Payment Risk and Bank Lending*

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Abstract

Deposits finance bank lending and serve as means of payment for bank customers. Under uncertain payment flows, deposits are debts with random maturities. Payment outflows drain reserves, and the risk is most prominent when funding markets are under stress and banks are unable to smooth out payment shocks. We provide the first evidence on the negative impact of payment risk on bank lending, bridging the literatures on payment systems and credit supply. An interquartile increase in payment risk is associated with a decline in loan growth rate that is 10% of standard deviation. Our findings are stronger in times of funding stress and robust across banks of different sizes and loans of long and short maturities. Banks with higher payment risk raise deposit rates to expand customer base and internalize payment flows. Finally, we show that payment risk dampens the bank lending channel of monetary policy transmission.

Keywords: Credit supply, deposits, payment, inside money, monetary policy transmission

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

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1 Introduction

Bank finances lending with newly issued deposits. When a bank makes a loan, it credits the borrower's account with a matching amount of new deposits. The borrower can freely use the newly created deposits as means of payment. This practice of credit and money (deposit) creation has been widely adopted throughout the history of banking (Wicksell, 1907; Gurley and Shaw, 1960; Tobin, 1963; McLeay, Radia, and Thomas, 2014; Donaldson, Piacentino, and Thakor, 2018).

Bank lending is a swap of new debts. The bank obtains the borrower's debt (loan) and, in exchange, issues new debt (deposits) to the borrower. When the borrower makes a payment to a depositor of the lending bank, the bank simply changes the owner of the new deposits from the borrower to her payee. If the payee is not a depositor of the lending bank, the bank sends reserves to the payee's bank, and the payee's bank expands its balance sheet adding reserves on the asset side and new deposits to the payee's account on the liability side.[1] While payment systems differ in overdraft standards, banks ultimately settle payments with reserves. Involuntary payment outflows drain reserves. To replenish reserves, the lending bank have to incur costs of prematurely liquidating assets or borrowing reserves from interbank markets or the central bank.

Therefore, lending carries payment risk as it is uncertain whether borrowers' payees are depositors of the lending bank. We provide the first evidence on the negative impact of payment risk on lending. We develop hypotheses in a simple model of credit and deposit creation based on Bolton, Li, Wang, and Yang (2020) and Parlour, Rajan, and Walden (2020) and more broadly the modern literature on banks as money creators (Cavalcanti and Wallace, 1999; Freixas, Parigi, and Rochet, 2000; Kiyotaki and Moore, 2000, 2002, 2005; Kahn and Roberds, 2007; Skeie, 2008; Bianchi and Bigio, 2014; Hart and Zingales, 2014; Jakab and Kumhof, 2015; Brunnermeier and Sannikov,

[1]The process can be viewed as the borrower withdrawing cash to pay and her payee depositing cash into the payee's bank. The lending bank loses reserves and deposits, while the payee's bank gains reserves and deposits.

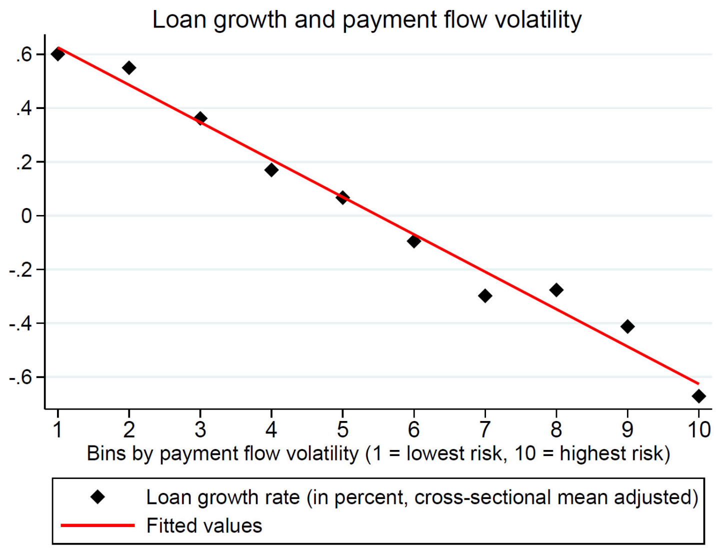

Figure 1: **Payment risk and bank lending.** This figure reproduces Figure 6A. It plots banks' loan growth rates (in percent, adjusted for the cross-sectional mean) against their payment risk deciles. Specifically, we sort bank-quarter observations into 10 bins based on their previous-quarter payment 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 is at the bank-quarter level and spans 11 years from 2010:Q1 to 2020:Q4.

2016; Piazzesi and Schneider, 2016; Bigio and Sannikov, 2019; Begenau, Bigio, Majerovitz, and Vieyra, 2019; d'Avernas, Vandeweyer, and Pariès, 2019; Donaldson and Piacentino, 2019; Wang, 2019; Piazzesi, Rogers, and Schneider, 2019; Faure and Gersbach, 2021; Garratt and Zhu, 2021).[2]

In Figure 1, we show the negative correlation between payment risk and loan growth. Our analysis is based on Fedwire payment data from 2010 to 2020 (merged with U.S. Call Report and RateWatch to form a bank-quarter sample). Fedwire processes trillions of dollars daily and is the primary U.S. network for large-value payments. For a bank-quarter, we measure payment risk by the volatility of daily net payment flows (normalized by gross payment volume) in the

[2]The theoretical literature on bank liquidity creation goes beyond inside money in the form of transferable debts (Bryant, 1980; Diamond and Dybvig, 1983; Diamond, 1984; Ramakrishnan and Thakor, 1984; Millon and Thakor, 1985; Bhattacharya and Gale, 1987; Jacklin, 1987; Postlewaite and Vives, 1987; Gorton and Pennacchi, 1990; Allen and Gale, 2004; Goldstein and Pauzner, 2005; Bansal, Coleman, and Lundblad, 2011; Stein, 2012; Allen, Carletti, and Gale, 2014; DeAngelo and Stulz, 2015; Krishnamurthy and Vissing-Jørgensen, 2015; Li, 2016; Quadrini, 2017).

previous quarter. We then sort bank-quarter observations into deciles of payment risk; within each decile, we plot the average loan growth rate adjusted by the cross-sectional mean to eliminate potential effects of credit cycles and seasonality. Our payment data provides identifiers that isolate payments initiated by customers (which cause involuntary outflows) from those initiated by banks themselves.[3] We measure payment risk with customer-initiated payments.

Our approach of measuring payment risk emphasizes payment flows in banks' regular operations rather than large deposit outflows at distressed banks (Martin, Puri, and Ufier, 2018; Brown, Guin, and Morkoetter, 2020).[4] Moreover, our measure of payment risk is based on fund transfers within the banking system to minimize the impact of aggregate cash withdrawal triggered by concerns on systematic banking crisis. Our findings that link the payment risk of deposits to bank lending contribute to the literature on funding stability and credit supply (Loutskina and Strahan, 2009; Ivashina and Scharfstein, 2010; Cornett, McNutt, Strahan, and Tehranian, 2011; Dagher and Kazimov, 2015; Carletti, De Marco, Ioannidou, and Sette, 2021).[5]

In our regression analysis on the impact of payment risks on bank lending, we control for various bank characteristics, bank type and location fixed effects, and time fixed effects.[6] We find that an interquartile increase in payment risk is associated with a decrease in quarterly loan growth rate by 0.5 percentage points. The magnitude is large in comparison with an average quarterly loan growth rate of 2% and a standard deviation of 5%. The negative impact is statistically significant

[3]More granular labels that differentiate new borrowers' payments and existing depositors' payments is not available. Such differentiation is not necessary because in a dynamic setting, banks lend out new deposits (issued directly to borrowers) and existing deposits, facing the risk of reserve outflows due to both borrowers' and depositors' payments.

[4]Large deposit outflows are triggered by fundamental news or coordination failure (Gorton, 1988; Saunders and Wilson, 1996; Calomiris and Mason, 1997; Iyer and Puri, 2012). This literature also studies withdrawal as depositors' discipline on risky banks (Park and Peristiani, 1998; Billett, Garfinkel, and O'Neal, 1998; Martinez Peria and Schmukler, 2001; Goldberg and Hudgins, 2002; Bennett, Hwa, and Kwast, 2015; Brown, Guin, and Morkoetter, 2020).

[5]The broader literature on funding stability and credit supply includes studies on the impact of legal and regulatory frameworks that restrict banks' funding access (Jayaratne and Strahan, 1996; Qian and Strahan, 2007; Adelino and Ferreira, 2016; Di Maggio and Kermani, 2017; Cortés, Demyanyk, Li, Loutskina, and Strahan, 2020).

[6]Bank types include banks, credit unions, and saving & loan banks.

at 1% level after we control for bank fixed effects and two-way fixed effects ($state \times quarter$ and bank $type \times quarter$). The economic magnitude is robust across specifications.

We also consider an alternative measure of payment risk, the concentration (Herfindahl–Hirschman Index) of payment counterparty banks. Intuitively, if a bank's customers send money to (or receive money from) customers of only a few other banks, its payment flows can be easily affected by shocks specific to these banks' idiosyncratic customer activities. Using this alternative measure of payment risk, we find even stronger statistical significance and economic magnitude of payment risk impact on lending: An interquartile-range increase in counterparty concentration is associated with a decrease in loan growth rate by 1 percentage points, which is 20% of its standard deviation.

An identification challenge is that bank loans may be driven by customers' loan demand (which may be correlated with payment activities). Our inclusion of $state \times quarter$ fixed effects alleviates the concern, as it controls for time-varying local demand at a bank's headquarter state. However, it does not fully control for loan demand for multi-state banks. Therefore, we exploit the branch-level information from RateWatch and extract a subsample of single-state banks (that is, banks with branches in just one state). Results using this subsample are similar to the full-sample results, both in economic magnitude and statistical significance. This suggests that our results are unlikely due to loan demand variation simultaneously driving loan growth and payment risk.

We conduct our tests separately for banks of different sizes. Banks of different sizes may differ in their lending decisions and have different exposure to payment risk and the associated funding costs (Kishan and Opiela, 2000; Afonso, Kovner, and Schoar, 2011; Ashcraft, McAndrews, and Skeie, 2011). We sort banks into four groups based on total assets in each quarter. The estimated coefficients on both payment risk measures are negative and highly significant across four subsamples. The magnitude of these coefficients are remarkably consistent across different size groups. Therefore, the negative impact of payment risks on lending is not specific to banks of certain sizes.

We expect our results are stronger among loans with longer maturities. For short-term loans, the bank expects repayments and the associated payment inflows in the near future so the concern over current outflows (due to borrowers' payments) is weaker. This is indeed what we find in data. The estimated coefficients on payment risks are statistically significant across different loan maturities and exhibit an monotonically increasing pattern in magnitude as maturities increase. The negative impact of payment risk on the growth rate of loans with maturities of five years or above is almost twice in magnitude compared to the negative impact on all loans.

Another prediction of the model is that higher payment risk is also associated with a higher liquidity ratio (the ratio of reserves and other liquid assets to total assets). A higher liquidity buffer reduces the bank's needs for costly external financing (e.g., interbank borrowing) when payment activities cause reserve outflows. We find that an interquartile-range increase in payment flow volatility is associated with an increase of 4 percentage points in liquidity ratio, that is 20% of the average liquidity ratio in our sample and 29% of the standard deviation. Our results echo the recent findings in Copeland, Duffie, and Yang (2021) that bank reserve holdings are important for managing payment flow uncertainty and that the reduction of aggregate reserves contributed to the repo market turmoil in September 2019. Payment data are often analyzed jointly with other high frequency (intraday or daily) bank decisions. Our findings show that payment risk propagates into banks' lending decisions and balance-sheet composition at lower (quarterly) frequencies.

