Payment Risk and Bank Lending: The Tension between the Monetary and Financing Roles of Deposits*

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Abstract

Banks finance lending with deposits and support the operation of payment system by allowing depositors to freely transfer funds in and out of their deposit accounts. This bundling of financial services creates a liquidity mismatch. Using granular payment data, we characterize a sizeable liquidity risk exposure that banks face due to highly volatile payment flows. Payment risk is a form of funding stability risk that is unique to banks. Our analysis demonstrates the tension between the monetary role and financing role of deposits. We find that payment risk dampens bank lending: An interquartile increase in payment risk is associated with a decline in loan growth that is 10%–20% of its standard deviation. This detrimental effect is amplified by funding stress in broader financial markets and is stronger for undercapitalized banks. Furthermore, payment risk impedes the bank lending channel of monetary policy transmission. Finally, we characterize how banks mitigate payment risk by adjusting deposit rates.

Keywords: Credit supply, deposits, payment, funding stability, monetary policy transmission

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

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1 Introduction

The money view of banking places emphasis on the liability side of a bank's balance sheet, highlighting the critical role of deposits as a means of payment (e.g., Friedman and Schwartz, 1963). The credit view focuses instead on the asset side, underscoring the significance of bank loans as unique sources of financing for the real economy (e.g., Bernanke, 1983). Banks have traditionally provided both payment services and credit, but is such bundling efficient?

In this paper, we present the first evidence on the negative impact of liquidity risk from payment activities on bank lending. Banks face a trade-off when financing loans with deposits. Depositors accept relatively low interest rates for the convenience of using deposits as means of payment or just out of inertia (Drechsler, Savov, and Schnabl, 2017).[1] However, deposits bear payment risk. To ensure the seamless operation of payment system, banks allow depositors to transfer funds freely in and out of their accounts. When a depositor sends money to depositors at a different bank, her bank loses an equal amount of reserves to the payee's bank under real-time gross settlement. This loss of liquidity is costly for the sender bank, especially given that frictions in the interbank market impede a smooth redistribution of liquidity from banks with a surplus to those in a deficit.

Payment risk is a form of funding stability risk that is unique to banks and inherent in the monetary role of deposits. Thus, our findings highlight the connection between funding risk and bank lending (Ivashina and Scharfstein, 2010; Cornett et al., 2011; Dagher and Kazimov, 2015; Ivashina et al., 2015). Deposits are often considered as a stable source of funding (e.g., Hanson et al., 2015). However, even insured deposits bear payment risk. Depositors may move funds out of their accounts not for the fear of bank failure but to transact. Banks are exposed to significant liquidity risk from payment flows. The average weekly transaction volume in Fedwire, the primary

[1] See recent studies on the premium on monetary assets (Krishnamurthy and Vissing-Jørgensen, 2012; Stein, 2012; Greenwood, Hanson, and Stein, 2015; Krishnamurthy and Vissing-Jørgensen, 2015; Sunderam, 2015; Nagel, 2016)

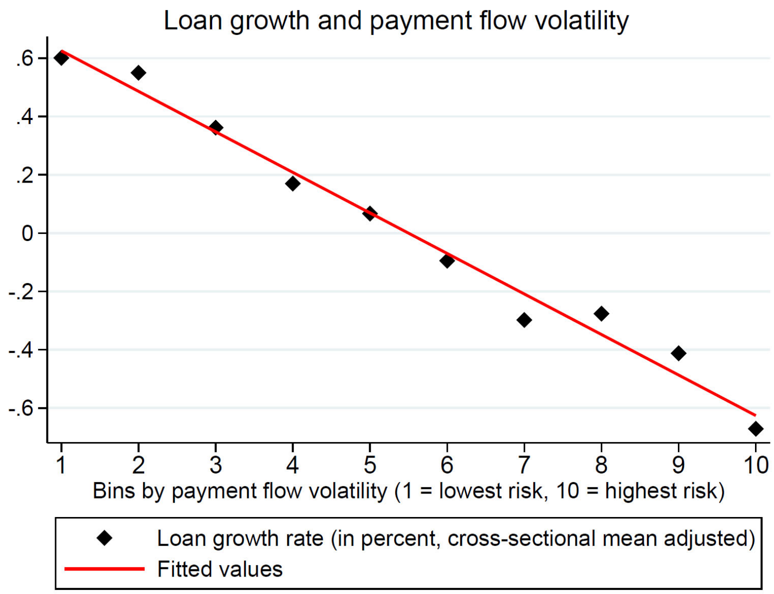


Figure 1: **Payment risk and loan growth (percentage).** This figure reproduces Figure 7A. We sort bank-quarter observations into 10 bins based on their previous-quarter payment flow volatility (defined in Section 3) with bin 1 representing the group with the lowest payment risk, and bin 10 the group 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.

payment system in the U.S. (our data source), exceeds GDP. The volatility of payment flows is more than 12% of a bank's reserve holdings on an average day.[2] Quantifying funding stability risk can be challenging. The Basel III definition of net stable funding ratio assigns ad hoc weights to funding sources, not based on bank characteristics.[3] In contrast, using granular payment data, we design measures of time-varying payment risk that are specific to a bank and its depositor clientele.

In Figure 1, we present a strong negative correlation between payment risk and loan growth. For a bank-quarter, we measure payment risk by the volatility of depositor-initiated payment flows in the previous quarter.[4] 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

[2]Payment flows do not automatically smooth out over time as the autocorrelation of payment flows is around zero.
[3]For example, retail deposits are assigned 100%, and bonds with a maturity of at least one year are assigned 85%.
[4]We focus on depositor-initiated transactions that banks cannot control rather than bank-initiated transactions.

eliminate potential effects of business cycles and seasonality.

The negative impact of payment risk on lending reflects banks' concern over liquidity mismatch: Deposits (and reserves) flow out of a bank following depositors' payment instructions, while loans cannot be readily sold to cover liquidity needs. Previous studies on liquidity mismatch have mainly focused on dramatic episodes such as bank runs or financial crises.[5] We focus instead on banks' day-to-day operations during a relatively stable period (2010-2020). Our sample is from 2010 to 2020, a relatively stable period. Our measures of payment risk are based on interbank transfers rather than system-wide cash withdrawals. Therefore, we emphasize that payment risk is relevant for all banks under all market conditions.

Our regression analysis confirms the negative impact of payment risks on bank lending, controlling for various bank characteristics, bank type (regular banks, credit unions, and saving & loan banks) fixed effects, location fixed effects, and year-quarter fixed effects. In an effort to bridge the payment literature and the literature on banking and macro-finance, we are the first to merge the payment-flow data (from the Fedwire Funds System) with the standard banking dataset, such as Call Report and RateWatch. 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 estimate is statistically significant and the magnitude is consistent across specifications.

To corroborate the economic mechanism, we consider an alternative measure of payment risk, namely the concentration (Herfindahl–Hirschman Index) of payment counterparty banks. Intuitively, if a bank's depositors send money to (or receive money from) depositors of only a few other banks, its payment flows can be easily affected by shocks specific to these banks' depositor

[5] The literature focuses on deposit outflows at distressed banks (e.g., Acharya and Mora, 2015; Martin, Puri, and Ufier, 2018; Brown, Guin, and Morkoetter, 2020). Outflows are triggered by fundamental news or due to coordination failure (i.e., bank runs) (Gorton, 1988; Saunders and Wilson, 1996; Calomiris and Mason, 1997; Iyer and Puri, 2012).

clienteles. Using this alternative measure, we find even stronger statistical significance and economic magnitude of the negative impact of payment risk impact on bank lending: An interquartile-range increase in counterparty concentration is associated with a decrease in loan growth rate by 1 percentage point, which is 20% of its standard deviation.

An identification challenge is that loan growth can be driven by demand (Khwaja and Mian, 2008; Puri, Rocholl, and Steffen, 2011; Jiménez, Ongena, Peydró, and Saurina, 2012; Becker and Ivashina, 2014). Including state$\times$quarter fixed effects alleviates the concern by controlling for time-varying local demand at bank headquarter state; nonetheless, this does not address the issue for multi-state banks. Therefore, we use the branch information from RateWatch to extract a subsample of single-state banks. Our results using this subsample are consistent with the full-sample results in terms of both magnitude and statistical significance. This suggests that our findings are unlikely to be explained by variations in loan demand driving both loan growth and payment risk.

To demonstrate the robustness of our findings, we conducted 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). Specifically, we sorted banks into four groups based on their total assets in each quarter. The estimated coefficients on both payment risk measures were found to be negative and significant across all subsamples. Furthermore, the magnitude of these coefficients was remarkably consistent across different size groups.

We anticipate that our results are stronger for loans with longer maturities. For short-term loans, banks expect repayments and associated liquidity inflows in the near future, so that the concern over liquidity drain due to depositors' payment outflows is weaker. This is indeed what we find. The estimated coefficients on payment risks are statistically significant across different loan maturities and display a monotonically increasing pattern in magnitude as the maturities increase.

The negative impact of payment risk on the growth rate of loans with maturities of five years or more is almost twice as large as the negative impact on all loans.

We then explore potential factors that may influence the extent to which payment risks affect bank lending. Intuitively, banks' concerns related to payment risk should be alleviated when the costs of obtaining short-term borrowings are low and heightened when the short-term funding markets are strained. Following Taylor (2009), we use the LIBOR–OIS spread as a 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 a median level of payment flow volatility, a 50-basis-point increase in the LIBOR–OIS spread significantly reduces loan growth by 3 percentage points, representing 60% of its standard deviation. We obtain similar results when using the TED spread as an alternative measure of funding stress and when using the counterparty HHI measure as an alternative proxy for payment risk.

Another factor that can influence the impact of payment risks on bank lending is overall availability of reserves. Bianchi and Bigio (2022) provide a theoretical analysis on how a reserve-supply increase improves the functioning of interbank liquidity market. We explore the variation in the balance of the Treasury General Account (TGA) as shocks to reserve supply (Correa, Du, and Liao, 2020; Copeland, Duffie, and Yang, 2021). We find that negative reserve shocks exacerbate the adverse effect of payment risk on bank lending. The advantage of this approach is that TGA variation is a relatively exogenous force while the interest-rate spreads tend to be affected by banks' aggregate liquidity needs that may correlate with payment activities or bank lending. Our results echo the recent findings in Copeland, Duffie, and Yang (2021) and highlight again that even though banks increased reserve holdings significantly after the global financial crisis, reserves may not be abundant, especially relative to the liquidity risk associated with the rising level of deposits

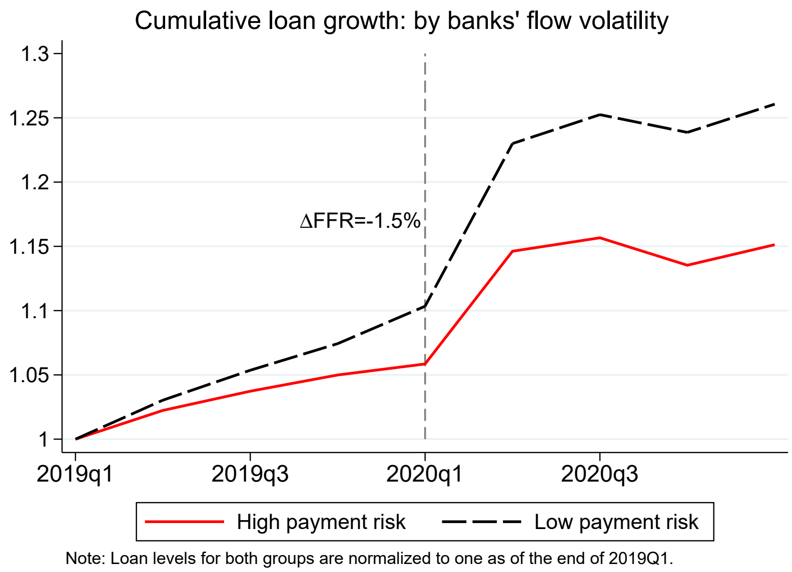


Figure 2: **Payment risk and monetary policy transmission.** We sort banks into tertiles based on their previous-quarter payment flow volatility and plot the cumulative loan growth based on average growth rate within the high and low tertiles, respectively. The reduction of 1.5% on target federal funds rates in 2020Q1 is marked in the figure.

