) and (2) of Table C3, we report the regression results. After separating payment risk into inflow risk and outflow risk, we find that the outflow risk is responsible for the negative impact of payment risk on lending. The second set of measures distinguishes between gross payment inflows and outflows on a given day. Specifically, $Gross\text{-}inflow\ volatility$ and $Gross\text{-}outflowvolatility$ are defined as the standard deviation of daily gross inflows and outflows, each scaled by the average daily gross volume of the quarter.[42] Columns (3) and (4) of Table C3 report the regression results. The measures based on both gross inflows and gross outflows have a significantly negative impact on bank lending, with a slightly stronger effect from outflows.[43] Naturally, payment outflow matters as it is about liquidity loss. However, inflow risk should also matter because, when a bank faces risk in the sources of liquidity, it tends to be conservative about investing in illiquid loans.

In summary, our analysis reveals that while outflow-based payment volatility measures have a more pronounced impact on bank lending in some instances, inflow-based measures also exhibit a comparable impact in other scenarios. Consequently, we will continue to use our baseline measure of payment risk that accounts for uncertainty in both the sources and uses of liquidity.

[41] Our baseline measure and this alternative measure differs in that for a day with large (small) gross volume, $Flow\ imbalance\ ratio_{i,t,d}$ is small (large) in the former, but the daily variation of denominator is absent in the latter.

[42] Note that if we normalize gross inflows and outflows with daily gross volume, the resulting standard deviations would be identical for gross inflows and outflows, as they are colinear (sum up to one). As such, we use average daily gross volume within the quarter as the scaling factor for daily gross inflows and daily gross outflows.

[43] The Wald test conducted for Column (3) reveals that the difference between the coefficients for $Gross\text{-}inflow\ volatility$ and $Gross\text{-}outflowvolatility$ is not statistically significant.

Table C3: **Payment risk and bank lending: Risks from inflows and outflows**

The bank-quarter sample spans 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. $Inflow$-$day\ volatility$ and $Outflow$-$day\ volatility$ represent the standard deviation of a bank's daily net payment flows (scaled by daily gross payment volume) on days when net payment flows are positive and negative, respectively, in quarter t. $Gross$-$inflow\ volatility$ and $Gross$-$outflow\ volatility$ are defined as the standard deviation of daily gross inflows and outflows for a given bank in quarter t, each scaled by the average volume of the quarter. Control variables are calculated as of quarter t and include $Liquidity\ ratio$, $Loan\ ratio$, $Trading\ ratio$, $Capital\ ratio$, $Deposit\ ratio$, $Return\ on\ asset$, $\log(Size)$, squared $\log(Size)$, and $Number\ of\ states$. 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	-0.0020	-0.0020		
	(-0.58)	(-0.58)		
Outflow-day volatility	-0.0146***	-0.0145***		
	(-4.19)	(-4.19)		
Gross-inflow volatility			-0.0019***	-0.0018***
			(-3.55)	(-3.35)
Gross-outflow volatility			-0.0027***	-0.0027***
			(-4.83)	(-4.77)
Bank controls	Yes	Yes	Yes	Yes
State FE	Yes		Yes	
Type FE	Yes		Yes	
Quarter FE	Yes		Yes	
State × Quarter FE		Yes		Yes
Type × Quarter FE		Yes		Yes
Adjusted R^2	0.075	0.092	0.073	0.089
N of Obs.	147766	147669	156588	156498