The impact of payment risk on lending should be weaker if banks can easily replenish reserves by accessing short-term funding markets at low costs. When funding markets are under stress, the impact of payment risk should strengthen. Following Taylor (2009), we use LIBOR–OIS spread as proxy for funding stress in the banking sector. We find that the interaction between payment risk and LIBOR–OIS spread has a negative and statistically significant coefficient in explaining loan growth. For a bank with median level of payment flow volatility, a 50-basis-point increase

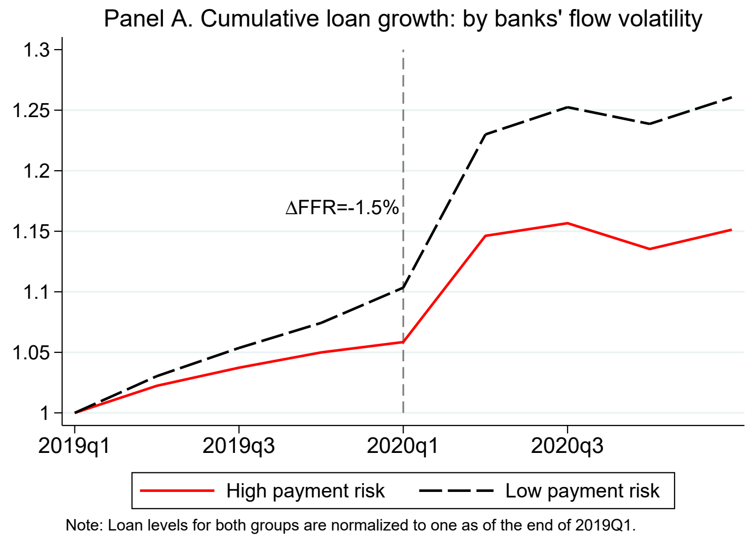

Figure 2: **The dampening effect of payment risk on expansionary monetary policy.** We sort banks into tertiles based on their previous-quarter payment flow volatility. We then calculate the average of quarterly loan growth rates for each tertile and accumulate them from 2019Q1 onward. We plot the cumulative loan growth for the top and bottom tertiles of payment risks. The reduction of 1.5% on target federal funds rates in 2020Q1 is marked in the figure.

in LIBOR–OIS spread significantly reduces loan growth by an additional 3%, which is 60% of its standard deviation in our sample. We obtain similar results using TED spread (the spread between 3-month LIBOR and Treasury bills) as a measure of funding stress in the broader economy and using the counterparty concentration measure as an alternative proxy for payment risk.

Our model features a bank lending channel of monetary policy transmission (Bernanke and Blinder, 1992; Kashyap and Stein, 2000; Jiménez, Ongena, Peydró, and Saurina, 2012, 2014; Iyer, Peydró, da Rocha-Lopes, and Schoar, 2013; Heider, Saidi, and Schepens, 2019).[7] A decrease in the short-term interest rate stimulates bank lending but monetary policy transmission is dampened by

[7]Our focus is on traditional monetary policy (rate target). A broader literature examines the impact of supply and market structure of reserves (Pérez Quirós and Rodríguez Mendizábal, 2006; Ennis and Weinberg, 2007; Berentsen and Monnet, 2008; Ennis and Keister, 2008; Ashcraft, McAndrews, and Skeie, 2011; Bech and Klee, 2011; Garcia-de-Andoain, Heider, Hoerova, and Manganelli, 2016; Martin, McAndrews, and Skeie, 2016; Diamond, Jiang, and Ma, 2020) and asset purchases on bank lending (Di Maggio, Kermani, Keys, Piskorski, Ramcharan, Seru, and Yao, 2017; Rodnyansky and Darmouni, 2017; Chakraborty, Goldstein, and MacKinlay, 2020; Peydró, Polo, and Sette, 2021).

payment risk. Intuitively, banks that face greater payment risk are more cautious in their response to a reduction in financing cost. In Figure 2, we mark the reduction of 1.5 percentage points in policy rate in 2020Q1 and plot the loan growth paths (indexed to one at 2019Q1) of banks in the top and bottom tertiles of payment flow volatility. This figure indicates that banks with higher payment risk are less responsive to monetary easing. In our regression analysis, we find that the stimulative effect of a rate cut is statistically significant and, more importantly, the interaction between rate change and payment flow volatility has a significant coefficient of large magnitude. Specifically, for two banks in the 25th and 75th percentiles of payment flow volatility, a one percentage point decrease in target federal funds rate leads to a 4.4-percentage-point increase in loan growth for the 25th-percentile bank and 3.6-percentage-point increase for the 75th-percentile bank. We find similar results using the counterparty concentration measure as proxy for payment risk.

Finally, we explore a key mechanism through which banks can manage payment risk. When a bank raises deposit rate, its depositor base is likely to expand (Drechsler, Savov, and Schnabl, 2017) and, as a result, a greater fraction of payment flows are internalized so the probability of reserve outflows decreases. Therefore, banks facing greater payment risk have incentives to set higher deposit rates. We consider three different types of deposit products: certificate of deposits, money market account, and saving account. An interquartile-range increase in payment flow volatility is associated with an increase of 4 basis points in one-year CD spread relative to target fed funds rate. Using the counterparty concentration measure as proxy for payment risk, the impact on one-year CD spread increases to 6 basis points.[8] In the existing literature, banks manage payment risk through their discretion over intraday payment timing.[9] We examine quarterly adjustment of

[8]Our findings are related to Acharya and Mora (2015) who examine a different type of liquidity needs and find that banks with high credit commitments increased deposit rates during the 2007–09 crisis. The literature also studies deposit rate adjustments following policy rate changes (Berger and Hannan, 1989; Hannan and Berger, 1991; Diebold and Sharpe, 1990; Neumark and Sharpe, 1992; Driscoll and Judson, 2013; Yankov, 2014). Drechsler, Savov, and Schnabl (2017) emphasize market power and the responses of both deposit rate and quantity to policy rate changes.

[9]The literature emphasizes coordination failure in banks' strategic decisions (Hamilton, 1996; McAndrews and

deposit rates in line with our focus on how payment risk affects bank decisions at lower (quarterly) frequencies.[10] We provide evidence that payment risk affects bank decisions on both the asset side (lending decisions) and liability side (deposit-rate decisions) of their balance sheets.

2 The Mechanism

We explain the main mechanism in this section. Specifically, we analyze the process of credit creation and the implications of payment settlement on bank liquidity management. The key ingredients are formalized in a simple model of bank lending and customers' payment activities. The model generates the empirical hypotheses that we test in Section 4.

2.1 The Mechanics of Bank Lending and Payment Flows

In Figure 3, a bank is established with a simple balance sheet of reserves on the asset side and shareholders' equity on the liability side. When the bank extend loans to agent A and B, it simultaneously issue new deposits to agent A and B. The creation of bank credit is essentially a debt swap. The borrowers obtain the bank's debts (newly issued deposits) while the bank obtain the borrowers' debts (loans). As pointed out by Tobin (1963), economists and practitioners have emphasized that a bank does not lend out loanable funds but rather issue debts (IOUs) to borrowers. Such practice dates back thousands of years and continues in the modern system of money and

Potter, 2002; Bech and Garratt, 2003; Ashcraft and Duffie, 2007; Bech, 2008; Afonso and Shin, 2011; Afonso, Kovner, and Schoar, 2011; Ashcraft, McAndrews, and Skeie, 2011; Bech, Martin, and McAndrews, 2012; Yang, 2020).

[10] Kahn and Roberds (2009) review the literature on payment economics. The literature largely focuses on payment activities and the directly related high-frequency (daily or intraday) decisions of banks, such as reserve management and intraday payment timing (Poole, 1968; Afonso, Kovner, and Schoar, 2011; Ashcraft, McAndrews, and Skeie, 2011; Ihrig, 2019) and short-term funding markets (Furfine, 2000; Ashcraft and Bleakley, 2006; Cocco, Gomes, and Martins, 2009; Bech and Atalay, 2010; Ashcraft, McAndrews, and Skeie, 2011; Acharya and Merrouche, 2013; Kuo, Skeie, Vickery, and Youle, 2013; Gabrieli and Georg, 2014; Hüser, 2016; Gofman, 2017; Blasques, Bräuning, and van Lelyveld, 2018; Craig and Ma, 2018; Chapman, Gofman, , and Jafri, 2019; d'Avernas and Vandeweyer, 2020; Correa, Du, and Liao, 2020; Copeland, Duffie, and Yang, 2021; Denbee, Julliard, Li, and Yuan, 2021).

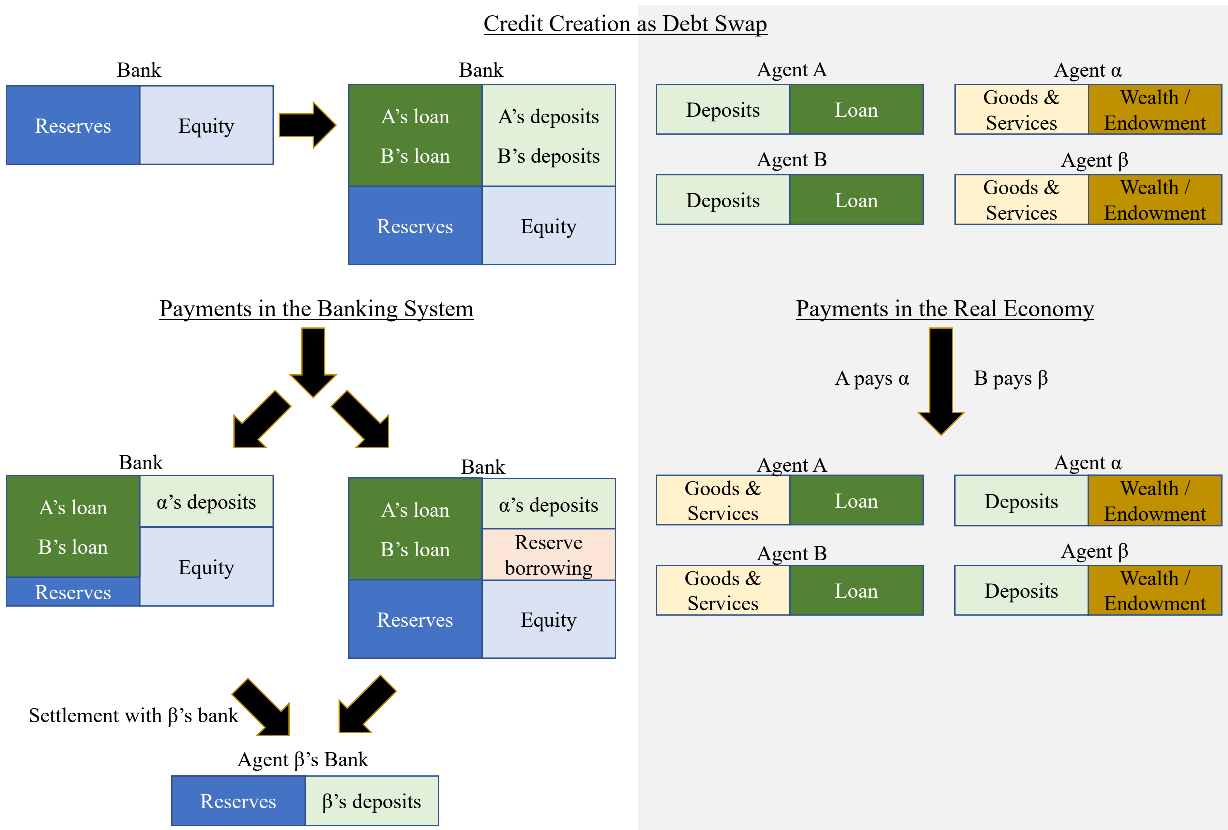

Figure 3: Credit Creation as Debt Swap and the Two-Tier Payment System.

banking (Donaldson, Piacentino, and Thakor, 2018). The deposits and loans may have different interest rates, and typically, the loan rate is higher so that the bank earns an interest spread.