(Acharya et al., 2023) and tighter liquidity regulations (d'Avernas and Vandeweyer, 2020).[6]

In addition to the aforementioned factors related to liquidity shortage, we consider how a bank's overall risk sensitivity affects the impact of payment risk on bank lending. Following Bolton et al. (2020), we use a bank's distance to breaching capital regulations as a proxy for its risk sensitivity and find that being close to the regulatory threshold amplifies the impact of payment risk. An interquartile-range increase in payment risk leads to a 1 percentage point decrease in loan growth rate for banks above the 5th percentile level of regulatory capital but a 1.6 percentage point decrease for those below this threshold. The effect is nonlinear: As a bank's regulatory capital deteriorates, the dampening effect of payment risk on lending becomes increasingly strong.

Next, we investigate how payment risk influences the effectiveness of monetary policy transmission through the bank lending channel (Bernanke and Blinder, 1992; Kashyap and Stein, 2000;

[6] Our results explain the findings in Kandrac and Schlusche (2021) on loan growth following reserve increase.

Jiménez, Ongena, Peydró, and Saurina, 2012, 2014; Iyer, Peydró, da Rocha-Lopes, and Schoar, 2013; Heider, Saidi, and Schepens, 2019; Ivashina, Laeven, and Moral-Benito, 2022). A decrease in the policy interest rate generally stimulates bank lending; however, payment risk weakens transmission. Intuitively, banks with higher payment risk are more prudent when responding to monetary easing. In Figure 2, we mark the 1.5 percentage point reduction in policy rate in 2020Q1 (in response to the COVID-19 crisis) and plot the loan growth paths (indexed to one at 2019Q1) for banks in the top and bottom tertiles of payment risks. Banks with higher payment risk are less responsive to monetary easing, as evidenced by the widening wedge between the loan growth paths of the high-risk and low-risk groups following the rate cut in 2020Q1. In our regression analysis, the interaction between rate change and payment risk has a significantly positive coefficient. Comparing two banks at the 25th and 75th percentiles of payment flow volatility, we find that a one percentage point decrease in the target federal funds rate leads to a 4.4-percentage-point increase in loan growth for the 25th-percentile and a 3.6-percentage-point increase for the 75th-percentile. We observe similar results when using the counterparty concentration to proxy for payment risk.

Finally, we explore a key mechanism through which banks can mitigate payment risk. When a bank raises deposit rate, its depositor base is likely to expand, thus allowing a greater fraction of payment flows to be internalized and a more stable deposit base secured. Therefore, banks facing greater payment risk have incentives to set higher deposit rates. To test this hypothesis, we consider three different types of deposit products: certificate of deposits, money market account, and saving account. We find that banks with greater payment risks set higher deposit rates across these major deposit products. Specifically, an interquartile-range increase in payment risk is associated with a 4–6 basis points increase in one-year CD spreads relative to the target Fed funds rate.

Literature review. Using confidential payment settlement data, we measure banks' liquidity risk exposure from depositors' payment activities and provide the first direct evidence of the tension between the financing role and monetary role of deposits.[7] When financing loans with deposits, banks are concerned about reserve depletion caused by deposit outflows due to payment activities because it is difficult to sell loans to replenish reserves.[8] Moreover, interbank market frictions limit banks' ability to smooth out payment shocks by lending reserves to each other.[9] Therefore, liquidity risk resulting from depositors' payment activities dampens banks' incentive to lend. Our findings offer a new perspective on the classic banking model of bundling payment services and credit provision and contribute to the broader debate on the synergy between bank lending and deposit-taking (e.g., Saidenberg and Strahan, 1999; Kashyap, Rajan, and Stein, 2002; Gatev and Strahan, 2006; Gatev, Schuermann, and Strahan, 2009; Acharya and Mora, 2015).

Payment risk is a form of funding stability risk inherent in the monetary role of deposits. Even insured deposits carry payment risk. Liquidity drain as a result of payment outflow does not arise from depositors' fear of bank failure, but rather from the transactions between depositors of different banks, which churn reserves in the banking system. As previously discussed, the volatility of payment flows is an average 12% of a bank's reserve holdings on a daily basis. Thus, payment risk is relevant for all banks and under all market conditions, and our focus is different from

[7] Historically, at the core of banking is financing illiquid assets such as loans with liquid liabilities such as deposits (Bryant, 1980; Diamond and Dybvig, 1983; Calomiris and Kahn, 1991; Donaldson, Piacentino, and Thakor, 2018). Empirically, both lending and deposit taking contribute to bank value (Egan, Lewellen, and Sunderam, 2021).

[8] Loutskina (2011) develops a measure of loan liquidity. Banks may influence loan resalability via covenants (Drucker and Puri, 2008) and obtain liquidity by exiting a loan syndicate (Irani and Meisenzahl, 2017). Loan commitment (lines of credit) may add to liquidity stress for banks in crises (Greenwald, Krainer, and Paul, 2020; Acharya, Engle, and Steffen, 2021; Kapan and Minoiu, 2021; Chodorow-Reich, Darmouni, Luck, and Plosser, 2022).

[9] A large empirical literature has documented a variety of frictions in interbank lending (e.g., Furfine, 2000; Ashcraft and Bleakley, 2006; Cocco, Gomes, and Martins, 2009; Bech and Atalay, 2010; Wetherilt, Zimmerman, and Soramäki, 2010; Afonso, Kovner, and Schoar, 2011; Angelini, Nobili, and Picillo, 2011; Ashcraft, McAndrews, and Skeie, 2011; Iyer and Peydró, 2011; Acharya, Gromb, and Yorulmazer, 2012; Schnabl, 2012; Acharya and Merrouche, 2013; Kuo, Skeie, Vickery, and Youle, 2013; Gabrieli and Georg, 2014; Afonso and Lagos, 2015; Gofman, 2017; Blasques, Bräuning, and van Lelyveld, 2018; Chapman, Gofman, and Jafri, 2019; Craig and Ma, 2021).

that of the existing literature on deposit outflows at distressed banks or during runs (e.g., Gorton, 1988; Saunders and Wilson, 1996; Calomiris and Mason, 1997; Iyer and Puri, 2012; Iyer, Puri, and Ryan, 2016; Egan, Hortaçsu, and Matvos, 2017; Martin, Puri, and Ufier, 2018; Brown, Guin, and Morkoetter, 2020; Chen, Goldstein, Huang, and Vashishtha, 2020; Jiang, Matvos, Piskorski, and Seru, 2023).[10] Moreover, our measures of payment risk capture the heterogeneity in banks' depositor clientele. This approach can be adopted in broader frameworks to improve the measurement of bank liquidity mismatch (Berger and Bouwman, 2009; Brunnermeier, Gorton, and Krishnamurthy, 2013; Bai, Krishnamurthy, and Weymuller, 2018) and to refine regulatory parameters such as the stability weights on different types of deposits in the Basel III net stable funding ratio.

Our findings of a negative impact of payment risk on bank lending contribute to the literature on bank funding risk and credit supply (e.g., Khwaja and Mian, 2008; Paravisini, 2008; Loutskina and Strahan, 2009; Ivashina and Scharfstein, 2010; Schnabl, 2012; Iyer, Peydró, da Rocha-Lopes, and Schoar, 2013; Benmelech, Meisenzahl, and Ramcharan, 2016; Acharya, Afonso, and Kovner, 2017).[11] Deposits are often regarded as a stable source of funds (e.g., Berlin and Mester, 1999; Drechsler, Savov, and Schnabl, 2017; Li, Loutskina, and Strahan, 2019; Drechsler, Savov, and Schnabl, 2021) and critical for financing loans (e.g., Gilje, Loutskina, and Strahan, 2016; Bustos, Garber, and Ponticelli, 2020; Carletti, De Marco, Ioannidou, and Sette, 2021). This paper does not challenge the reliability of deposits as sources of funds, especially relative to wholesale funding; rather, our emphasis is on the role of deposits as a means of payment and how such monetary function creates a unique form of funding risk. Bank may try to manage such risk, for example,

[10] A related topic is deposit withdrawal as discipline on 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).

[11] A 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; Diamond, Jiang, and Ma, 2020; Cortes, Demyanyk, Li, Loutskina, and Strahan, 2023).

through deposit-rate adjustment as we have documented.[12]

Our findings show that the liquidity churn in payment systems can significantly affect the broader macroeconomy through its impact on credit supply. While we focus on how payment risk propagates into bank balance-sheet management at quarterly frequencies, the literature on payment systems typically focuses on banks' decisions at higher frequencies and the operational efficiency of payment infrastructure. In particular, banks' intraday or daily reserve management and their discretion over intraday settlement timing (and the associated coordination failure) have been extensively studied (Poole, 1968; Hamilton, 1996; McAndrews 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; Ihrig, 2019; Yang, 2020; Denbee, Julliard, Li, and Yuan, 2021).[13] Our contribution is to provide the first evidence of the impact of payment risk on bank lending and deposit rate setting.

Payment risk weakens the bank lending channel of monetary policy transmission. This finding contributes to the vast literature on bank lending channel (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; Ivashina, Laeven, and Moral-Benito, 2022).[14] Bank characteristics have been shown to affect the bank lending channel of monetary policy transmission. For example, Acharya et al. (2020) find that undercapitalized banks respond less

[12]Related, Acharya and Mora (2015) focus on a different source of liquidity risk and find that banks with liquidity stress from loan 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; Heider, Saidi, and Schepens, 2019; Altavilla, Burlon, Giannetti, and Holton, 2022).

[13]Kahn and Roberds (2009) review the literature on payment systems.

[14]Our focus is on traditional monetary policy (rate target). A broader literature examines the impact of reserve supply and reserve market structure (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) 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; Luck and Zimmermann, 2020).

to monetary stimulus. Payment risk can be regarded as another important bank characteristic that is tied to the payment behavior of depositor clientele and weakens monetary policy transmission.

The rest of the paper is organized as follows: Section 2 lays out our empirical hypotheses; Section 3 describes the data sources and the methodology for calculating payment risk measures, and provides summary statistics; Section 4 presents the empirical results; and Section 5 concludes.

2 Hypothesis Development

In Section 2.1, we discuss the economic intuitions behind our empirical hypotheses. In Section 2.2, we develop a simple model to formalize these hypotheses.

2.1 Hypotheses

When a depositor of a bank sends money to a depositor of another bank, the 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 receiver's banks, shrinking the asset side as well.[15] Interbank market may facilitate risk sharing (Bhattacharya and Gale, 1987). After a deposit transfer, the sender's bank loses liquidity while the receiver's bank gains liquidity. Banks in a deficit may borrow from banks with a surplus. However, in reality, interbank borrowing is costly, involving various frictions and subject to occasional market freeze (e.g., Afonso, Kovner, and Schoar, 2011; Ashcraft, McAndrews, and Skeie, 2011; Iyer and Peydró, 2011; Schnabl, 2012; Acharya and Merrouche, 2013; Bianchi and Bigio, 2022; Afonso and Lagos, 2015; Gofman, 2017; Craig and Ma, 2021).[16]

[15] Fedwire adopts real-time gross settlement (RTGS). Kahn and Roberds (2015) analyze the difference between RTGS and deferred net settlement (DNS). In spite of the different degrees of netting across countries, banks ultimately settle payments with reserves held at their central bank accounts.