Agent A and B spend the new deposits on purchasing goods and services from agent α and β, respectively. Agent α has an account at the lending bank. The bank simply changes the owner of deposits from agent A to agent α. Agent β is at a different bank. When agent B pays agent β, agent β's bank credits agent β's account with newly issued deposits and requests the lending bank to send a matching amount of reserves.[11] The lending bank can send its own reserves (out of its

[11] Kahn and Roberds (2015) analyze the difference between real-time gross settlement (RTGS) and deferred net settlement (DNS). In spite of the different degrees of netting, banks ultimately settle payments with reserves.

account at the central bank) to agent β's bank or send reserves that are borrowed from other banks or the central bank. In the former case, the lending bank's balance sheet shrinks by the amount of agent B's deposits and reserves sent to agent β's bank. In the latter case, the size of the lending bank's balance sheet stays the same, and agent B's deposits are replaced by reserve borrowings.

When the bank lends to agent A and B, it is unaware of whether their payees (i.e., agent α and β) are its own depositors or hold accounts at other banks. In general, when the bank lends to many agents, the bank faces the uncertainty in the fraction of borrowers whose payees are other banks' depositors, and such uncertainty, which we call the "payment risk", is the focus of this paper. Why does payment risk matter? If the cost of interbank borrowing is equal to the deposit rate, replacing agent B's deposits with interbank liabilities does not affect the bank's profits. However, this is rarely the case. Interbank borrowing is typically more costly as it is involves various frictions and transaction costs (Ashcraft, McAndrews, and Skeie, 2011; Bianchi and Bigio, 2014; Afonso and Lagos, 2015). Any turmoil in the interbank market that elevates the cost of interbank borrowing amplifies the bank's concern over payment risk and thereby discourages lending. The central bank may intervene in the interbank market. In fact, such intervention (for example, the Federal Reserve adjusting the target federal funds rate) has been one of the main policy instruments of central banks. The transmission of monetary policy to credit supply depends on banks' payment risk exposure.

As shown in Figure 3, the bank can use its own reserves to settle payments with agent β's bank. However, spending reserves incurs an opportunity cost as the bank can lend out reserves or use these precautionary savings to buffer other forms of uncertainty and meet regulatory requirements (Ihrig, 2019; Correa, Du, and Liao, 2020; d'Avernas and Vandeweyer, 2020). Bush, Kirk, Martin, Weed, and Zobel (2019) emphasize special intraday liquidity benefits of reserves and point out that in stress scenarios, even monetizing liquid assets such as Treasuries can be challenging.

In sum, the focus of this paper is on the payment risk that a bank faces when extending credit.

It is uncertain what fraction of borrowers have payees outside of the bank. A borrower's payment to other banks' depositors causes the bank to incur the costs of interbank borrowing or spending its own reserves. When the payment risk becomes more prominent, the bank may reduce lending. Any disruption in the interbank market amplifies the impact of payment risk. Next, we present a model that closely represents the process of credit creation and payment settlement in Figure 3.

2.2 Model

We analyze a single bank's lending decision. At $t = 0$, the bank is endowed with m amount of fiat money (contributed by shareholders and equal to equity) in its reserve account at the central bank. The bank lends at $t = 0$. Borrowers make payments at $t = 1$. Loans are repaid at $t = 2$. The loans cannot be resold at $t = 1$, so the bank can only cover payment outflows with reserves. This timing assumption is in line with the literature (Diamond and Dybvig, 1983) and, in practice, payment settlement is done at a higher frequency (intraday or overnight) than loan book adjustment.

The bank extends y amount of loans financed by newly created deposits. At $t = 1$ (before the loans are repaid), the borrowers (entrepreneurs) pay households for goods and services as inputs for their projects. Payees may hold accounts at other banks. Let g denote the fraction of payees outside of the bank. The borrowers' payments imply reserve outflow of $x = gy$. Following Bolton, Li, Wang, and Yang (2020), we assume g is random with mean μ and variance σ^2. Deposits are debts with random maturities. A random fraction g matures at $t = 1$ while the rest mature at $t = 2$.

Note that payment outflow can also be viewed as borrowers withdraw cash to make payments (rather electronic payments to payees' bank accounts). Different from Diamond and Dybvig (1983) who also model deposits as long-term liabilities but assume a constant fraction of deposit holders must withdraw at $t = 1$, here the withdrawal fraction g is random.[12] Our focus is on payment risk,

[12]Related, Drechsler, Savov, and Schnabl (2021) emphasize that deposits are long-duration liabilities.

$\mathbb{V}ar(g) = \sigma^2$, and its impact on bank lending, y. Another difference from the loanable-fund setup in Diamond and Dybvig (1983) is that in our model, withdrawal is not due to consumption timing shocks but arises from borrowers' payment needs. Here borrowers are the first holders of newly issued deposits, and naturally, they obtain loans for purchases. After payments, the payees hold deposits (or cash), and the bank intermediates between borrowers and their payees.

The cost of covering payment outflow is $\tau_1(x-m) + \frac{\tau_2}{2}(x-m)^2$. When $x - m > 0$ (i.e., the bank does not have enough reserves to cover the outflow), this represents an increasing and convex cost of interbank borrowing. The convexity, as microfounded in Bigio and Sannikov (2019) and Parlour, Rajan, and Walden (2020), captures the impact of interbank market frictions (Afonso and Lagos, 2015).[13] When $x - m < 0$, this quadratic form presents an increasing and concave return on interbank lending, and the concavity is again due to the frictions in the interbank market. While the parameter τ_1 (a baseline interbank rate) depends on monetary policy, the coefficient on the quadratic term, τ_2, captures interbank market frictions. This quadratic form implies a linear first order condition for y that directly maps to our regression specification.

Before solving y, we clarify that the bank finances lending with deposits instead of reserves. Deposit issuance only causes a probabilistic reserve drawdown (as some of the borrowers' payees may be the bank's own depositors) while lending out reserves causes a direct drawdown. Therefore, as long as the marginal cost of spending reserves (encoded in the quadratic form) is above the deposit rate, the bank prefers lending in the form of a debt swap (i.e., issuing deposits for loans) over lending out reserves. We assume this is the case in line with the evidence that deposits rates are below the fed funds rate in our sample and other findings (e.g., Rose and Kolari, 1985; Drechsler, Savov, and Schnabl, 2017). Moreover, because non-bank borrowers do not have accounts at the central bank, dollar bills have to be redeemed if the bank decides to lend out reserves. This

[13] 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).

institutional barrier implies that it is more convenient to credit borrowers' checking accounts with newly issued deposits than to lend out reserves.

Next, we solve the optimal credit and money (deposit) creation, y. When the bank lends out y and issues an equal amount of deposits, it earns an exogenous interest spread, $y(R+\varepsilon-i)$, where R represents a baseline loan rate, ε captures the characteristics of bank-specific lending opportunities, and i is the deposit rate. For simplicity, it is assumed that the bank has a zero time-discount rate. The bank chooses y to maximize the expected net profits:

$$\begin{aligned} &\max_y \mathbb{E}\left[(R+\varepsilon-i)y-\tau_1(x-m)-\frac{\tau_2}{2}(x-m)^2\right] \qquad (1)\\ =&\max_y (R+\varepsilon-i)y-\tau_1\mu y+\tau_1 m-\frac{\tau_2}{2}(\sigma^2+\mu^2)y^2+\tau_2\mu m y-\frac{\tau_2}{2}m^2 \end{aligned}$$

For simplicity, we assume that the return on lending, $R+\varepsilon$, is risk-free. The bank takes the loan rate as given (i.e., the credit demand at $R+\varepsilon$ is perfectly elastic). The implicit assumption behind a fixed deposit rate i is that when borrowers (entrepreneurs) pay deposits to households, households accept deposits as means of payment because they have a perfectly elastic demand for deposits at the interest rate i. As pointed out by Tobin (1963), a bank cannot create an infinite amount of money (deposits) because its capacity of deposit issuance ultimately depends on the deposit demand. Later we study an inelastic deposit demand following Drechsler, Savov, and Schnabl (2017) and endogenize the bank's choice of deposit rate.

We solve the optimal y via the first-order condition:

$$y^*=\frac{R+\varepsilon-i-\tau_1\mu}{\tau_2\left(\sigma^2+\mu^2\right)}+\frac{\mu}{\left(\sigma^2+\mu^2\right)}m\,. \qquad (2)$$

In our model, the focus is on a bank's normal-time operations rather than banking crises. We impose the following parameter restriction so that the bank has enough equity capital (and reserves) to buffer risk and never becomes insolvent. The bank stays solvent even in the worst case of payment outflow (i.e., $g = 1$ and $x = y^*$):

$$m + (R + \varepsilon - i)y^* - \tau_1(y^* - m) - \frac{\tau_2}{2}(y^* - m)^2 > 0\,, \tag{3}$$

where the left side is the realized earnings plus initial equity position at $t = 2$ given the realized g equal to one. Note that the assumption 3 also rules out bank run (Diamond and Dybvig, 1983; Goldstein and Pauzner, 2005) because even when all deposits are withdrawn, the bank can borrow reserves to cover the outflows and the borrowing cost is not high enough to cause insolvency.

The optimal lending solution y^* given by (2) generates our main hypotheses:

Hypothesis 1 (H1): *Bank lending y decreases in payment risk, σ^2.*

Hypothesis 2 (H2): *When payment risk increases, bank lending decreases so the liquidity ratio (i.e., the ratio of reserves to total bank assets), $m/(m + y)$, increases.*

Hypothesis 3 (H3): *When there is stress or disruption in the interbank market (i.e., τ_2 increases), bank lending declines, and the impact of τ_2 depends on the size of payment risk.*

Hypothesis 4 (H4): *When the central bank intervenes in the interbank market and lowers interest rate (i.e., τ_1 decreases), bank lending increases but the response is weaker when the payment risk exposure is higher.*

In sum, payment risk discourages bank lending, encourages liquidity hoarding, amplifies the impact of interbank market stress, and dampens the transmission of monetary policy.

Substituting (2) into the profit function in (1), we obtain the maximized expected profits, π:

$$\pi \equiv \frac{\tau_2}{2(\sigma^2 + \mu^2)} \left(\frac{R + \varepsilon - i}{\tau_2} - \frac{\tau_1}{\tau_2}\mu + \mu m \right)^2 + \tau_1 m - \frac{\tau_2}{2}m^2 \tag{4}$$

The first term represent the profits from lending and the associated costs due to payment activities, and the last two terms represent the baseline profits from not extending loans and investing all reserves in interbank lending. We impose the following parametric assumption so that the marginal profits from lending reserves in the interbank market stays positive:

$$\tau_1 - \tau_2 m > 0\,. \tag{5}$$

Next, we extend our model to allow the bank optimally set deposit rate i before its lending decisions. A higher i attracts deposit (and reserve) inflows and thereby reduces μ ($\mu'(i) < 0$). The rationale is that a higher deposit rate attracts more depositors and expand the customer base (Drechsler, Savov, and Schnabl, 2017), so it is more likely that a borrower's payee happens to be the bank's depositor. For simplicity, we consider μ as a linear function of i: $\mu(i) = \mu_0 - \mu_1 i$ where $\mu_1 > 0$. We solve the first-order condition for i (i.e., $d\pi(i)/di = 0$) and differentiate the equation with respect to σ^2 to obtain the sensitivity of deposit rate on payment risk:

$$\frac{di}{d(\sigma^2)} = \frac{2\mu(i) + (\tau_1 - \tau_2 m)}{\mu_1\tau_2(R + \varepsilon - i) + \mu(i)\tau_2} > 0\,, \tag{6}$$

as long as the bank maintains a positive net interest margin (i.e., $R + \varepsilon - i > 0$). Intuitively, when the bank faces higher payment risk, it sets a higher deposit rate to attract deposit inflow and thus reduces the probability of raising costly funding in the interbank market. The result on optimal deposit rate leads to our fifth hypothesis:

Hypothesis 5 (H5): *The bank's optimal deposit rate increases in its payment risk.*

Discussion: Payment risk overhang. In our analysis, we start with a bank that does not have existing loans and deposits. Next we show that given the liquidity m, the existing loans (denoted by ℓ) do not affect the choice of new loans but the existing deposits (denoted by d), which already carry payment risk, affect the bank's lending decisions. As in the main model, a g fraction of the existing deposits may flow out of the bank, draining reserves. Now the bank's objective function for choosing y is given by

$$\max_y \mathbb{E}\left[(R+\varepsilon-i)(y+\ell)-\tau_1(x+gd-m)-\frac{\tau_2}{2}(x+gd-m)^2\right] \tag{7}$$
$$=\max_y (R+\varepsilon-i)(y+\ell)-\tau_1\mu y-\tau_1\mu d+\tau_1 m-\frac{\tau_2}{2}(\sigma^2+\mu^2)(y+d)^2+\tau_2\mu m(y+d)-\frac{\tau_2}{2}m^2$$

The optimal y only differs from the baseline solution in (8) by a reduction of d:

$$y = \frac{R+\varepsilon-i-\tau_1\mu}{\tau_2\left(\sigma^2+\mu^2\right)}+\frac{\mu}{\left(\sigma^2+\mu^2\right)}m-d\,. \tag{8}$$

The existing deposit liabilities already imply a potential reserve drain, which discourages the bank from taking on more payment risk through the creation of new loans and deposits. In Section 4, we include deposits-to-total asset ratio ("deposit ratio") as a control variable in the loan growth regression and find a negative coefficient that is consistent with the payment risk overhang effects.

3 Data and Variable Construction

In this section, we first describe our data sources and sample construction, followed by the summary statistics. We then explain the calculation of our key measures of payment risks.

3.1 Data sources and sample

We collect data from multiple sources. For payments, we use confidential Fedwire transaction-level data that span from 2010 to 2020. Fedwire is a real-time gross settlement system used by Federal Reserve banks to electronically settle U.S. dollar payments among member institutions, and the system processes trillions of dollars daily. The Federal Reserve maintains accounts for both senders and receivers and settles individual transactions immediately without netting. For each transaction, the Fedwire data provide information on the time and date of the transaction, identities of sender and receiver, payment amount, and transaction type. We focus on transactions instructed by customers, which are out of the banks' control as in our theoretical model. More precisely, we exclude bank-scheduled transfers and banks' purchases and sales of federal funds. Customer-initiated transactions make up about 85% of transactions (in terms of number of transactions).

We obtain data on bank balance sheets and income statements from U.S. Call Report for the period from 2010:Q1 to 2021:Q1. The Call Report data are at the quarterly frequency and include standard balance sheet items, including total asset, loan amount (by type and maturity), deposit amount (by type and maturity), capital amount, etc. The data also provide detailed information on banks' income statements. We merge the Fedwire data with the Call Report data using Federal Reserve's internal identity system.

We also 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.[14] The data contain 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 at the $2.5K tier. We aggregate branch-level information to bank

[14]For larger institutions with numerous branches, only one branch per region is surveyed and then matched with all other branches in that region with the same rates.

levels and merge the RateWatch data with the Call Report data using the FDIC bank identifier.

Our final data set includes 3,466 banks with merged information from all three sources. Figure 4 shows the coverage of our data set relative to the Call Report universe for the period of 2010 to 2020. In particular, it shows that on average our sample covers 83% of banks in Call Report (in terms of total assets). It is worth noting that our paper is the first to merge payment data with other banking data such as Call Report and RateWatch, thus the first paper to empirically study how banks' payment risks affect bank decisions that are outside of the traditional focus of intraday payment settlement and liquidity management. Our focus is on banks' lending decision, deposit rates, and balance sheet composition.

Table 1 provides summary statistics for our bank-quarter sample. For an average bank, it has $4.5 billion assets. Among its assets, there are 20% of liquid assets (cash and available-for-trade securities) and 65% of loans. The bank's 61% of funding comes from non-transaction deposits and 11% from equity capital, and its return on asset is 0.23% over a quarter. Over our sample period, on average banks offer deposit rates lower than target the federal funds rates.

3.2 Payment risk measures

For each bank in each quarter, we use the Fedwire data to construct two normalized measures that gauge the risks associated with banks' payment flows and network: namely, flow volatility and counterparty HHI. The first measure captures the fluctuation magnitude of unexpected payment flows of a bank, and the second measure captures the concentration levels of that bank's payment network on both the receiving and sending sides.

The first measure, $Flow\ volatility$, is calculated as follows. For a given quarter t, on each day

d we calculate bank i's payment flow excess ratio:

$$Flow\ excess\ ratio_{i,t,d} = \frac{Amount\ received_{i,t,d} - Amount\ sent_{i,t,d}}{Amount\ received_{i,t,d} + Amount\ sent_{i,t,d}}, \tag{9}$$

where $Amount\ received_{i,t,d}$ is the aggregate amount of customer payments received by bank i on date d from all other Fedwire counterparties, and $Amount\ sent_{i,t,d}$ is the aggregate amount of customer payments sent by bank i on date d to all other Fedwire counterparties. Therefore, $Flow\ excess\ ratio_{i,t,d}$ measures how much excess inflow received by bank i on date d, relative to the total payment activity of bank i on that day. By definition, $Flow\ excess\ ratio_{i,t,d}$ takes value between -1 and 1, with -1 representing the case when all payments are outflows and 1 the case when all payments are inflows. We then calculate the standard deviation of $Flow\ excess\ ratio_{i,t,d}$ within quarter t as $Flow\ volatility$:

$$Flow\ volatility_{i,t} = S.D.(Flow\ excess\ ratio_{i,t,d}), \tag{10}$$

which measures how volatile unexpected payment flows are for bank i over quarter t.

The second measure, $Counterparty\ HHI$, is designed to gauge how concentrated a bank's payment senders and receivers are. Intuitively, if a bank's customers receive money from (or send money to) a very limited number of other banks, the total payments will be easily affected by unexpected flows between a pair of banks. Thus, this second measure captures the potential fragility stemming from having large and limited counterparties. We first calculate bank i's receiver HHI on day d in quarter t:

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

where $Amount\ sent_{i,j,t,d}$ is defined as payment amount sent by bank i' to bank j on day d in quarter t. Therefore, $Receiver\ HHI_{i,t,d}$ is defined as the HHI measure of bank i's payment receivers 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:

$$Sender\ HHI_{i,t,d} = \sum_{j \neq i} \left(\frac{Amount\ received_{i,j,t,d}}{Amount\ received_{i,t,d}} \right)^2, \tag{12}$$

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

$$Counterparty\ HHI_{i,t} = (Receiver\ HHI_{i,t} + Sender\ HHI_{i,t})/2. \tag{13}$$

By definition, $Counterparty\ HHI_{i,t}$ is between zero and one, and it measures concentration levels of bank i's payment network on both the receiving and sending ends over quarter t.

Figure 5 plots the frequency distributions of the two payment risk measures. These two measures bear substantial cross-sectional variation. 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 $Counterparty\ HHI$. In our sample, the maximum value for $Flow\ volatility$ and $Counterparty\ HHI$ are 1.05 and 1, respectively, and the minimum value for both is zero.

4 Empirical Results

We first analyze how payment risks affect banks' lending decisions. We then show that the impact of payment risks on bank lending is amplified by funding stress. Next, we provide strong evidence that payment risk hinders monetary policy transmission. Finally, we show that banks bearing higher payment risks set higher deposit rates to attract deposit inflows.

4.1 Payment risk and bank lending

In Panel A of Figure 6 (i.e., Figure 1 in Introduction), we plot sort bank-quarter observations into ten bins based on the bank's *Flow volatility* from the previous quarter and, within each bin, we calculate the average adjusted loan growth rate. To remove the time trend and the mechanical effects of seasonality, we adjust the loan growth rate for a bank-quarter by deducting the cross sectional mean of that quarter. The figure shows a robust negative relation that suggests a negative impact of payment risk on bank lending. $Flow\ volatility$ is highly persistent for a given bank (with an autocorrelation of over 0.9). Therefore, such a strong relation is unlikely due to reverse causality. If we replace the previous quarter's $Flow\ volatility$ with $Flow\ volatility$ at the beginning of our sample, we obtain very similar results. In Panel B of Figure 6, we replace $Flow\ volatility$ with $Counterparty\ HHI$ and show the same pattern.

Next, we analyze how payment risks affect banks' lending decisions through the following regression model where we control for state fixed effects, time fixed effects, and the bank characteristics that are commonly included as explanatory variables for loan growth (Loutskina and Strahan, 2009; Cornett, McNutt, Strahan, and Tehranian, 2011):

$$Loan\ growth_{i,t+1} = \alpha + \beta \times Flow\ volatility_{i,t} + \gamma \times Controls_{i,t} + \mu_{state} + \mu_{type} + \mu_t + \epsilon_{i,t+1}, \quad (14)$$

where the dependent variable, $Loan\ growth_{i,t+1}$ is defined as the loan growth rate of bank i over quarter $t+1$:

$$Loan\ growth_{i,t+1} = (Loan_{t+1} - Loan_t)/Loan_t. \tag{15}$$

We control for the following bank characteristics: $Liquidity\ ratio$ (the sum of cash and available-for-trade securities, divided by total asset), $Loan\ ratio$ (the ratio of loan amount to total asset), $Trading\ ratio$ (the ratio of trading assets to total asset), $Capital\ ratio$ (the ratio of risk-base capital to total asset), $Deposit\ ratio$ (the ratio of nontransaction deposit amount to total asset), and $Return\ on\ asset$ (net income divided by total asset), 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 and its squared term to control for potential nonlinear effects of bank size on loan provision (Kishan and Opiela, 2000). In addition, we control for the number of states that the bank operates as a depository institution based on information from RateWatch. Moreover, we control for bank state fixed effects (μ_{state}, based on banks' headquarters), bank type fixed effects (μ_{type}), and time fixed effects (μ_t). Standard errors are clustered at the bank and quarter levels.

We report regression results of Equation (14) in Table 2. Column (1) shows that loan growth rate is negatively associated with payment flow volatility, significant at the 1% level. The result is economically significant as well. Specifically, an interquartile-range increase in $Flow\ volatility$ is associated with a decrease in loan growth rate by 0.5 percentage points ($0.34 \times (-0.0141) = -0.5\%$). This estimate has a significant economic magnitude. The average loan growth rate in our sample is 2 percentage points and the standard deviation is 5 percentages points. To control for potential time-varying effects of bank type and location, in column (2) we include State$\times$Quarter and Type$\times$Quarter two-way fixed effects (thus absorbing μ_{state}, μ_{type}, and μ_t) and obtain similar results. In column (3), we further control for bank fixed effects and our results remain robust with a smaller coefficient on $Flow\ volatility$, suggesting that for a given bank, changes in its flow volatility affect its loan provision but in a smaller magnitude compared to the cross-sectional effects. This is not surprising given the fact that the $Flow\ volatility$ is highly persistent for a given bank (with an autocorrelation of over 0.9), and the cross-sectional variation of $Flow\ volatility$ is far more informative than within-bank variation.

Next, we replace $Flow\ volatility_{i,t}$ with $Counterparty\ HHI_{i,t}$ and re-estimate Equation (14). Regression results, presented in columns (4)–(6) of Table 2, show that loan growth rate is negatively associated with payment network concentration, significant at the 1% level and robust across various specifications. The economic significance of these results is even stronger than that for $Flow\ volatility$. In particular, column (4) shows that an interquartile-range increase in $Counterparty\ HHI$ is associated with a decrease in loan growth rate by 1 percentage point $(0.44 \times (-0.0248) = -1\%)$, which is equivalent to 50% of the average loan growth rate in our sample and 20% of the standard deviation.