[16] It can also be costly for a bank to not replenish reserves. Reserves serve as precautionary savings and meet regulatory requirements on high-quality liquid assets (HQLA) (e.g., Ihrig, 2019; Correa, Du, and Liao, 2020; d'Avernas

Payment risk is a unique form of funding risk for banks because deposits serve as means of payment among non-bank entities (Piazzesi and Schneider, 2016). We focus on the implications of payment risk on bank lending. Financing loans with deposits adds liquidity risk exposure because depositors' payment outflows drain reserves but loans cannot be easily sold to replenish reserves. In contrast, raising deposits for acquiring securities that can be resold does not create liquidity risk. A bank unwilling to bear more liquidity risk has to either seek (more expensive) non-deposit financing or give up the lending opportunities and invest in liquid securities with lower yields. Our primary goal is to test whether payment risk makes banks more cautious in extending new loans.

Hypothesis 1: *Bank lending decreases in payment risk.*

If the interbank market is in stress, its risk-sharing role is compromised. Under such conditions, banks tend to be more cautious in financing loans with deposits and more sensitive to payment risk. Therefore, the negative impact of payment risk on bank lending is likely to be more prominent.

Hypothesis 2: *The negative impact of payment risk on bank lending is stronger when there is stress in the interbank reserve market.*

Empirically, we measure the stress in the interbank market (Fed funds market) by the commonly used TED spread and LIBOR-OIS spread. Moreover, we use variations in the Treasury General Account (TGA) as shocks to the net 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 interbank market. TGA variation has the advantage of being more exogenous to banks' lending decisions than the interest-rate spreads tied directly to the prices of interbank liquidity.

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 selling liquid assets such as Treasuries can be challenging.

The overall level of risk aversion affects a bank's sensitivity to payment risk and willingness to take on more payment risk by financing loans with deposits. In Bolton et al. (2020), a bank's distance to violating capital regulations is proxy for risk sensitivity. We test the following hypothesis on whether the lack of regulatory capital amplifies the impact of payment risk on lending.

Hypothesis 3: *The negative impact of payment risk on bank lending is stronger for more risk-sensitive banks with less regulatory capital.*

There is a large literature on the bank lending channel of monetary policy transmission, but payment risk, as a determinant of bank balance-sheet elasticity, has not been examined. We test whether under heightened liquidity risk, banks become less responsive to central banking lowering its interest rate target. Intuitively, the benefit of a lower cost of financing is partially offset by the liquidity risk associated with financing loans with deposits.

Hypothesis 4 (H4): *The positive impact of monetary easing on bank lending is dampened by payment risk.*

A bank concerned with deposit outflow and the draining of reserves may raise its deposit rate to attract deposit inflow. Moreover, a higher deposit rate expands a bank's depositor base (Drechsler, Savov, and Schnabl, 2017), so that when its depositors send money, the receivers are more likely to be its own depositors and, as a result, the bank does not incur any liquidity loss.

Hypothesis 5 (H5): *Banks with larger exposure to payment risk set higher deposit rates.*

2.2 Model

Next, we develop a stylized model that formalizes our hypotheses. We analyze a single bank's problem. At $t = 0$, the bank is endowed with m amount of reserves that are contributed by shareholders and equal to equity. Reserves are held at the central bank. The bank lends at $t = 0$. Depositors 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 finances y amount of loans with deposits. At $t = 1$, depositors make payments, and we denote the random fraction of deposits flowing out of the bank by g. When the bank's depositors send money, gy, to depositors of other banks, the bank sends out reserves to settle the transactions. Therefore, the reserve outflow is also $x = gy$. Following Bolton et al. (2020), we assume g is random with mean μ and variance σ^2. Note that payment outflow can also be viewed as depositors withdrawing cash. 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. In our model, deposits are debts with random maturities. A random fraction g matures at $t = 1$ while the rest mature at $t = 2$. Our focus is on payment risk, $\mathbb{V}ar(g) = \sigma^2$, and its impact on deposit-financed lending, y.

The cost of deposit and reserve outflow is given by $\tau_1(x - m) + \frac{\tau_2}{2}(x - m)^2$. When $x - m > 0$, the bank does not have enough reserves to cover the outflow, and this quadratic form represents an increasing and convex cost of obtaining external liquidity, for example, through interbank borrowing. The convexity, as microfounded in Bigio and Sannikov (2019) and Parlour, Rajan, and Walden (2020), can be motivated by frictions in the interbank market for reserve borrowing and lending (Afonso and Lagos, 2015).[17] When $x - m < 0$, this quadratic form presents an increasing and concave return on reserve lending. The concavity can also be motivated by frictions in the reserve market. Overall, the coefficient of the quadratic term, τ_2, captures frictions associated with the

[17] 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).

market for borrowing and lending reserves, and such frictions are more prominent (τ_2 increases) when the interbank market is under stress (see, e.g., Afonso, Kovner, and Schoar, 2011). The parameter τ_1 can be interpreted as a baseline cost of borrowing or return on lending reserves, which depends on the macroeconomic environment and monetary policy.

Before solving y, we clarify that the bank finances lending with deposits instead of reserves. Deposit issuance only causes a probabilistic reserve drawdown by a random fraction g (< 1) while lending out reserves causes a direct drawdown of liquidity. Therefore, as long as the marginal cost of spending reserves is above the deposit rate, the bank prefers financing loans with deposits rather than reserves. This assumption is in line with the evidence that deposits rates are below the Fed funds rate in our sample period (see, e.g., Drechsler, Savov, and Schnabl, 2017).

Next, we fully set up the bank's optimization problem and solve y. When the bank finances y amount of loans with deposits, it earns an interest spread, $y(R-i)$ (the net interest margin), where R represents a baseline loan rate 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:

$$\max_{y} \mathbb{E}\left[(R-i)y - \tau_1(x-m) - \frac{\tau_2}{2}(x-m)^2\right] \tag{1}$$

For simplicity, we assume that the return on lending, R, is risk-free, as our focus is on payment risk. Therefore, the expectation operator is taken over the randomness in g (and in $x = gy$). In our baseline model, we fix the deposit rate i. After solving the optimal y and developing our main hypothesis on the impact of payment risk on bank lending, we consider the bank's choice of i.

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

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

Intuitively, the first term captures the risk-adjusted profits from financing loans with deposits. The second term captures the fact that a higher liquidity endowment helps the bank to buffer the payment risk associated with deposit financing and thereby allows the bank to lend more.[18]

The first five hypotheses are summarized in (2). An increase in payment risk σ^2 reduces bank lending y^* (H1). An increase in τ_2 amplifies the negative impact of σ^2 on y^* (H2). The first term on the right side of (2) is akin to the optimal portfolio weight on risky assets under a mean-variance preference, and τ_2 plays the role of risk aversion coefficient. Therefore, if payment risk of deposit financing generates meaningful uncertainty in bank earnings, other contributors to the overall level of risk aversion, for example, the distance to hitting regulatory constraints (Bolton et al., 2020), should play a similar role as τ_2 (H3). Finally, y^* decreases in τ_1, which sets a baseline cost of reserves and varies with monetary policy, and the sensitivity decreases in payment risk (H4).

Substituting the optimal y^* into the objective function, we solve the maximized expected profit that is a function of the deposit rate i. Next, we allow the bank to optimize i and derive the optimal deposit rate i^* in the appendix. Empirically, deposit rates adjust slowly and less frequently than a bank's loan book (Driscoll and Judson, 2013). Therefore, when a bank chooses its lending amount, the decision is most likely made after the bank has set a deposit rate (rather than jointly with the deposit rate). Accordingly, the bank in our model chooses i first and then y. By choosing a higher deposit rate, the bank can reduce the expected deposit outflow: $\mu(i) = \mu_0 - \mu_1 i$ where $\mu_1 > 0$. Intuitively, a higher level of payment risk incentivizes the bank to manage risk by raising deposits

[18]Our 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 payment risk and never becomes insolvent even in the worst case of payment outflow ($g = 1$): $m + (R - i)y^* - \tau_1(y^* - m) - \frac{\tau_2}{2}(y^* - m)^2 > 0$. The bank net worth starts with m, adds the net interest margin $R - i$, and subtracts the quadratic cost of the worst-case ($g = 1$) payment outflows. Note that throughout our analysis, we rule out bank run: Even when all deposits are withdrawn ($g = 1$), the bank still can cover outflows by borrowing reserves (albeit at an increasing and convex cost).

to reduce outflow and preserve liquidity. The following property corresponds to hypothesis H5:

$$\frac{di^*}{d(\sigma^2)} > 0\,. \tag{3}$$

Discussion: Payment risk overhang and control variables. Our baseline model characterizes a bank without existing loans or deposits. Next, we extend the model to incorporate existing loans, denoted by ℓ, and existing deposits, denoted by d. As in the baseline model, a g fraction of the existing deposits flow out of the bank at $t = 1$. The objective function is given by

$$\max_{y} \mathbb{E}\left[(R-i)(y+\ell) - \tau_1(x+gd-m) - \frac{\tau_2}{2}(x+gd-m)^2\right] \tag{4}$$

The optimal y differs from the baseline solution only by a reduction of d amount:

$$y = \frac{R-i-\tau_1\mu}{\tau_2\left(\sigma^2+\mu^2\right)} + \frac{\mu}{\left(\sigma^2+\mu^2\right)}m - d\,. \tag{5}$$

The existing deposit liabilities already imply a liquidity drain, which discourages the bank from taking on more payment risk by financing new loans with more 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 that is consistent with the payment risk overhang effects. Note that the amount of existing loans ℓ does not affect the choice of new loans y. This is due to the fact that our model does not feature loan risk and only emphasizes deposit risk related to payment activities and cash withdrawal. If the return on bank lending is risky, it is likely that the risk overhang effects apply to existing loans as well as existing deposits. In our empirical model, we include the loans-to-total asset ratio ("loan ratio") as a control variable in the loan growth regression and find either a statistically insignificant coefficient or a significantly negative coefficient in line with the conjecture of risk overhang effects.

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 a variety of sources. Specifically, for payments, we use confidential Fedwire transaction-level data that span from 2010 to 2020. The Fedwire Funds Service is a real-time gross settlement system used by Federal Reserve banks to electronically settle U.S. dollar payments among member institutions; the system processes trillions of dollars daily. The Federal Reserve maintains accounts for both sender banks and receiver banks and settles individual transactions immediately without netting.[19] Our data includes information such as the time and date of each transaction, the identities of sender banks and receiver banks, payment amount, and transaction type. We focus on transactions instructed by customers, meaning transactions that are out of the banks' control and contribute to liquidity risk. These customer-initiated transactions account for roughly 85% of all transactions (in terms of number of transactions).[20]

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 provided at a quarterly frequency and include standard balance sheet items such as total asset, loan amount (by type and maturity), deposit amount, capital amount, etc. Additionally, the data provide detailed information on banks'

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

[20]We do not include bank-initiated transfer of funds or banks' purchases and sales of federal funds (reserves).

income statements. We merge the Fedwire data with the Call Report data using the Federal Reserve's internal identity system.

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.[21] 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. Aggregating branch-level information to bank levels, we merge the RateWatch data with the Call Report data using the FDIC bank identifier.

Our final dataset includes 3,466 banks with merged information from all three sources. Figure 3 shows that on average our sample covers 83% of banks in the Call Report universe for the period of 2010 to 2020 in terms of total assets. To the best of our knowledge, our paper is the first to merge payment data with Call Report and RateWatch data, 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. Specifically, we study how banks' payment risks affect banks' lending decisions and the effectiveness of monetary policy transmission.