A key identification challenge for our tests on the effects of payment risks on banks' loan provision is that the equilibrium amount of bank loans also depends on the loan demand (which may in turn correlate with payment activities), especially if loan demand varies across different regions. Our inclusion of $State \times Quarter$ two-way fixed effects in Table 2 should partially alleviate such concerns, as it effectively controls for time-varying local demand at the headquarter state level. However, it does not fully control for potential loan demand for multi-state banks (especially those banks with branches in many states). To further address the challenge of uneven loan demand, we exploit branch-level information from RateWatch and use a subsample that contains only single-state banks (that is, banks with branches in just one state). If our results remain strong for this single-state subsample with the inclusion of $State \times Quarter$ two-way fixed effects, the concern for local demand should be minimized.[15]

[15]For a bank with multiple branches within the same state, its branches can usually pool their funds and coordinate their loan decisions. This contrasts the case with deposits, where branches within the same state may face different

Using the single-state subsample, we repeat our tests and report the regression results in Table 3. Across all specifications, we include $State \times Quarter$ two-way fixed effects. Table 3 shows that when restricting our sample to single-state banks, test results are similar to those in Table 2, both in terms of magnitude and significance, suggesting that our results are unlikely driven by client demand, but by banks' lending decisions.

4.2 Payment risk and bank lending: robustness

In this section, we show the robustness of our key findings on the negative impact of payment risks on bank lending. First, it is well known that banks of different sizes behave differently (Kishan and Opiela, 2000; Afonso, Kovner, and Schoar, 2011; Ashcraft, McAndrews, and Skeie, 2011). A multi-state big bank with numerous branches may make its loan decisions quite differently from what a small local bank does. To address the concern that the negative relationship between loan growth and payment risk measures is driven by certain group of banks, we conduct our tests separately for banks of different sizes. Specifically, we sort banks into four groups based on their asset sizes in each quarter and estimate the following model:

$$Loan\ growth_{i,t+1} = \alpha + \beta \times Payment\ risk_{i,t} + \gamma \times Controls_{i,t} + \mu_{state,t} + \mu_{type,t} + \epsilon_{i,t+1}, \quad (16)$$

where $Payment\ risk$ indicates either $Flow\ volatility$ or $Counterparty\ HHI$, control variables are the same as in Model (14), $\mu_{state,t}$ is State$\times$Quarter two-way fixed effect, and $\mu_{type,t}$ is Type$\times$Quarter two-way fixed effect.

We report regression results of Equation (16) for four subsamples in Table 4, where "bottom size quartile" representing the group of smallest banks and "top size quartile" the group of largest

levels of local competition (Drechsler, Savov, and Schnabl, 2017).

banks. Our results show that the estimated coefficients on $Flow\ volatility$ and $Counterparty\ HHI$ are all negative and highly significant across four subsamples, and the magnitude of the coefficients are comparable across subsamples. Therefore, we show that the negative effect of payment risks on lending holds for banks of different sizes.

Next, we calculate loan growth rates based on different types of loans: core loan (the sum of real estate loan, commercial and industrial loan, and consumer loan), loan with maturity over three years, and loan with maturity over five years. We then replace total loan growth rate with these alternative loan growth rates as dependent variables and repeat our tests.

Table 5 reports test results using alternative loan growth rates as dependent variables. Columns (1)–(2) show that the regression results are similar to those in Table 2 when using core loan to calculate loan growth rate. Columns (3)–(6) show that the estimated coefficients on payment risks remain negative and highly significant when we focus on long-term loans, with the magnitude increased by almost 50% for over-three year loans and almost doubled for over-five-year loans compared to that of all loan. It is worth noting that adjusted R^2 decrease notably for tests on long-term loans, suggesting that the predictive power of other bank characteristics on long-term loans deteriorates substantially while the predictive power of payment risks remains strong. The finding that payment risk affects long-term loans more is consistent with the timing assumption in our model – for payment risk to matter, loans cannot be repaid or resold before payment settlement. Long-term loans have longer maturities and are likely to be more illiquid in secondary markets due to riskiness and information sensitivity, so our mechanism is stronger among long-term loans.

4.3 Payment risk and bank liquidity holdings

So far we have tested Hypothesis H1 in Section 2 that payment risk negatively affects bank lending. Another prediction of the model (i.e., Hypothesis H2) is that payment risk is also associated with a higher liquidity ratio (the ratio of reserves or other liquid assets to total assets). Lending comes with payment risk, while reserves do not bear such risk and can actually buffer the negative impact of payment risk by reducing the bank's needs for costly interbank borrowing. So a bank facing higher payment risk sets a higher liquidity ratio.

To test this hypothesis, we start by estimating the following model:

$$Liquidity\ ratio_{i,t+1} = \alpha + \beta \times Payment\ risk_{i,t} + \gamma \times Controls_{i,t} + \mu_{state,t} + \mu_{type,t} + \epsilon_{i,t+1}, \quad (17)$$

where $Liquidity\ ratio_{i,t+1}$ is defined as the ratio of liquid assets (including cash and available-for-trade securities) to total assets in quarter $t+1$, and $Payment\ risk$ indicates either $Flow\ volatility$ or $Counterparty\ HHI$. Control variables include $Trading\ ratio$, $Capital\ ratio$, $Deposit\ ratio$, $Return\ on\ asset$, $\log(Size)$, squared $\log(Size)$, and $Number\ of\ states$. $\mu_{state,t}$ represents State$\times$Quarter two-way fixed effects, and $\mu_{type,t}$ represents Type$\times$Quarter two-way fixed effects. Standard errors are clustered at the bank and quarter levels.

We present regression results of Equation (17) in Table 6. Column (1) shows that the estimated coefficient on $Flow\ volatility$ is strongly positive and significant, suggesting that banks bearing higher payment risks tend to hold more liquid assets on their balance sheets. Specifically, an interquartile-range increase in $Flow\ volatility$ is associated with an increase of 4 percentage points in liquidity ratio (20% of the average liquidity ratio and 29% of the standard deviation). We further control for bank fixed effects in column (2), and our results remain robust, although the coefficient on $Flow\ volatility$ is smaller in magnitude.

We use $Counterparty\ HHI$ as the payment risk measure in columns (3)–(4) of Table 6 and obtain even stronger results. In particular, column (3) shows that an interquartile-range increase in $Counterparty\ HHI$ is associated with an increase of 8 percentage points in liquidity ratio

(40% of the average liquidity ratio and 57% of the standard deviation). Our results hold with the inclusion of bank fixed effects, as shown in column (4).

In sum, we find that banks on average hold more liquid assets when their payment risks are higher, and this result holds both cross-sectionally and for a given bank. Our results echo the recent finding from Copeland, Duffie, and Yang (2021) on the repo market turmoil induced by the reduction of aggregate reserves held by banks and the associated intraday payment timing stresses. Payment risk is often studied with other high frequency (intraday or daily) variables such as interbank borrowing and repo market activities. Our findings show that payment risk propagates into banks' lending decisions at lower (quarterly) frequencies.

4.4 Can funding stress amplify the impact of payment risks?

We explore potential factors that can amplify or dampen the impact of payment risks on bank lending. Specifically, we test Hypothesis H3 in Section 2. Intuitively, banks' concerns for payment risk should be alleviated when the costs of covering payment outflows with interbank borrowings are low, and such concerns should heighten when the interbank market is under stress. That is, the impact of payment risks on bank lending should be amplified by interbank market stress. To test this hypothesis, we estimate the following model:

$$\begin{aligned}Loan\ growth_{i,t+1} = \alpha + \beta_1 \times \textbf{\textit{LIBOR–OIS}}\ spread_{t+1} \times Payment\ risk_{i,t} + \\ \beta_2 \times Payment\ risk_{i,t} + \gamma \times Controls_{i,t} + \mu_{state,t} + \mu_{type,t} + \mu_i + \epsilon_{i,t+1}, \quad (18)\end{aligned}$$

where $LIBOR--OIS\ spread_{t+1}$ is the spread between the 1-month London Interbank Offered Rate (LIBOR) and the overnight index swap (OIS) of the same maturity (in percent), which is a key measure of credit risk and funding stress within the banking sector (Taylor, 2009; Klingler and Syrstad, 2021). $Payment\ risk$ indicates either $Flow\ volatility$ or $Counterparty\ HHI$, control variables are defined the same as in Equation (14), $\mu_{state,t}$ represents State×Quarter two-way fixed effects, $\mu_{type,t}$ represents Type×Quarter two-way fixed effects, and μ_i is bank fixed effects.[16] Standard errors are clustered at the bank and quarter levels.

We report regression results of Equation (18) in Table 7. 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. This result is economically significant. Specifically, for a bank with a median level of $Flow\ volatility$ (0.54), a 50-basis-point increase in $LIBOR\text{-}OIS\ spread$ is associated with an additional decrease in loan growth by 3 percentage points ($-0.1039 \times 0.54 \times 0.5 = 3\%$), which is 1.5 times the average loan growth rate in our sample.

We also use an alternative measure to gauge funding costs for banks, namely, $TED\ spread$, which is the spread between 3-month LIBOR based on US dollars and 3-month Treasury Bill. While ***LIBOR–OIS*** $spread$ is a key measure of funding stress within the banking sector, $TED\ spread$ is generally considered as the indicator for credit risk and funding pressure in the broader economy. We replace ***LIBOR–OIS*** $spread$ with $TED\ spread$ and re-estimate Equation (18). Column (2) of Table 7 shows that the interaction term between $Flow\ volatility$ and $TED\ spread$ also has a negative and significant coefficient, albeit with a smaller magnitude and less significance. In columns (3)–(4), we focus on the second payment risk measure, $Counterparty\ HHI$, and obtain similar results. In sum, we show that for a given bank, short-term funding market stress is a key factor that determines how much payment risks affect bank lending. The higher funding costs are, the more payment risks inhibit lending.[17]

[16]Note that 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 less strict specifications.

[17]Our results are robust cross-sectionally, i.e., without bank fixed effects (available upon request).

4.5 Payment risks and monetary policy transmission

In this section, we study how payment risks affect the credit channel of monetary policy transmission (Hypothesis H4 in Section 2). Our model features the bank lending channel of monetary policy transmission (Bernanke and Blinder, 1992; Bernanke and Gertler, 1995; Kashyap and Stein, 2000; Adrian and Song Shin, 2010; Gertler and Kiyotaki, 2010; Woodford, 2010; Jiménez, Ongena, Peydró, and Saurina, 2012; Iyer, Peydró, da Rocha-Lopes, and Schoar, 2013; Jiménez, Ongena, Peydró, and Saurina, 2014; Heider, Saidi, and Schepens, 2019). When the central bank intervenes in the interbank market and lowers interest rate, the bank lends more. However, the transmission is dampened by payment risk. Intuitively, for banks that face greater payment risk, they are more cautious in their response to a more favorable funding environment.

In Figure 7, we start our analysis by presenting the response in bank lending to different ranges of policy rate changes. Given the level of payment risk, we find that a lower policy rate is associated with more lending (i.e., the bank lending channel of monetary policy transmission). Within each rate change category, banks with high payment risk respond less, suggesting that payment risk dampens the bank lending channel. Next we estimate the following regression:

$$\begin{aligned} Loan\ growth_{i,t+1} &= \alpha + \beta_1 \times \Delta FF\ rate_t + \beta_2 \times Payment\ risk_{i,t} + \\ &\beta_3 \times \Delta FF\ rate_t \times Payment\ risk_{i,t} + \gamma \times Controls_{i,t} + \mu_{state} + \mu_{type} + \epsilon_{i,t+1}, \quad (19) \end{aligned}$$

where $\Delta FF\ rate_t$ is the change of target federal funds rates over quarter t (in percent), $Payment\ risk$ indicates either $Flow\ volatility$ or $Counterparty\ HHI$, and control variables and fixed effects are defined the same as in Equation (14). Standard errors are clustered at bank and quarter levels.

We report regression results of Equation (19) in Table 8. Column (1) shows that $\Delta FF\ rate$ has a strongly negative coefficient, significant at 1% levels. This result suggests that increase (decrease) in policy rates leads to reduction (expansion) in loan provision, confirming the channel of policy rates in affecting credit supply. More importantly, the interaction term of $\Delta FF\ rate$ and $Flow\ volatility$ loads a positive coefficient, significant at the 1% level, suggesting that payment risks hinders monetary policy transmission. Specifically, for two banks in the 25th and 75th percentiles in terms of $Flow\ volatility$, a one-percentage-point decrease in target federal funds rates leads to a 4.4-percentage-point increase in loan growth for the 25th-percentile bank, while the same one-percentage-point decrease in rates leads to a 3.6-percentage-point increase in loan growth for the 75th-percentile bank.[18] In the extreme case of comparing two banks with the highest and the lowest $Flow\ volatility$ (1.05 and 0, respectively), the sensitivity of loan growth to policy rate change is reduced by half for the bank with highest payment risks. In column (2) of Table 8, we include State×Quarter and Type×Quarter two-way fixed effects, which renders $\Delta FF\ rate$ redundant. Our key results on the interaction term remain strong in this stricter specification. We further control for bank fixed effects in column (3) and obtain similar results, suggesting that for a given bank, its reaction to monetary policy change is strongly affected by payment risk.