Table 1 provides summary statistics for our bank-quarter sample. On average, banks have \$4.5 billion in assets, of which 20% are liquid assets (cash and available-for-sale securities) and 65% are loans. Non-transaction deposits make up 61% of the funding, while 11% comes from equity capital. The average return on assets for the quarter is 0.23%. Over the sample period, banks typically offer deposit rates lower than the target federal funds rate.

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

3.2 Payment risk measures

A bank can experience highly volatile daily payment flows, as demonstrated by Figure 4, which shows the frequency distribution of within-quarter standard deviations of a bank's normalized daily payment flows. In the upper panel, we report the result for deposit-normalized payment flows. On average, the standard deviation of daily payment flows is 0.6% of deposit amount. In the lower panel, we report the result for reserve-normalized payment flows. On average, the standard deviation of deposit-normalized payment flows is 12% of a bank's reserve holdings. Therefore, despite the increase in bank reserves after the global financial crisis, payment flows still lead to significant liquidity risk for banks. Moreover, a bank cannot count on payment flows to automatically smooth out over time. In Figure 5, the within-quarter autocorrelation of a bank's daily payment flows clusters around zero. In sum, the large magnitude and unpredictability of payment flows present non-trivial risks to banks, motivating us to develop measures to quantify such risks.

For each bank in each quarter, we use data from the Fedwire system to construct two normalized measures that assess the risks associated with banks' payment flows and networks: flow volatility and counterparty Herfindahl-Hirschman Index (counterparty HHI). The first measure captures the magnitude of the fluctuations in a bank's payment flows, while the second measure captures the concentration levels of its payment network on both the receiving and sending sides.

The first measure, $Flow\ volatility$, is calculated as follows. As a first step, we calculate bank i's payment flow imbalance ratio for a given quarter t, on each day d:

$$Flow\ imbalance\ ratio_{i,t,d} = \frac{Amount\ received_{i,t,d} - Amount\ sent_{i,t,d}}{Amount\ received_{i,t,d} + Amount\ sent_{i,t,d}}, \tag{6}$$

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, $Flow\ imbalance\ ratio_{i,t,d}$ 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, $Flow\ imbalance\ ratio_{i,t,d}$ 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. Within quarter t for bank i We define $Flow\ volatility_{i,t}$: as the standard deviation of $Flow\ imbalance\ ratio_{i,t,d}$:

$$Flow\ volatility_{i,t} = S.D.(Flow\ imbalance\ ratio_{i,t,d}), \tag{7}$$

which measures how volatile the payment-flow (and the associated liquidity) imbalance is.

The second measure, $Counterparty\ HHI$, measures the concentration of a bank's payment senders and receivers. It captures the potential fragility of having large and a limited number of counterparties, as large flows between any pair of banks could significantly impact the total payments if the bank's customers only receive money from (or send money to) a very small number of other banks. We first calculate bank i's receiver HHI on day d in quarter t:

$$Receiver\ HHI_{i,t,d} = \sum_{j \neq i} \left(\frac{Amount\ sent_{i,j,t,d}}{Amount\ sent_{i,t,d}} \right)^2, \tag{8}$$

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:

$$Sender\ HHI_{i,t,d} = \sum_{j \neq i} \left(\frac{Amount\ received_{i,j,t,d}}{Amount\ received_{i,t,d}} \right)^2, \tag{9}$$

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:

$$Counterparty\ HHI_{i,t} = (Receiver\ HHI_{i,t} + Sender\ HHI_{i,t})/2. \tag{10}$$

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 6 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 $Counterparty\ HHI$.

4 Empirical Results

We begin by examining the impact of payment risks on banks' lending decisions. We then show that such effects are significantly strengthened by interbank funding stress, shocks to reserve supply, and regulatory constraints that amplify banks' risk sensitivity. Next, we provide strong evidence that payment risk hinders monetary policy transmission. Finally, we show that banks facing higher payment risks set higher deposit rates in order to attract liquidity inflows.

4.1 Payment risk and bank lending

We provide our main results regarding Hypothesis 1—Bank lending decreases in payment risk.

The main results. In Panel A of Figure 7 (i.e., Figure 1 in the introduction), 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 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 subtracting the cross-sectional mean of that quarter. The figure reveals a robust negative relationship, suggesting a negative impact of payment risk on bank lending. In Panel B of Figure 7, we replace $Flow\ volatility$ with $Counterparty\ HHI$ and find the same pattern.

Next, we analyze how payment risk affects bank lending through the following regression where we control for state fixed effects, time fixed effects, and bank characteristics that are commonly included as explanatory variables for loan growth (see, e.g., Loutskina and Strahan, 2009):

$$Loan\ growth_{i,t+1} = \alpha+\beta\times Flow\ volatility_{i,t}+\gamma\times Controls_{i,t}+\mu_{state}+\mu_{type}+\mu_t+\epsilon_{i,t+1}, \quad (11)$$

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

$$Loan\ growth_{i,t+1} = (Loan_{t+1} - Loan_t)/Loan_t. \quad (12)$$

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 assets), $Trading\ ratio$ (the ratio of trading assets to total assets), $Capital\ ratio$ (the ratio of risk-based capital to total assets), $Deposit\ ratio$ (the ratio of nontransaction 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.[22] 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 (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 saving & loan banks. Standard errors are clustered at the bank and quarter levels.

We report regression results of equation (11) in Table 3. 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, as the standard deviation of loan growth rate in our sample is 5 percentages points. To control for potential 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. 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, 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 (11). With this alternative measure, we examine the robustness of the relationship between payment risk and lending and also test the underlying economic mechanism. We develop our hypotheses

[22]Table 2 reports the correlations between payment risk measures and these bank characteristics.

under the assumption that the liquidity risk associated with payment flows originates from the randomness in depositors' payment needs. Such randomness has a systematic and an idiosyncratic component. 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 depositor bases. Idiosyncratic payment flows tend to be smoothed out across these counterparty banks' depositor clienteles. Therefore, bank i is less exposed to payment risk and willing to lend more. The regression results, presented in columns (4)–(6) of Table 3, confirm this conjecture. Loan growth rate is negatively associated with counterparty 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 20% of the standard deviation of loan growth rate in our sample.

Controlling for credit demand. 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, especially if loan demand varies across different regions. Our inclusion of $State \times Quarter$ two-way fixed effects in Table 3 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 potential loan demand for multi-state banks (especially those banks with branches in many states). To further address the concern that our results are driven by uneven loan demand rather than banks' lending decisions, 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.[23]

Using the single-state subsample, we repeat our tests and report the regression results in Table 4. Across all specifications, we include $State \times Quarter$ two-way fixed effects. Table 4 shows that when restricting our sample to single-state banks, test results are very close to those in Table 3, both in terms of magnitude and statistical significance, suggesting that our results are unlikely driven by client demand, but instead by banks' decisions on loan supply.

Results by bank size. It is widely acknowledged that banks of various sizes behave differently (Kishan and Opiela, 2000; Afonso, Kovner, and Schoar, 2011; Ashcraft, McAndrews, and Skeie, 2011). We address the potential concern that the negative relationship between loan growth and payment risk measures is driven by certain groups of banks, by conducting our tests separately for banks of different sizes. Specifically, we sort banks into four groups based on their total assets in each quarter and estimate the following model:

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

where $Payment\ risk$ indicates either $Flow\ volatility$ or $Counterparty\ HHI$, control variables are the same as in equation (11), $\mu_{state,t}$ is State×Quarter two-way fixed effect, and $\mu_{type,t}$ is Type×Quarter two-way fixed effect.

We report regression results of equation (13) for four subsamples in Table 5, where "bottom size quartile" representing the group of smallest banks and "top size quartile" the group of largest banks. The coefficients on $Flow\ volatility$ and $Counterparty\ HHI$ are all negative and highly significant for the four subsamples, with comparable magnitudes across subsamples. This suggests

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

that the negative effect of payment risks on lending holds for large and small banks.

Results by loan types. We calculate loan growth rates for three different types of loans: the core loans (comprising real estate loans, commercial and industrial loans, and consumer loans), loans with maturity over three years, and loans with maturity over five years. We replace the total loan growth rate with these alternative loan growth rates as the dependent variables and repeat our tests.

Table 6 reports the results of tests using alternative loan growth rates as dependent variables. Columns (1)–(2) show that the regression results are similar to those in Table 3 when using core loans to calculate loan growth rate. Columns (3)–(6) reveal that the estimated coefficients on payment risks remain negative and highly significant when the focus is shifted to long-term loans, with the magnitude increasing by almost 50% for loans with maturity over three years and almost doubling for loans with maturity over five years compared to the all loan growth rate. The adjusted R^2 decreases 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. This finding is consistent with the timing assumption in our model, as payment risk, by exposing banks to uncertain liquidity needs, can only affect banks' provision of illiquid loans, i.e., loans that 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; thus, our mechanism should be stronger among long-term loans.

4.2 Can funding stress amplify the impact of payment risks?

Funding market stress. We explore potential factors that may influence the extent to which payment risks affect bank lending. Specifically, we test Hypothesis 2. Intuitively, banks' concerns related to payment risk and the associated uncertainty in liquidity needs should be alleviated when the costs of interbank borrowing are low, and such worries should increase when the interbank market (or short-term funding markets in general) is strained. To test this hypothesis, we estimate the following model:

$$\begin{aligned} Loan\ growth_{i,t+1} &= \alpha + \beta_1 \times \textit{LIBOR–OIS spread}_{t+1} \times Payment\ risk_{i,t} + \\ &\beta_2 \times Payment\ risk_{i,t} + \gamma \times Controls_{i,t} + \mu_{state,t} + \mu_{type,t} + \mu_i + \epsilon_{i,t+1}, \quad (14) \end{aligned}$$

where $LIBOR\text{–}OIS\ spread_{t+1}$ 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 (11), $\mu_{state,t}$ represents State×Quarter two-way fixed effects, $\mu_{type,t}$ represents Type×Quarter two-way fixed effects, and μ_i is bank fixed effects.[24] Standard errors are clustered at the bank and quarter levels.

We report regression results of equation (14) 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 a decrease in loan growth by 3 percentage points ($-0.1039 \times 0.54 \times 0.5 = 3\%$), which is 60% of the standard deviation of loan growth rate in our sample.

We also use an alternative measure to gauge funding stress, namely, $TED\ spread$, which is the spread between the 3-month LIBOR based on US dollars and the 3-month Treasury Bill. While

[24] 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.

$LIBOR–OIS\ spread$ 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 (14). Column (2) of Table 7 shows that the interaction term between $Flow\ volatility$ and $TED\ spread$ also has a negative and significant coefficient. In columns (3)–(4), we use $Counterparty\ HHI$ as a proxy for payment risk, 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.

Reserve availability shocks. A potential 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 short-term funding markets. To address this concern, we consider a relatively more exogenous force that affects the liquidity availability in the banking sector. Bianchi and Bigio (2022) develop a theoretical model of bank liquidity management that emphasizes the frictions in the interbank market for reserve borrowing and lending. A key result of their analysis is that an increase in reserve supply alleviates the stress in the interbank market. Following Correa, Du, and Liao (2020) and Copeland, Duffie, and Yang (2021), we use the variations of the balance in Treasury General Account (TGA) as shocks to net reserve supply to the banking sector. TGA is the account of the U.S. Treasury at the Federal Reserve, which serves as the primary operational account. An increase in the TGA balance drains reserves from the banking system. For example, when depositors pay taxes, their bank lose deposits on the liability side of balance sheet and, on the asset side, lose reserves to TGA, leaving the banking system.[25]

[25]The significant liquidity stress 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).

we estimate the following model:

$$Loan\ growth_{i,t+1} = \alpha + \beta_1 \times TGA\ growth_{t+1} \times Payment\ risk_{i,t} + \beta_2 \times Payment\ risk_{i,t} + \gamma \times Controls_{i,t} + \mu_{state,t} + \mu_{type,t} + \mu_i + \epsilon_{i,t+1}, \quad (15)$$

where $TGA\ growth_{t+1}$ is the quarterly growth rate of the TGA balance. All other variables and fixed effects are defined as in equation (14), and standard errors are clustered at the bank and quarter levels. We report the regression results in Table 8. Column (1) shows that the interaction term between $Flow\ volatility$ and $TGA\ growth$ has a negative and statistically significant coefficient. 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. This result has an economically significant implication. Specifically, for a bank with a median level of $Flow\ volatility$ (0.54), an increase in the TGA growth rate of 50 percentage points (which is commonly observed in our sample) is associated with a decrease in loan growth by 0.3 percentage points ($-0.0126 \times 0.54 \times 0.45 = 0.3\%$). Column (2) reports the result using $Counterparty\ HHI$ as the payment risk measure. The results are is consistent with those based on $Flow\ volatility$ and even stronger.