We next use $Counterparty\ HHI$ as an alternative measure of payment risk and study its impact on the bank lending channel of monetary policy. Column (4) shows that an interquartile-range increase in $Counterparty\ HHI$ reduces the sensitivity of loan growth to policy rate change by 27% (from -4.5% to -3.3%).[19] The results remain robust with the inclusion of two-way fixed effects and bank fixed effects, as shown in columns (5)–(6).

In sum, our analysis shows that payment risks diminish the effectiveness of monetary policy on bank lending. It is also worth noting that even without any policy rate changes (i.e., when $\Delta FF\ rate = 0$), payment risk measures load strongly negative coefficients, suggesting that our

[18]The 4.4 percentage points are calculated as: $-0.0528 \times (-1) + 0.024 \times (-1) \times 0.37 = 4.4\%$. The 3.6 percentage points are calculated as: $-0.0528 \times (-1) + 0.024 \times (-1) \times 0.71 = 3.6\%$

[19]The -4.5% is calculated as: $-0.0536 + 0.0269 \times 0.31 = -4.5\%$, and the -3.3% is calculated as: $-0.0536 + 0.0269 \times 0.75 = -3.3\%$.

findings in Section 4.1 remain robust in the absence of monetary policy changes (that is, not driven by business or monetary cycles).

4.6 Payment risks and deposit rates

So far, we have tested the first four hypotheses in the baseline model in Section 2. Next, we test Hypothesis H5 in the extended model where the bank manages payment risk by raising deposit rate to attract cash inflows. In Figure 8, we plot the average deposit spread (relative to the fed funds rate) for each decile of payment risk. For both measures of payment risk, there exists a positive correlation between deposit rate and payment risk. Next, we estimate the following regression:

$$Deposit\ spread_{i,t+1} = \alpha + \beta \times Payment\ risk_{i,t} + + \gamma \times Controls_{i,t} + \mu_{state,t} + \mu_{type,t} + \epsilon_{i,t+1}, \quad (20)$$

where the dependent variable is defined as the spread of deposit rate relative to the federal funds rate in quarter $t+1$ (in percent). $Payment\ risk$ indicates either $Flow\ volatility$ or $Counterparty\ HHI$, control variables are defined the same as in Equation (14), $\mu_{state,t}$ represents State×Quarter two-way fixed effects, and $\mu_{type,t}$ represents Type×Quarter two-way fixed effects. Standard errors are clustered at the bank and quarter levels.

We report regression results of Equation (20) in Table 9. To illustrate the robustness of our results, we use deposit spreads for three different types of products: one-year CD at the 10K tier (columns (1)–(2)), money market account at the 10K tier (columns (3)–(4)), and saving account at the 2.5K tier (columns (5)–(6)).[20] Deposit rate information is obtained from RateWatch survey data and at the branch-week level. We aggregate such information to bank-quarter level. Across all

[20]The RateWatch data contain 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 use 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.

specifications, our results are consistent: banks with greater payment risks set higher retail deposit rates. Specifically, an interquartile-range increase in $Flow\ volatility$ is associated with an increase of 4 basis points in one-year CD spreads ($0.1059 \times 0.34 = 0.04$), as shown in column (1) of Table 9, and one interquartile-range increase in $Counterparty\ HHI$ is associated with an increase of 6 basis points in one-year CD spreads ($0.1289 \times 0.44 = 0.06$), as shown in column (2). Using deposit spreads of alternative products, we obtain consistent results (columns (3)–(6)).

In sum, we show that banks with higher payment risks set higher deposit rates across major deposit products, after controlling for various bank characteristics and fixed effects. This result is consistent with the notion that banks with high payment risks spend more effort in securing more stable funding by setting more competitive rates. Thus, we provide evidence that banks manage their payment risks not only on the asset side (through the response in their lending decisions) but also on the liability side of their balance sheets (through the adjustment of deposit rates).

5 Conclusion

Deposits are often regarded as stable sources of funding. This paper challenges this notion. Deposits serve as means of payment and carry payment risk. When banks issue deposits to finance lending, it is uncertain whether borrowers' payees are the lending banks' own depositors. Unexpected fund transfers drain reserves and may trigger costly financing in short-term funding markets.

Following Bolton, Li, Wang, and Yang (2020), our model treats deposits as debts with random maturities. Specifically, uncertain payment flows translate into a random fraction of deposits that are withdrawn at the interim dates. Our main hypothesis is that payment risk reduces bank lending. We find robust evidence for banks of different sizes and loans of short and long maturities. Banks address payment risk by raising deposit rates so that deposit flows can be internalized in a greater customer base. Consistent with our model, the negative impact of payment risk on bank lending is most prominent when wholesale funding markets are under stress. Finally, we find that payment risk dampens the bank lending channel of monetary policy transmission. Banks with higher payment risk expand lending less in response to rate cuts. Our findings support the mechanism in Bigio and Sannikov (2019) that emphasizes the jointly cutting rates and supplying reserves (with the latter alleviating the stress in frictional interbank markets (Afonso and Lagos, 2015)).

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Figure 4: **Data merge: Fedwire, RateWatch, and Call Report**

This figure shows the time series of total bank assets, separately for all 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 11 years from 2010:Q1 to 2020:Q4.

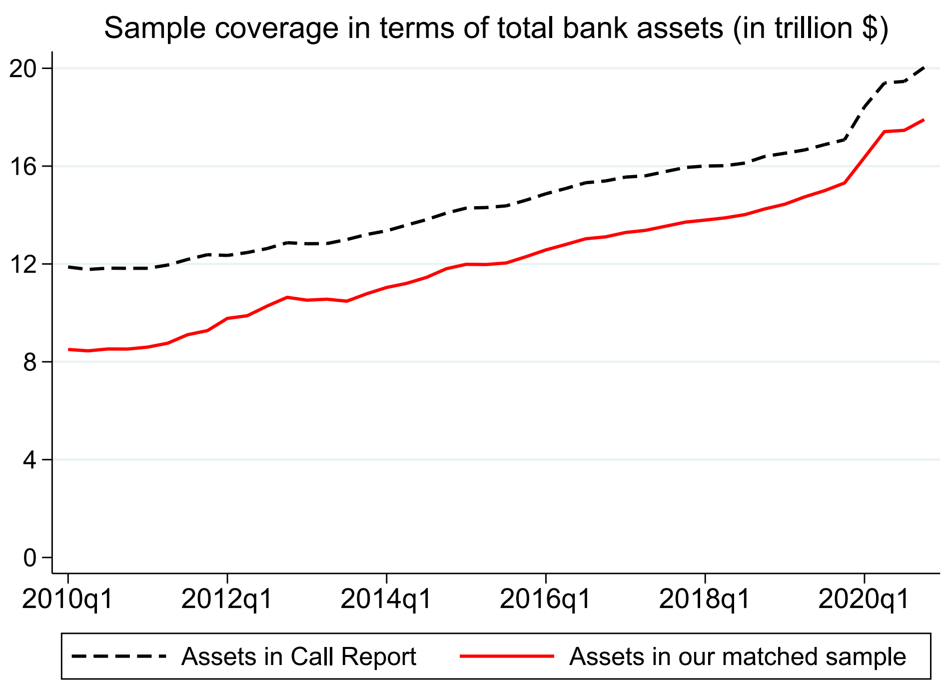


Figure 5: **Distribution of payment risk measures**

This figure shows the distribution of two normalized measures that gauge the instability of banks' payment flows and network: $Flow\ volatility$ (Panel A) and $Counterparty\ HHI$ (Panel B). $Flow\ volatility$ is defined as in Equation (9) and (10), and $Counterparty\ HHI$ is defined as in Equation (13). The sample is at the bank-quarter level and spans 11 years from 2010:Q1 to 2020:Q4.

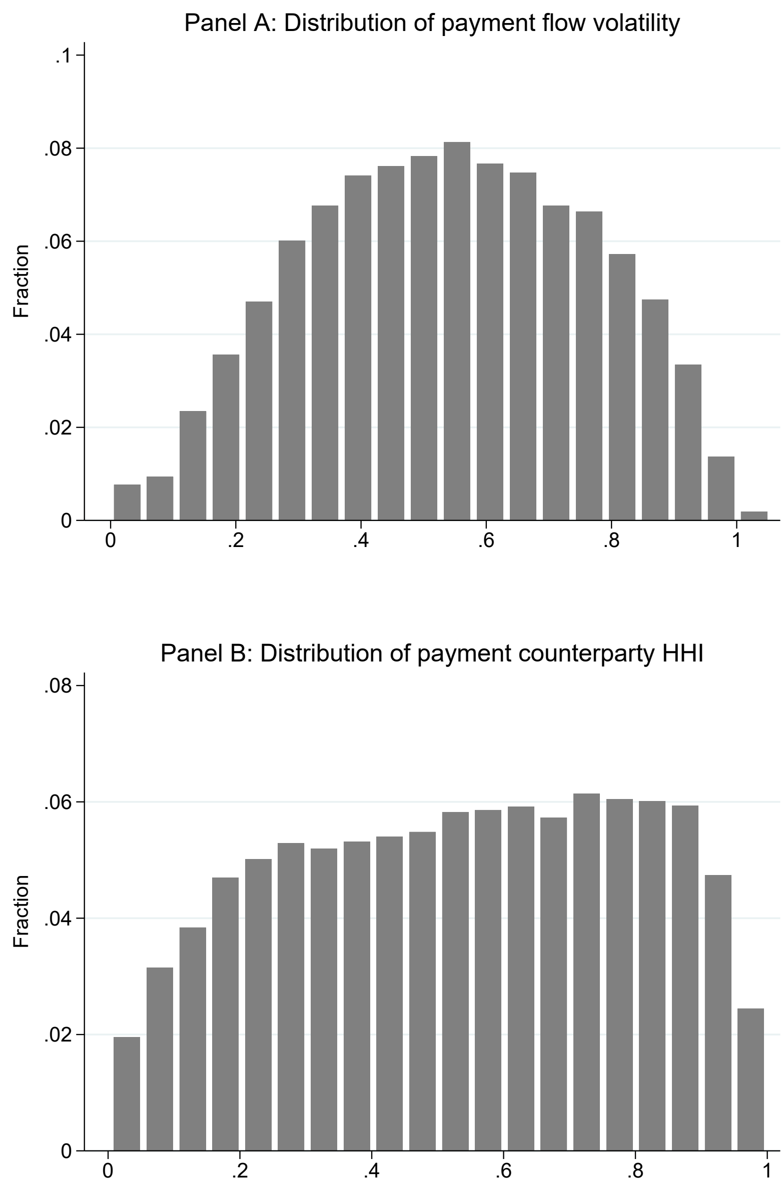
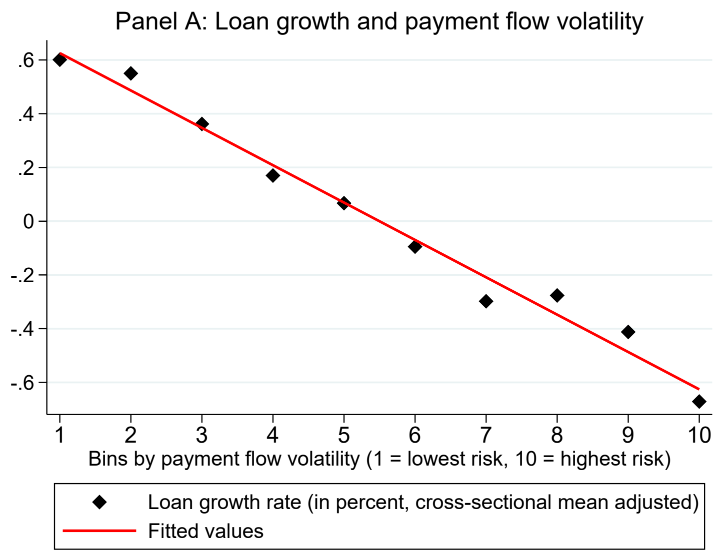


Figure 6: **Payment risk and bank lending**

This figure plots 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 (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 11 years from 2010:Q1 to 2020:Q4.