In addition to the growth in the TGA, which represents a negative shock in reserve supply, the volatility of TGA should also be taken into consideration, as a more volatile TGA translates into a more volatile liquidity condition for the whole banking system. Each quarter, we calculate the standard deviation of weekly TGA levels and use it as a proxy for the TGA volatility. The average TGA volatility over our sample period is approximately 0.05 trillion dollars. We then include the interaction term between $TGA\ volatility$ and payment risk measures to the specification in equation (15) and report the regression results in Columns (3)–(4) of Table 8. Column (3) shows that the interaction term between $Flow\ volatility$ and $TGA\ volatility$ has a negative and statistically significant coefficient, signifying that the negative effect of $Flow\ volatility$ on bank lending is intensified when the TGA is more volatile. For example, for a bank with a median level of $Flow\ volatility$ (0.54), an increase in the TGA volatility by 0.05 is associated with a decrease in loan growth by 0.2 percentage points ($-0.063 \times 0.54 \times 0.05 = 0.2\%$). Column (4) provides further evidence of this relationship using $Counterparty\ HHI$ as a proxy of payment risk.

4.3 Regulatory constraints and the impact of payment risks

In our theoretical model, the optimal lending given by equation (2) is akin to the optimal risky investment under a mean-variance preference, with τ_2, a proxy for funding market stress, playing a similar role as a risk aversion coefficient. A model that emphasizes a bank's overall risk aversion via a mean-variance objective function would deliver similar optimal lending, as the randomness in payment flows and costs of liquidity drain translates into uncertainty in earnings. Thus, our model may adopt a broader interpretation. Next, we measure banks' risk sensitivity and test Hypothesis 3—payment risk has a stronger dampening effect on lending for more risk-sensitive banks.

Bolton et al. (2020) show theoretically that a bank with less regulatory capital exhibits a high level of overall risk sensitivity (even if its shareholders have risk-neutral preferences). It is more averse to both lending risk and payment-related risk in deposit flows when it is close to breaching the leverage requirements. The regulatory requirement on leverage ratio obligates a bank to maintain a certain level of risk-absorbing capital (primarily equity) relative to assets. A bank's capital position can be adversely affected by payment outflows through the impact on earnings.[26] Thus, banks that are closer to violating the stipulated leverage ratio are more vulnerable to payment risk.

U.S. banks have long been subject to a leverage requirement based on the ratio of a bank's

[26] Payment outflows drain reserves, so the bank may either incur costs of replenishing its reserve holdings through interbank or discount-window borrowing or wait until future liquidity needs to emerge and incur borrowing costs then.

Tier 1 capital to its average total consolidated assets in its quarterly regulatory report, namely, 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. As illustrated in Figure 8, there was an overall upward trend in the Tier 1 leverage ratio. During the COVID-19 pandemic, U.S. regulators relaxed the leverage regulation and restored it later in April 2021 after the financial conditions stabilized.[27] This indicates the regulators' concern over the dampening effect of regulatory constraints on banks' risk-taking capacity. We explore the cross-sectional heterogeneity in banks' exposure to leverage regulations and construct a dummy variable ($Low\ regulatory\ capital$) for each bank-quarter that is equal to one if the bank's Tier 1 leverage ratio is equal to or below the 5th percentile in that quarter. This dummy variable captures the relatively undercapitalized banks.

We next examine whether the detrimental effect of payment risk on lending is more severe for undercapitalized banks, and report our main results in Table 9. In Columns (1) and (3), we add the $Low\ regulatory\ capital$ dummy and its interaction with payment risk measures to our baseline specification. The interaction term has a negative and statistically significant coefficient, indicating that payment risk has a greater negative impact on lending for banks closer to the binding of regulatory constraints. Specifically, Column (3) reveals that an interquartile-range increase in $Counterparty\ HHI$ leads to a 1 percentage point decrease in loan growth rate for banks above the 5th percentile level of regulatory capital, while an equivalent increase in $CounterpartyHHI$ results in a 1.6 percentage point decrease in loan growth rate for banks below this threshold. This finding supports our hypothesis that undercapitalized banks are more vulnerable to payment risk. In Columns (2) and (4), we further introduce bank fixed effects to the regression model. The coefficients on the interaction term remain highly significant, suggesting that the tightness level of

[27]The regulators relaxed the supplementary leverage ratio (SLR) requirement during the Covid-19 pandemic. The SLR applies to banks with at least $250 billion in total consolidated assets or $10 billion of on-balance sheet foreign exposures. In comparison with the ratio of Tier 1 capital to total consolidated (on balance sheet) assets ("U.S. leverage ratio"), SLR takes into account both on- and certain off-balance sheet assets and exposures.

regulatory constraint drives the within-bank variation of lending sensitivity to payment risk.

In Table 10, we introduce more granular dummy variables to examine the nonlinear effect of regulatory capital on lending sensitivity to payment risk.[28] Specifically, we consider a dummy variable for banks with regulatory capital (measured as Tier 1 leverage ratio) equal to or below the 3rd percentile, another dummy variable for banks between the 3rd and 5th percentiles, and a third dummy variable for banks between the 5th and 7th percentiles. The results without bank fixed effects are featured in Columns (1) and (3), while the results with bank fixed effects are shown in Columns (2) and (4). A consistent pattern across all specifications is that the coefficient of the interaction between payment risk and the dummy for banks below the 3rd percentile of regulatory capital is more significant than, and twice the magnitude of, the coefficient of the interaction between payment risk and the dummy for banks between the 3rd and 5th percentiles. The interaction between payment risk and the dummy for banks between the 5th and 7th percentiles barely has any effect. Specifically, Column (3) reveals that an interquartile-range increase in $Counterparty\ HHI$ is associated with a 2.4, 1.3, and 1.1 percentage point decrease in loan growth rate for banks with regulatory capital below the 3rd percentile, between the 3rd and 5th percentiles, and between the 5th and 7th percentiles, respectively. This suggests that as a bank's regulatory capital deteriorates, the dampening effect of payment risk on bank lending becomes increasingly strong.

Intuitively, for undercapitalized banks, any variation in earnings and equity capital induced by payment risk poses a significant risk of breaching the leverage regulation, which can potentially trigger costly equity issuances or regulatory interventions in the form of restrictions on managerial compensation and share repurchases. In contrast, well-capitalized banks are unlikely to be affected by such regulatory pressure. Our findings provide a new rationale for the regulators' decision to relax the leverage regulations during the Covid-19 pandemic. Banks supply credit and, by allowing

[28]In Bolton et al. (2020), under payment-flow volatility, a bank's effective risk aversion to lending risk increases in a convex fashion as it gets closer to violating the leverage requirement.

depositors to freely move money in and out of deposit accounts, support the functioning of payment system. Relaxing the regulatory pressure may help banks fulfill both roles during crises.

4.4 Payment risks and monetary policy transmission

In this section, we investigate how payment risk influences the credit channel of monetary policy transmission and test Hypothesis 4. Our analysis draws upon 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), which works as follows: When the central bank intervenes in the interbank market and decreases the interest rate target, banks lend more. Nonetheless, payment risk may weaken this channel. Intuitively, banks that face higher payment risk are more cautious when responding to accommodative monetary policies.

In Figure 9, we sort banks into terciles based on their payment risk levels and analyze the response of bank lending to different ranges of policy rate changes. Group 1 consists of banks with the lowest payment risk and Group 3 of banks with the highest payment risk. We define three monetary policy environments: very expansionary (FFR decreasing by 1.5 percentage points), expansionary (FFR decreasing by 0.25 to 0.5 percentage points), and roughly unchanged. After calculating the average loan growth rate for each risk group under each monetary policy scenario, we find that within each payment risk group, a more accommodating policy rate change is generally associated with more bank lending (i.e., the bank lending channel of monetary policy transmission). Additionally, within each rate change category, banks with higher payment risk respond less, suggesting that payment risk dampens the bank lending channel of monetary policy.

To formally test Hypothesis 4, we estimate the following regression:

$$Loan\ growth_{i,t+1} = \alpha + \beta_1 \times \Delta FF\ rate_t + \beta_2 \times Payment\ risk_{i,t} + \\ \beta_3 \times \Delta FF\ rate_t \times Payment\ risk_{i,t} + \gamma \times Controls_{i,t} + \mu_{state} + \mu_{type} + \epsilon_{i,t+1}, \quad (16)$$

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 as in equation (11). Standard errors are clustered at bank and quarter levels.

We report the results of (16) in Table 11. Column (1) shows that $\Delta FF\ rate$ has a strongly negative coefficient, significant at 1% level. This result suggests that an increase (decrease) in policy rates leads to a reduction (expansion) in loan provision, confirming the influence of policy rates on credit supply. Importantly, the interaction term of $\Delta FF\ rate$ and $Flow\ volatility$ loads a positive coefficient, significant at the 1% level, indicating that payment risks impede monetary policy transmission. Specifically, for two banks at 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, and a 3.6-percentage-point increase in loan growth for the 75th-percentile bank.[29] In the extreme case of comparing two banks with the highest and the lowest $Flow\ volatility$, our results show that the sensitivity of loan growth to policy rate change is halved for the bank with higher payment risks. In Column (2), we include two-way fixed effects of State×Quarter and Type×Quarter, and our results on the interaction term remain robust. We further control for bank fixed effects in column (3) and find consistent results, suggesting that for a given bank, its reaction to monetary policy change is significantly influenced by payment risk.

We next use $Counterparty\ HHI$ as a proxy for payment risk exposure and study its impact

[29] 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: $-0.0528 \times (-1) + 0.024 \times (-1) \times 0.71 = 3.6\%$

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 percentage points to -3.3 percentage points).[30] 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 reduce the efficacy of the bank lending channel of monetary policy transmission. Furthermore, even when there have been no changes to the policy rate (i.e., if we plug in $\Delta FF\ rate = 0$ into the regression equation), payment risk measures themselves still have negative and significant coefficients, suggesting that our findings in Section 4.1 hold even in periods without any monetary policy changes.

4.5 Payment risks and deposit rates

In this section, we test Hypothesis 5 that banks mitigate their payment risk by raising deposit rates to induce more deposit and reserve inflows. We start by plotting the average deposit spread (relative to the Fed funds rate) for each decile of banks sorted by payment risk in Figure 10. 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:

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

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 either $Flow\ volatility$ or $Counterparty\ HHI$, control variables are defined the same as in equation (11), $\mu_{state,t}$ represents State×Quarter two-way fixed effects, and $\mu_{type,t}$ represents Type×Quarter two-way fixed effects. Standard errors are

[30]The -4.5 percentage points are calculated as: $-0.0536 + 0.0269 \times 0.31 = -4.5\%$, and the -3.3 percentage points are calculated as: $-0.0536 + 0.0269 \times 0.75 = -3.3\%$.

clustered at the bank and quarter levels.

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 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)).[31] Deposit rate information is obtained from the RateWatch survey data at the branch-week level and aggregated to the bank-quarter level. Across all 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 seen in column (1) of Table 12, while 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 seen in column (2). Furthermore, consistent results are obtained when utilizing deposit spreads of alternative 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 other bank characteristics and fixed effects. This is consistent with the idea that banks with higher payment risks are more likely to secure more stable funding by increasing the competitiveness of their deposit rates. Therefore, our findings suggest that banks manage their payment risks both on the asset side (through changes in their lending decisions) and on the liability side (through the adjustment of deposit rates).

[31] 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 the seamless operation of payment system, 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 the existing studies on bank liquidity mismatch, our focus is not on dramatic episodes 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.

Payment risk is critical for understanding the transmission of monetary policy through bank lending. On the quantity side, an increase in reserve supply alleviates liquidity stress in the banking system and therefore mitigates the negative impact of payment risk on bank lending. Moreover, we find that when the central bank adjusts its policy rate, the transmission to credit supply depends on the elasticity of bank balance sheets, which in turn is function of payment risk exposure.

Our findings highlight the challenges that banks face when combining credit provision and payment services. In recent times, 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 FinTech 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., B. Imbierowicz, S. Steffen, and D. Teichmann (2020). Does the lack of financial stability impair the transmission of monetary policy? *Journal of Financial Economics 138*(2), 342–365.

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.

Adrian, T. and H. Song Shin (2010). Chapter 12 - financial intermediaries and monetary economics. Volume 3 of *Handbook of Monetary Economics*, pp. 601–650. Elsevier.

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.

Altavilla, C., L. Burlon, M. Giannetti, and S. Holton (2022). Is there a zero lower bound? the effects of negative policy rates on banks and firms. *Journal of Financial Economics 144*(3), 885–907.

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.

Bech, M. L. and E. Klee (2011). The mechanics of a graceful exit: Interest on reserves and segmentation in the federal funds market. *Journal of Monetary Economics 58*(5), 415–431. Carnegie-Rochester Conference on public policy: Normalizing Central Bank Practice in Light of the credit Turmoi, 12–13 November 2010.

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

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.

Berentsen, A. and C. Monnet (2008). Monetary policy in a channel system. *Journal of Monetary Economics 55*(6), 1067–1080.

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

Berger, A. N. and T. H. Hannan (1989). The price-concentration relationship in banking. *The Review of Economics and Statistics 71*(2), 291–299.

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.

Bernanke, B. S. and M. Gertler (1995, December). Inside the black box: The credit channel of monetary policy transmission. *Journal of Economic Perspectives 9*(4), 27–48.

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.

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

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, 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.

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.

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.

Cortes, K., Y. Demyanyk, L. Li, E. Loutskina, and P. E. Strahan (2023). Stress tests and small business lending. *Journal of Financial Economics forthcoming*.

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.

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.

Di Maggio, M. and A. Kermani (2017). Credit-induced boom and bust. *The Review of Financial Studies 30*(11), 3711–3758.

Di Maggio, M., A. Kermani, B. J. Keys, T. Piskorski, R. Ramcharan, A. Seru, and V. Yao (2017, November). Interest rate pass-through: Mortgage rates, household consumption, and voluntary deleveraging. *American Economic Review 107*(11), 3550–88.

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

Diamond, W., Z. Jiang, and Y. Ma (2020). The reserve supply channel of unconventional monetary policy. Working paper, Columbia University, Northwestern University, and University of Pennsylvania.

Diebold, F. X. and S. A. Sharpe (1990). Post-deregulation bank-deposit-rate pricing: The multivariate dynamics. *Journal of Business & Economic Statistics 8*(3), 281–291.

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.

Driscoll, J. C. and R. A. Judson (2013). Sticky deposit rates. Working paper 2013-80, Federal Reserve Board.

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

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.

Egan, M., S. Lewellen, and A. Sunderam (2021, 08). The Cross-Section of Bank Value. *The Review of Financial Studies 35*(5), 2101–2143.

Ennis, H. M. and T. Keister (2008). Understanding monetary policy implementation. *Economic Quarterly 94*(Sum), 235–263.

Ennis, H. M. and J. A. Weinberg (2007). Interest on reserves and daylight credit. *Economic Quarterly 93*(Spr), 111–142.

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.

Garcia-de-Andoain, C., F. Heider, M. Hoerova, and S. Manganelli (2016, 02). Lending-of-last-resort is as lending-of-last-resort does:central bank liquidity provision and interbank market functioning in the euro area1. *Journal of Financial Intermediation 28*.

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.

Gertler, M. and N. Kiyotaki (2010). Chapter 11 - Financial intermediation and credit policy in business cycle analysis. In B. M. Friedman and M. Woodford (Eds.), *Handbook of Monetary Economics*, Volume 3 of *Handbook of Monetary Economics*, pp. 547 – 599. Elsevier.

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.

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.

Greenwood, R., S. G. Hanson, and J. C. Stein (2015). A comparative-advantage approach to government debt maturity. *The Journal of Finance 70*(4), 1683–1722.

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

Hannan, T. H. and A. N. Berger (1991). The rigidity of prices: Evidence from the banking industry. *The American Economic Review 81*(4), 938–945.

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.

He, Z., S. Nagel, and Z. Song (2021). Treasury inconvenience yields during the covid-19 crisis. *Journal of Financial Economics*.

Heider, F., F. Saidi, and G. Schepens (2019, 02). Life below Zero: Bank Lending under Negative Policy Rates. *The Review of Financial Studies 32*(10), 3728–3761.

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., L. Laeven, and E. Moral-Benito (2022). Loan types and the bank lending channel. *Journal of Monetary Economics 126*, 171–187.

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.

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.

Jayaratne, J. and P. E. Strahan (1996, 08). The Finance-Growth Nexus: Evidence from Bank Branch Deregulation*. *The Quarterly Journal of Economics 111*(3), 639–670.

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.

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.

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.

Krishnamurthy, A. and A. Vissing-Jørgensen (2012). The aggregate demand for treasury debt. *Journal of Political Economy 120*(2), 233–267.

Krishnamurthy, A. and A. Vissing-Jørgensen (2015). The impact of Treasury supply on financial sector lending and stability. *Journal of Financial Economics 118*(3), 571–600.

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.

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.

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.

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

Nagel, S. (2016, 07). The Liquidity Premium of Near-Money Assets*. *The Quarterly Journal of Economics 131*(4), 1927–1971.

Neumark, D. and S. A. Sharpe (1992). Market structure and the nature of price rigidity: Evidence from the market for consumer deposits. *The Quarterly Journal of Economics 107*(2), 657–680.

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*.

Pérez Quirós, G. and H. Rodríguez Mendizábal (2006). The daily market for funds in europe: What has changed with the emu? *Journal of Money, Credit and Banking 38*(1), 91–118.

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.

Piazzesi, M. and M. Schneider (2016). Payments, credit and asset prices. Working paper, Stanford University.

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.

Qian, J. and P. E. Strahan (2007). How laws and institutions shape financial contracts: The case of bank loans. *The Journal of Finance 62*(6), 2803–2834.

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.

Stein, J. C. (2012). Monetary policy as financial stability regulation. *The Quarterly Journal of Economics 127*(1), 57–95.

Sunderam, A. (2015). Money creation and the shadow banking system. *Review of Financial Studies 28*(4), 939–977.

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.

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.

Woodford, M. (2010). Financial intermediation and macroeconomic analysis. *Journal of Economic Perspectives 24*(4), 21–44.

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

Yankov, V. (2014). In Search of a Risk-free Asset. Finance and Economics Discussion Series 2014-108, Board of Governors of the Federal Reserve System (U.S.).

Appendix A Deriving the Optimal Deposit Rate

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

$$\pi \equiv \frac{\tau_2}{2(\sigma^2+\mu^2)}\left(\frac{R-i}{\tau_2}-\frac{\tau_1}{\tau_2}\mu+\mu m\right)^2+\tau_1 m-\frac{\tau_2}{2}m^2 \tag{18}$$

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

$$\tau_1-\tau_2 m>0\,. \tag{19}$$

Next, we extend our model to allow the bank optimally set the deposit rate i before its lending decision. A higher i attracts deposit (and reserve) inflows and thereby reduces $\mu=\mathbb{E}[g]$ ($\mu'(i)<0$). The rationale is that a higher deposit rate attracts more depositors and expands the customer base (Drechsler, Savov, and Schnabl, 2017), so it is more likely that a depositor's payee happens to be the bank's depositor. Moreover, a higher deposit rate may attract new depositors and liquidity inflow. 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 derivative of deposit rate on payment risk:

$$\frac{di^*}{d(\sigma^2)}=\frac{2\mu(i)+(\tau_1-\tau_2 m)}{\mu_1\tau_2(R-i)+\mu(i)\tau_2}>0\,. \tag{20}$$

Appendix B Background Information on U.S. Payment Systems

The Fedwire Funds Service is the primary payment system in the United States for large-value domestic and international transactions denominated in US dollars. 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 United States 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 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 of Fedwire Funds Service 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. Therefore, banks, 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, 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. eastern standard time (EST) 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.

The usage of Fedwire Funds Service grows over our sample period from 2010 to 2020, with total number of transfers and transaction dollar value increasing by 47% and 38%, respectively. In 2020, approximately 5,000 participants initiate funds transfers over the Fedwire Funds Service, and the Fedwire Funds Service processed an average daily volume of 727,313 payments, with an average daily value of approximately $3.3 trillion.[32] The distribution of these payments is highly skewed, with a median value of $24,500 and an average value of approximately $4.6 million. In particular, only about 7 percent of Fedwire fund transfers are for more than $1 million.

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

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

[33] Please refer to CHIPS Annual Statistics.

Figure 3: **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.