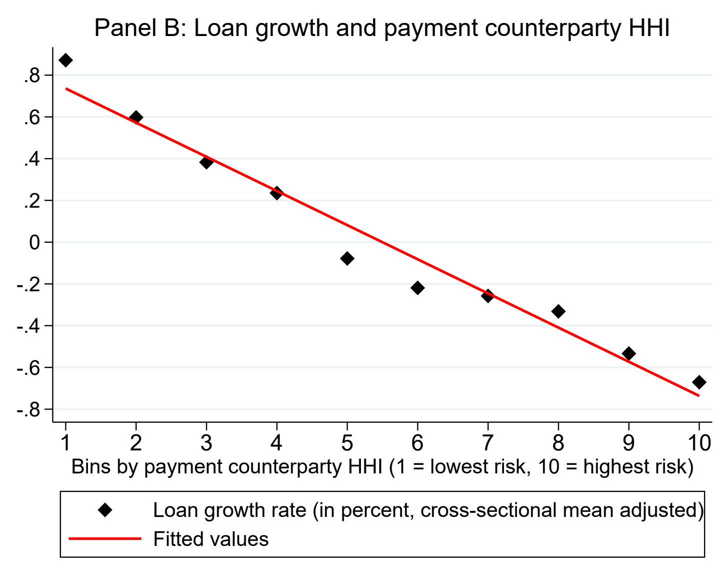
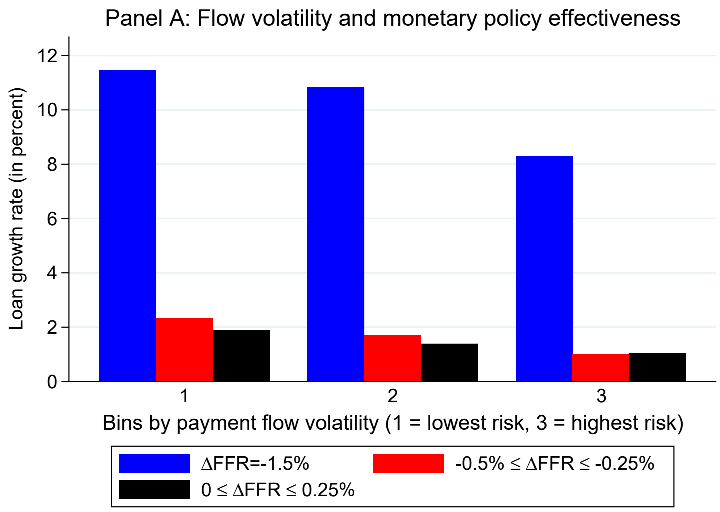


Figure 7: **Impact of payment risks on monetary policy effectiveness**

This figure depicts the impact of payment risks on monetary policy effectiveness. Specifically, for banks with different levels of payment risks, we plot their average loan growth rates following monetary policy changes. We define three monetary policy environments: very expansionary ($\Delta FFR = -1.5\%$), expansionary ($-0.5\% \leq \Delta FFR \leq -0.25\%$), and unchanged/slightly tightening ($0\% \leq \Delta FFR \leq 0.25\%$). We then sort banks into three 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 3 the group with the highest payment risk. We finally calculate the average loan growth rate for each risk bin under each monetary policy scenario. The sample is at the bank-quarter level and spans 11 years from 2010:Q1 to 2020:Q4.



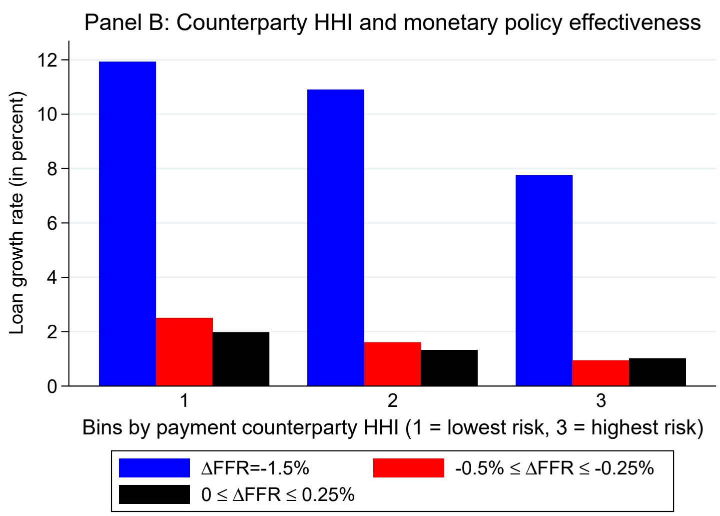
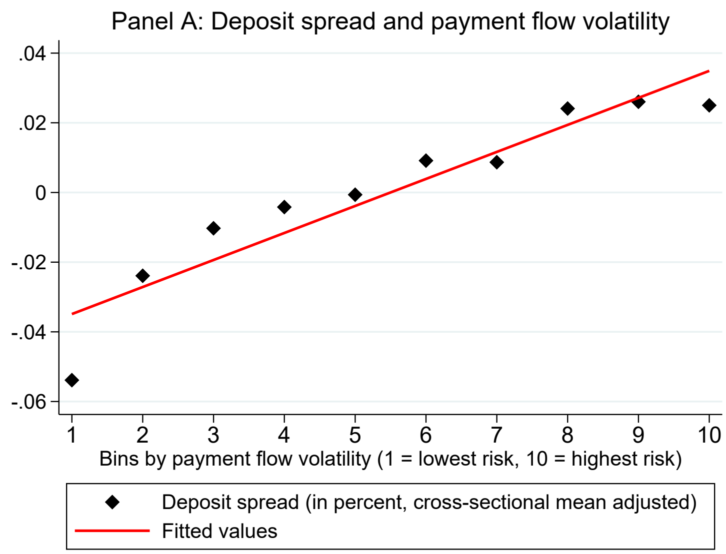


Figure 8: **Payment risks and deposit rates**

This figure plots the relationship between banks' deposit 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 deposit rate (based on 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 11 years from 2010:Q1 to 2020:Q4.



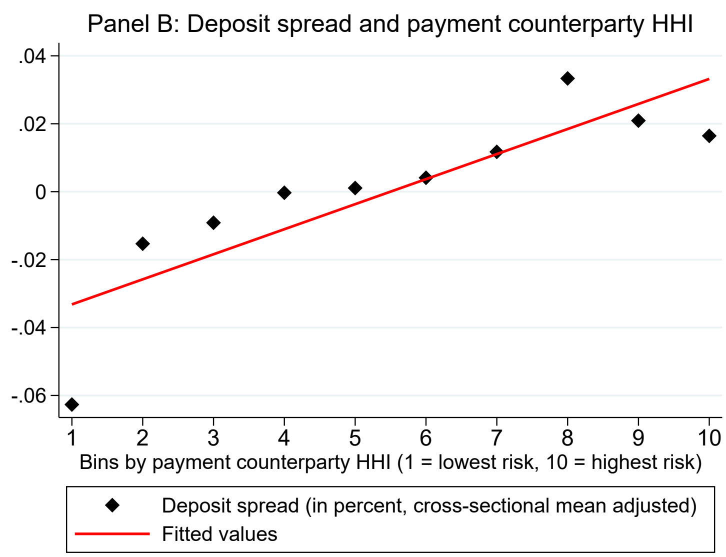


Table 1: **Summary Statistics**

This table provide summary statistics for key variables in our empirical analysis. The sample is at the bank-quarter level. $Asset$ is total bank asset, denominated in thousand dollars. $Liquidity\ ratio$ is defined as the sum of cash 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 $Asset$), $Capital\ ratio$ (risk-base capital divided by$Asset$), $Deposit\ ratio$ (nontransaction deposit divided $Asset$), 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 excess payment flows, and $Counterparty\ HHI$ gauges the concentration levels of a bank's payment receivers and senders. Both measures are calculated from transaction-level Fedwire data.

Variable	**N**	**Mean**	**S.D.**	**P25**	**P50**	**P75**
Asset (in thousands)	92546	4500179	56100000	194196	391999	881144
Liquidity ratio	92546	0.20	0.14	0.10	0.18	0.28
Loan ratio	92546	0.65	0.15	0.56	0.67	0.76
Trading ratio	92546	0.0001	0.0010	0.0000	0.0000	0.0000
Capital ratio	92546	0.11	0.03	0.09	0.11	0.12
Deposit ratio	92546	0.61	0.14	0.51	0.61	0.72
Return on asset	92546	0.0023	0.0024	0.0014	0.0023	0.0032
Number of states	92546	1.29	1.44	1	1	1
Loan growth rate	92546	0.02	0.05	-0.01	0.01	0.03
Spread of 10K 1-year CD	92093	-0.06	0.69	-0.37	0.13	0.35
Spread of 10K money market	88873	-0.41	0.74	-0.88	-0.07	0.04
Spread of 2.5K saving	91624	-0.45	0.75	-0.93	-0.08	0.03
Flow volatility	92546	0.54	0.22	0.37	0.54	0.71
Counterparty HHI	92546	0.53	0.26	0.31	0.54	0.75

Table 2: **Payment risks and loan growth rate**

The dependent variable is loan growth rate in quarter $t+1$ ($loan_{t+1}/loan_t - 1$), winsorized at the top and bottom 0.5% levels. The sample is at the bank-quarter levels, spanning from 2010:Q1 to 2020:Q4. $Flow\ volatility$ is the standard deviation of a bank's daily excess payment flows, and $Counterparty\ HHI$ gauges the concentration levels of a bank's payment receivers and senders. Both measures are calculated from transaction-level Fedwire data in quarter t. Control variables are calculated from Call Report data as of quarter t. $Liquidity\ ratio$ is defined as the sum of cash and available-for-trade securities, normalized by bank total asset. $Loan\ ratio$ (loan), $Trading\ ratio$ (trading assets), $Capital\ ratio$ (risk-base capital), $Deposit\ ratio$ (nontransaction deposit), and $Return\ on\ asset$ (net income) are similarly defined, 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)	(5)	(6)
Flow volatility	-0.0141***	-0.0140***	-0.0052**			
	(-4.35)	(-4.30)	(-2.07)			
Counterparty HHI				-0.0248***	-0.0245***	-0.0157***
				(-4.90)	(-4.76)	(-3.28)
Liquidity ratio	0.0014	0.0015	0.0040	0.0031	0.0032	0.0044
	(0.34)	(0.38)	(0.66)	(0.82)	(0.86)	(0.72)
Loan ratio	0.0038	0.0057	-0.0965***	0.0026	0.0045	-0.0976***
	(0.94)	(1.45)	(-9.42)	(0.63)	(1.13)	(-9.42)
Trading ratio	-0.0974	-0.0833	-0.5810***	-0.0722	-0.0598	-0.5578***
	(-0.29)	(-0.25)	(-3.30)	(-0.21)	(-0.18)	(-3.15)
Capital ratio	0.0320*	0.0341**	0.1185***	0.0354**	0.0375**	0.1185***
	(1.91)	(2.06)	(3.28)	(2.10)	(2.24)	(3.28)
Deposit ratio	-0.0084***	-0.0073***	-0.0049	-0.0075***	-0.0065**	-0.0044
	(-3.33)	(-2.94)	(-0.90)	(-3.02)	(-2.64)	(-0.81)
Return on asset	0.5948**	0.4932*	0.5615***	0.6109**	0.5125*	0.5500***
	(2.20)	(1.79)	(3.05)	(2.27)	(1.88)	(3.01)
log(Size)	0.0172***	0.0167***	0.0226	0.0074*	0.0071*	0.0161
	(3.97)	(3.96)	(0.93)	(1.92)	(1.88)	(0.66)
(log(Size))^2	-0.0006***	-0.0006***	-0.0018**	-0.0004**	-0.0003**	-0.0016*
	(-3.82)	(-3.82)	(-2.12)	(-2.46)	(-2.46)	(-1.91)
Number of states	0.0010***	0.0010***	-0.0023*	0.0010**	0.0010**	-0.0023*
	(2.75)	(2.71)	(-1.96)	(2.63)	(2.60)	(-1.99)
State FE	Yes			Yes		
Type FE	Yes			Yes		
Quarter FE	Yes			Yes		
State × Quarter FE		Yes	Yes		Yes	Yes
Type × Quarter FE		Yes	Yes		Yes	Yes
Bank FE			Yes			Yes
Adjusted R^2	0.122	0.138	0.222	0.124	0.141	0.222
N of Obs.	92546	92528	92449	92546	92528	92449