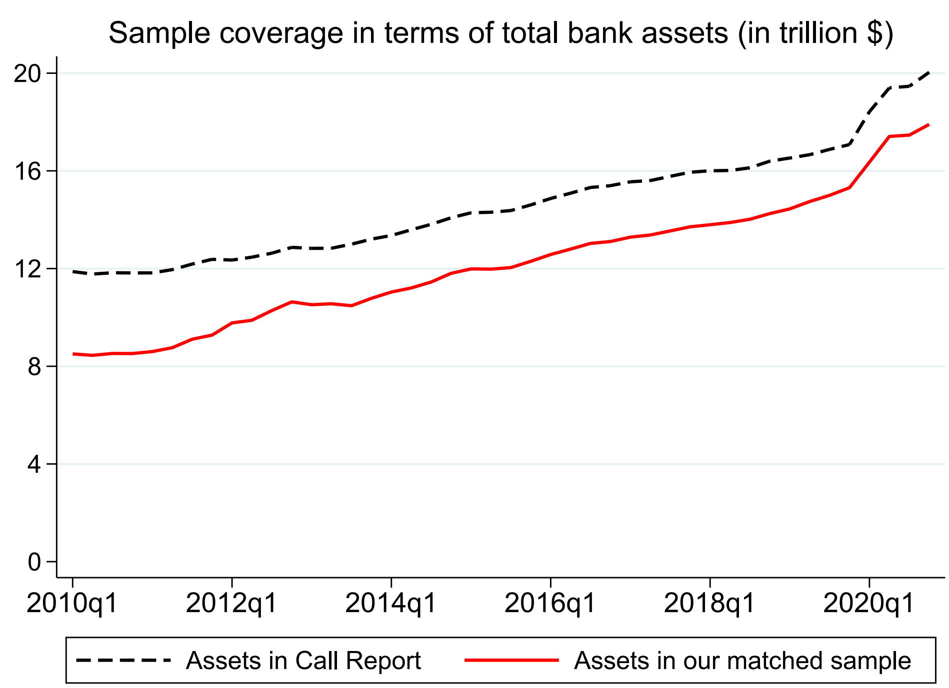
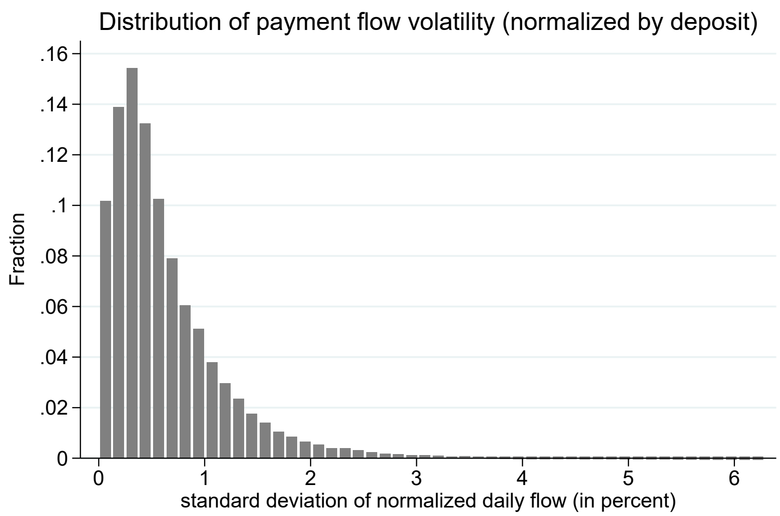
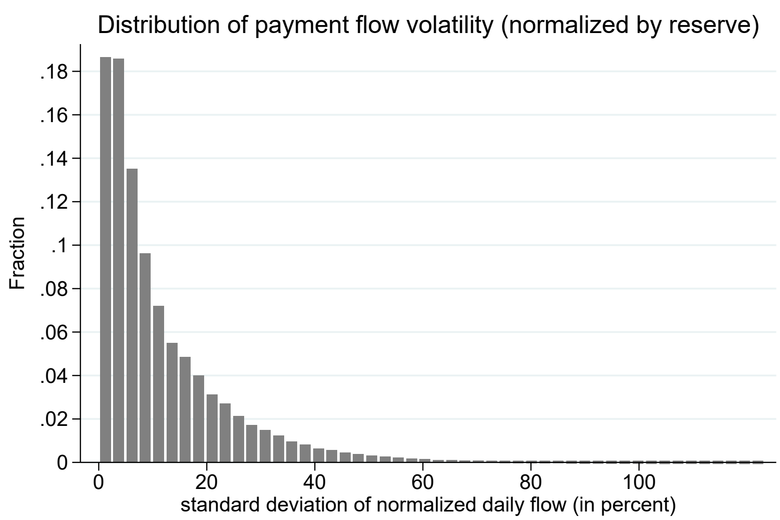


Figure 4: **How volatile can daily payment flows be?**

This figure demonstrates the distribution of within-quarter standard deviations of normalized daily payment flows. The daily payment flows are first normalized with the bank's total deposits as of the most recent quarter-end (upper panel) and total reserves, including vault cash and balances at the Federal Reserve (lower panel). The standard deviation of the normalized daily flow within a quarter is then calculated for each bank, and the results are presented as a histogram distribution of the standard deviations at the bank-quarter level.



Note: normalized daily flow=(daily inflow - outflow) / bank deposit *100.
Standard deviation is calculated at the bank-quarter level.



Note: normalized daily flow=(daily inflow - outflow) / bank reserve *100.
Standard deviation is calculated at the bank-quarter level.

Figure 5: **Do payment flows smooth out over time?**

This figure demonstrates the distribution of within-quarter autocorrelations of daily payment flows. For each bank in a given quarter, we first calculate the autocorrelation of its daily payment flows. We then present a histogram distribution of the autocorrelations at the bank-quarter level.

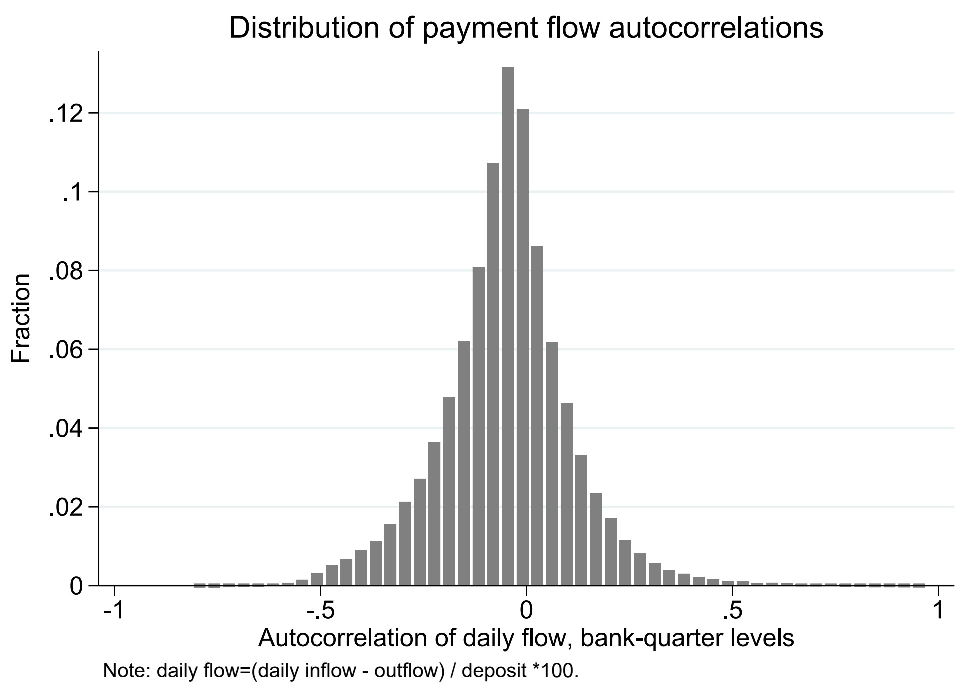


Figure 6: **Distribution of payment risk measures**

This figure shows the distribution of two normalized measures that gauge the instability of banks' payment flows: $Flow\ volatility$ (Panel A) and $Counterparty\ HHI$ (Panel B). $Flow\ volatility$ is defined as in equations (6) and (7), and $Counterparty\ HHI$ is defined as in equation (10). The sample is at the bank-quarter level and spans 11 years from 2010:Q1 to 2020:Q4.

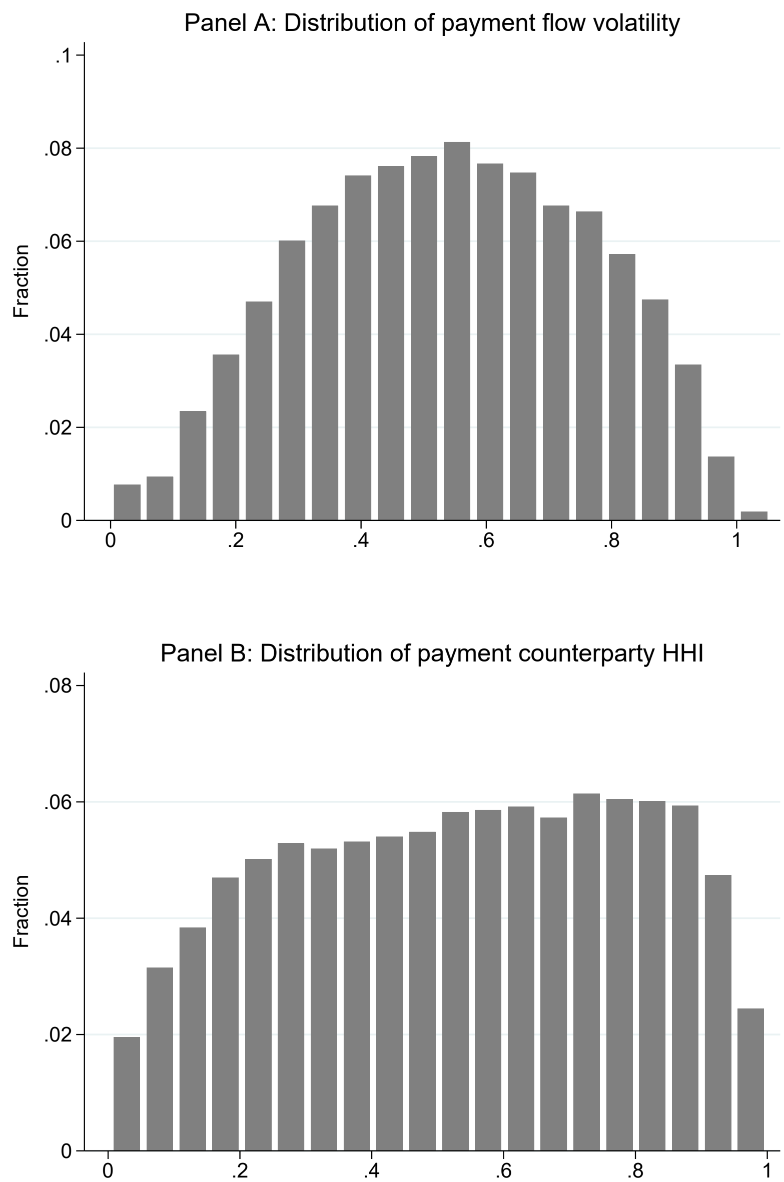
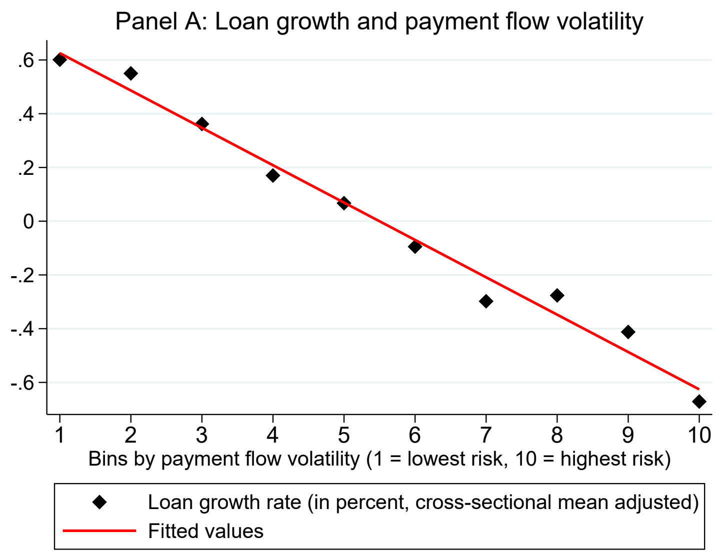


Figure 7: **Payment risk and loan growth**

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.



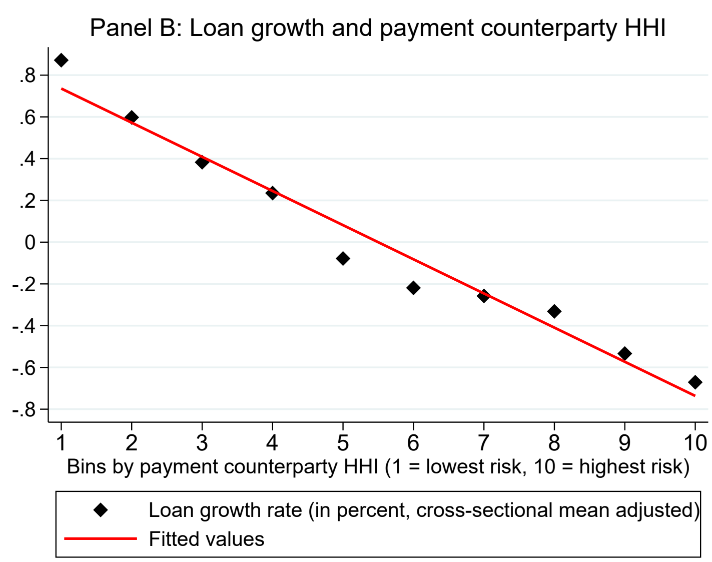


Figure 8: **Time trend of Tier 1 leverage ratios**

This figure shows the distribution of banks' Tier 1 leverage ratios over time. The sample period spans 11 years from 2010:Q1 to 2020:Q4. Tier 1 leverage ratio is defined as the ratio of a bank's Tier 1 capital to its average total consolidated on-balance sheet assets. A bank needs to maintain a Tier-1 leverage ratio of at least 5% to be considered well-capitalized.