Table 3: **Payment risks and loan growth rate: control for loan demand**

The dependent variable is loan growth rate in quarter $t + 1$, winsorized at the top and bottom 0.5% levels. The sample is at the bank-quarter levels and includes only banks with branches in a single state, spanning from 2010:Q1 to 2020:Q4. $Flow\ volatility$ is the standard deviation of a bank's daily excess payment flows, and $Counterparty\ HHI$ gauges the concentration levels of a bank's payment receivers and senders. Both measures are calculated from transaction-level Fedwire data in quarter t. Control variables are calculated as of quarter t and include $Liquidity\ ratio$, $Loan\ ratio$, $Trading\ ratio$, $Capital\ ratio$, $Deposit\ ratio$, $Return\ on\ asset$, $\log(Size)$, 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	-0.0138***	-0.0051*		
	(-4.22)	(-1.96)		
Counterparty HHI			-0.0241***	-0.0169***
			(-4.47)	(-3.27)
Liquidity ratio	0.0025	0.0046	0.0040	0.0051
	(0.64)	(0.68)	(1.07)	(0.74)
Loan ratio	0.0062	-0.1006***	0.0047	-0.1019***
	(1.57)	(-9.40)	(1.15)	(-9.38)
Trading ratio	0.0303	-0.3186	0.1010	-0.2793
	(0.06)	(-1.59)	(0.20)	(-1.39)
Capital ratio	0.0367**	0.1339***	0.0402**	0.1340***
	(2.07)	(3.39)	(2.25)	(3.39)
Deposit ratio	-0.0076***	-0.0066	-0.0067**	-0.0061
	(-2.95)	(-1.10)	(-2.62)	(-1.00)
Return on asset	0.4325	0.4920**	0.4485	0.4776**
	(1.50)	(2.57)	(1.57)	(2.51)
log(Size)	0.0043	0.0414	-0.0036	0.0358
	(0.73)	(1.44)	(-0.70)	(1.25)
$(\log(\text{Size}))^2$	-0.0002	-0.0024**	0.0001	-0.0023**
	(-0.67)	(-2.39)	(0.25)	(-2.27)
Controls	Yes	Yes	Yes	Yes
State × Quarter FE	Yes	Yes	Yes	Yes
Type × Quarter FE	Yes	Yes	Yes	Yes
Bank FE		Yes		Yes
Adjusted R^2	0.150	0.238	0.153	0.238
N of Obs.	80486	80402	80486	80402

Table 4: **Payment risks and loan provision: by bank size**

The dependent variable is loan growth rate in quarter $t+1$, winsorized at the top and bottom 0.5% levels. The sample is at the bank-quarter levels and in each quarter sorted into four subsamples based on bank size, spanning from 2010:Q1 to 2020:Q4. $Flow\ volatility$ is the standard deviation of a bank's daily excess payment flows, and $Counterparty\ HHI$ gauges the concentration levels of a bank's payment receivers and senders. Both measures are calculated from transaction-level Fedwire data in quarter t. Control variables are calculated as of quarter t and include $Liquidity\ ratio$, $Loan\ ratio$, $Trading\ ratio$, $Capital\ ratio$, $Deposit\ ratio$, $Return\ on\ asset$, $\log(Size)$, 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 quartile		**2nd size quartile**		**3rd size quartile**		**Top size quartile**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Flow volatility	-0.0118***		-0.0123***		-0.0151***		-0.0140**	
	(-2.72)		(-3.49)		(-3.48)		(-2.41)	
Counterparty HHI		-0.0302***		-0.0230***		-0.0256***		-0.0209***
		(-3.43)		(-3.76)		(-4.64)		(-3.29)
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	0.136	0.151	0.154	0.152	0.155	0.120	0.121
N of Obs.	22993	22993	22964	22964	22945	22945	22987	22987

Table 5: **Payment risks and loan provision: by loan type**

The dependent variable is loan growth rate in quarter $t+1$, winsorized at the top and bottom 0.5% levels, with columns (1)–(2) based on core loan (real estate, commercial and industrial, and consumer loan), columns (3)–(4) on loans with maturity over three years, and columns (5)–(6) on loans with maturity over five years. The sample is at the bank-quarter levels, spanning from 2010:Q1 to 2020:Q4. $Flow\ volatility$ is the standard deviation of a bank's daily excess payment flows, and $Counterparty\ HHI$ gauges the concentration levels of a bank's payment receivers and senders. Both measures are calculated from transaction-level Fedwire data in quarter t. Control variables are calculated as of quarter t and include $Liquidity\ ratio$, $Loan\ ratio$, $Trading\ ratio$, $Capital\ ratio$, $Deposit\ ratio$, $Return\ on\ asset$, $\log(Size)$, 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	-0.0138***		-0.0198***		-0.0231***	
	(-4.27)		(-6.13)		(-2.96)	
Counterparty HHI		-0.0233***		-0.0329***		-0.0451***
		(-4.53)		(-6.54)		(-4.80)
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	0.131	0.133	0.056	0.057	0.008	0.008
N of Obs.	92528	92528	91109	91109	90943	90943

Table 6: **Payment risks and banks' liquid assets**

The dependent variable is liquidity ratio (cash and available-for-trade securities, normalized by bank asset) in quarter $t+1$, winsorized at the top and bottom 0.5% levels. The sample is at the bank-quarter levels, spanning from 2010:Q1 to 2020:Q4. $Flow\ volatility$ is the standard deviation of a bank's daily excess payment flows, and $Counterparty\ HHI$ gauges the concentration levels of a bank's payment receivers and senders. Both measures are calculated from transaction-level Fedwire data in quarter t. Control variables are calculated as of quarter t and include $Trading\ ratio$, $Capital\ ratio$, $Deposit\ ratio$, $Return\ on\ asset$, $\log(Size)$, 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: Liquidity ratio$_{t+1}$				
	(1)	(2)	(3)	(4)
Flow volatility	0.1154***	0.0210***		
	(7.72)	(3.67)		
Counterparty HHI			0.1805***	0.0611***
			(10.38)	(6.61)
Controls	Yes	Yes	Yes	Yes
State × Quarter FE	Yes	Yes	Yes	Yes
Type × Quarter FE	Yes	Yes	Yes	Yes
Bank FE		Yes		Yes
Adjusted R^2	0.130	0.876	0.147	0.877
N of Obs.	92528	92449	92528	92449

Table 7: **Can funding stress amplify the impact of payment risks?**

The dependent variable is loan growth rate in quarter $t + 1$, winsorized at the top and bottom 0.5% levels. The sample is at the bank-quarter levels, spanning from 2010:Q1 to 2020:Q4. $LIBOR - OIS\ spread$ is the spread between the 1-month London Interbank Offered Rate (LIBOR) and the overnight index swap (OIS), and $TEDspread$ is the spread between 3-month LIBOR based on US dollars and 3-month Treasury Bill yield, both calculated as of quarter $t + 1$.[21] $Flow\ volatility$ is the standard deviation of a bank's daily excess payment flows, and $Counterparty\ HHI$ gauges the concentration levels of a bank's payment receivers and senders. Both measures are calculated from transaction-level Fedwire data in quarter t. Control variables are calculated as of quarter t and include $Liquidity\ ratio$, $Loan\ ratio$, $Trading\ ratio$, $Capital\ ratio$, $Deposit\ ratio$, $Return\ on\ asset$, $\log(Size)$, squared $\log(Size)$, and $Number\ of\ states$, as defined in Table 2. Columns (1)–(2) additionally control for $Flow\ volatility$, and columns (3)–(4) control for $Counterparty\ HHI$. 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 × LIBOR-OIS spread	-0.1039**			
	(-2.46)			
Flow volatility × TED spread		-0.0377*		
		(-1.93)		
Counterparty HHI × LIBOR-OIS spread			-0.1039**	
			(-2.26)	
Counterparty HHI × TED spread				-0.0395*
				(-1.93)
Controls	Yes	Yes	Yes	Yes
State × Quarter FE	Yes	Yes	Yes	Yes
Type × Quarter FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.223	0.223	0.222	0.223
N of Obs.	92449	92449	92449	92449

Table 8: **Payment risks and (in)effectiveness of monetary policy**

The dependent variable is loan growth rate in quarter $t+1$, winsorized at the top and bottom 0.5% levels. The sample is at the bank-quarter levels, spanning from 2010:Q1 to 2020:Q4. $\Delta FF\ rate$ is the change of target federal funds rates over quarter t. $Flow\ volatility$ is the standard deviation of a bank's daily excess payment flows, and $Counterparty\ HHI$ gauges the concentration levels of a bank's payment receivers and senders. Both measures are calculated from transaction-level Fedwire data in quarter t. Control variables are calculated as of quarter t and include $Liquidity\ ratio$, $Loan\ ratio$, $Trading\ ratio$, $Capital\ ratio$, $Deposit\ ratio$, $Return\ on\ asset$, $\log(Size)$, 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)	(5)	(6)
ΔFF rate	-0.0528***			-0.0536***		
	(-3.31)			(-3.54)		
ΔFF rate×Flow volatility	0.0240***	0.0175***	0.0187***			
	(4.12)	(3.19)	(2.90)			
ΔFF rate×Counterparty HHI				0.0269***	0.0199***	0.0205***
				(5.50)	(3.57)	(3.12)
Flow volatility	-0.0100***	-0.0140***	-0.0051*			
	(-3.72)	(-4.94)	(-1.99)			
Counterparty HHI				-0.0215***	-0.0243***	-0.0153***
				(-5.17)	(-5.39)	(-3.40)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes			Yes		
Type FE	Yes			Yes		
State × Quarter FE		Yes	Yes		Yes	Yes
Type × Quarter FE		Yes	Yes		Yes	Yes
Bank FE			Yes			Yes
Adjusted R^2	0.062	0.139	0.222	0.065	0.141	0.223
N of Obs.	92546	92528	92449	92546	92528	92449

Table 9: **Payment risks and deposit rates**

The dependent variable is the spread of 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. The sample is at the bank-quarter levels, spanning from 2010:Q1 to 2020:Q4. $Flow\ volatility$ is the standard deviation of a bank's daily excess payment flows, and $Counterparty\ HHI$ gauges the concentration levels of a bank's payment receivers and senders. Both measures are calculated from transaction-level Fedwire data in quarter t. Control variables are calculated as of quarter t and include $Liquidity\ ratio$, $Loan\ ratio$, $Trading\ ratio$, $Capital\ ratio$, $Deposit\ ratio$, $Return\ on\ asset$, $\log(Size)$, 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	0.1059***		0.0481***		0.0594***	
	(4.20)		(3.34)		(4.69)	
Counterparty HHI		0.1289***		0.0727***		0.0984***
		(4.14)		(3.38)		(5.42)
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	0.830	0.830	0.956	0.956	0.972	0.972
N of Obs.	92074	92074	88844	88844	91606	91606