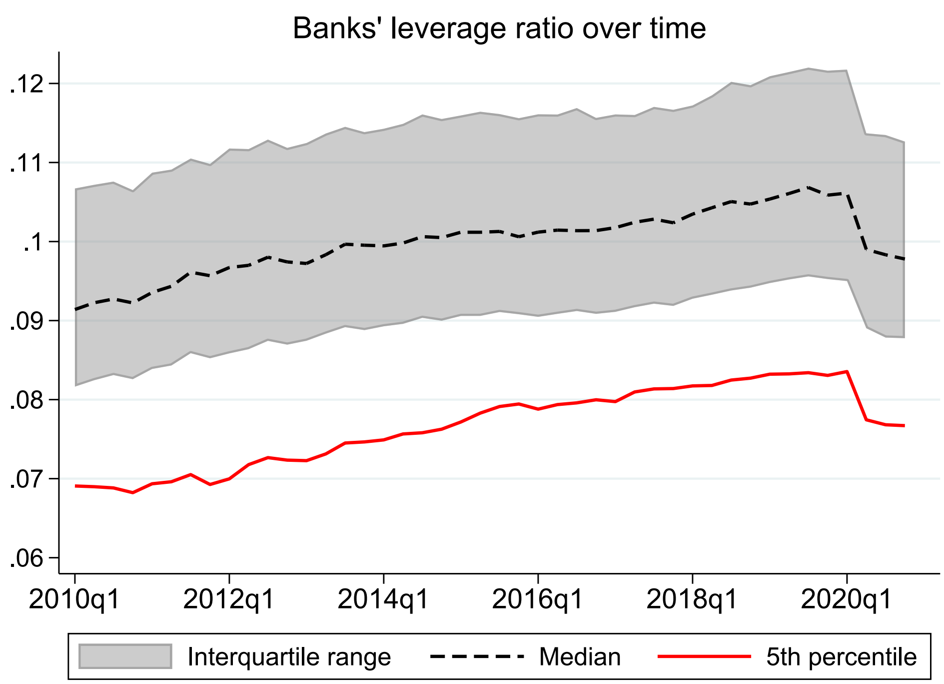


Figure 9: **Impact of payment risk on monetary policy transmission**

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.

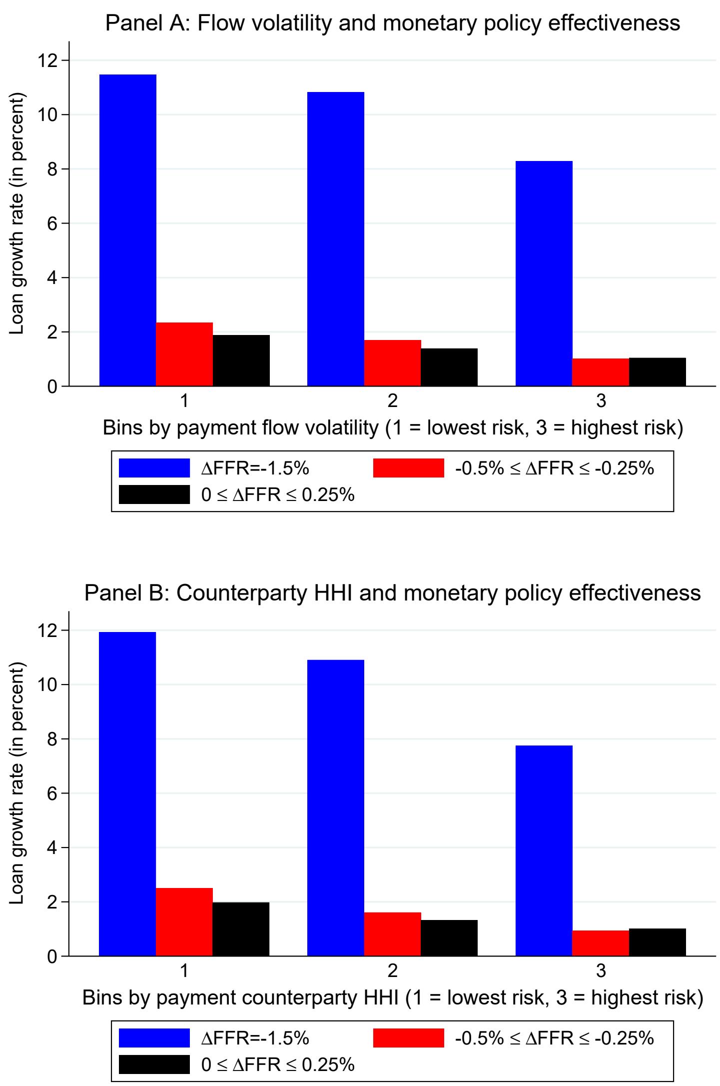


Figure 10: **Payment risk and deposit rate**

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 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 11 years from 2010:Q1 to 2020:Q4.

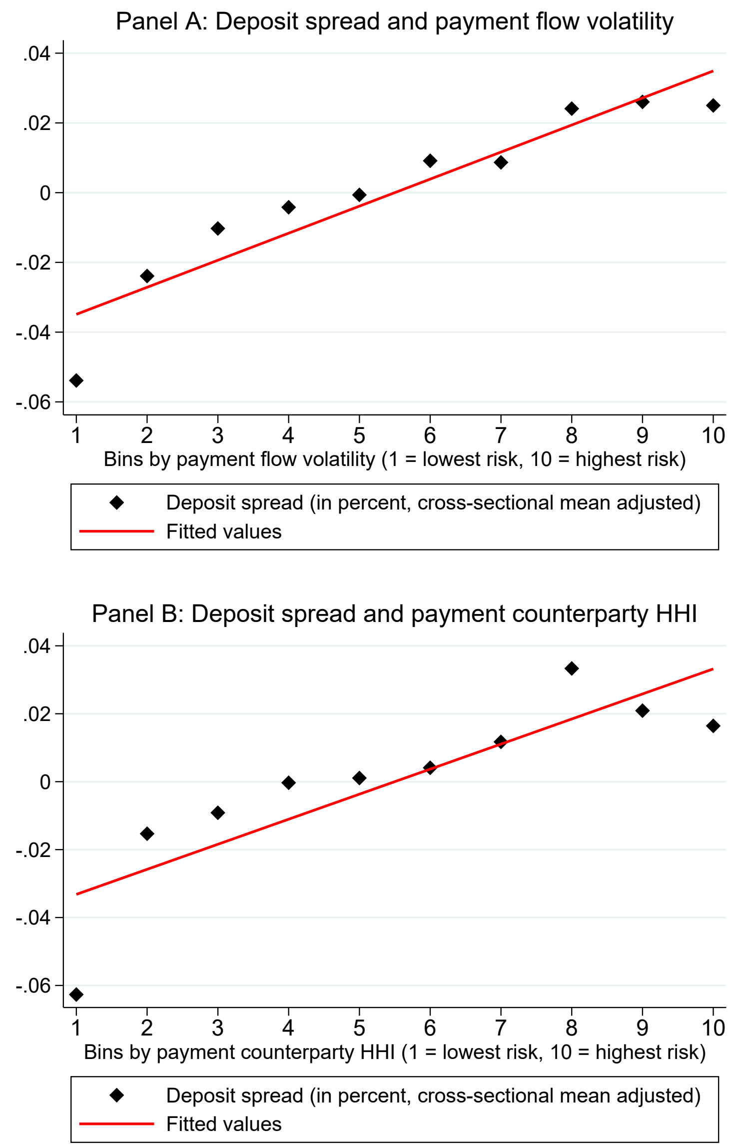


Table 1: **Summary statistics**

This table provides 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-based Tier 1 and Tier 2 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: **Correlations between payment risk measures and bank characteristics**

This table shows the correlation between banks' payment risk measures and other characteristic variables. The sample is at the bank-quarter level. $Flow\ volatility$ 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. $Asset$ is total bank asset. $Liquidity\ ratio$ 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-based Tier 1 and Tier 2 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.

	Flow volatility	**Counterparty HHI**
Asset	-0.14	-0.13
Liquidity ratio	0.16	0.20
Loan ratio	-0.21	-0.24
Trading ratio	-0.12	-0.12
Capital ratio	0.12	0.13
Deposit ratio	-0.24	-0.28
Return on asset	-0.12	-0.12
Number of states	-0.25	-0.26

Table 3: **Payment risk and bank lending**

The dependent variable is the 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-based 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 4: **Payment risk and loan growth: control for loan demand**

The dependent variable is the 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, as defined in Table 3. 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)
State $\times$ Quarter FE	Yes	Yes	Yes	Yes
Type $\times$ 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 5: **Payment risk and loan growth: by bank size**

The dependent variable is the 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 3. 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 6: **Payment risk and loan growth: by loan type**

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. 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 3. 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 7: **Funding stress and the impact of payment risk**

The dependent variable is the 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 $t+1$.[34] $Flow\ volatility$ 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 3. 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: **Reserve supply and the impact of payment risk**

The dependent variable is the 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. $TGA\ growth$ is the quarterly growth rate of Treasury General Account (TGA) based on average levels of the TGA within a quarter, $TGA\ volatility$ 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 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 3. Columns (1) and (3) additionally control for $Flow\ volatility$, and columns (2) and (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 × TGA growth	-0.0126**		-0.0092**	
	(-2.60)		(-2.34)	
Counterparty HHI × TGA growth		-0.0141***		-0.0102**
		(-2.87)		(-2.69)
Flow volatility × TGA volatility			-0.0630*	
			(-1.87)	
Counterparty HHI × TGA volatility				-0.0730**
				(-2.38)
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	0.223	0.224
N of Obs.	92449	92449	92449	92449

Table 9: **Bank capital and the impact of payment risk**

The dependent variable is the 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. $Low\ capital\ ratio$ is a dummy variable that takes the value of 1 when a bank's leverage ratio is below the cross-sectional 5th percentile level in a given quarter and zero otherwise. $Capital\ ratio$ is defined as the ratio of a bank's Tier 1 capital to its average total consolidated on-balance sheet assets. $Flow\ volatility$ is the standard deviation of a bank's daily excess payment flows, and $Counterparty\ HHI$ gauges the concentration levels of a bank's payment receivers and senders. Both measures are calculated from transaction-level Fedwire data in quarter t. Control variables are calculated as of quarter t and include $Liquidity\ ratio$, $Loan\ ratio$, $Trading\ ratio$, $Capital\ ratio$, $Deposit\ ratio$, $Return\ on\ asset$, $\log(Size)$, squared $\log(Size)$, and $Number\ of\ states$, as defined in Table 3. 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 × Low regulatory capital	-0.0143**	-0.0259***		
	(-2.69)	(-3.72)		
HHI × Low regulatory capital			-0.0149***	-0.0252***
			(-3.61)	(-4.32)
Flow volatility	-0.0134***	-0.0038		
	(-4.08)	(-1.53)		
Counterparty HHI			-0.0240***	-0.0143***
			(-4.65)	(-2.98)
Low regulatory capital	-0.0015	0.0022	-0.0014	0.0014
	(-0.44)	(0.69)	(-0.49)	(0.53)
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	0.140	0.224	0.142	0.224
N of Obs.	92528	92449	92528	92449

Table 10: **Payment risk and bank lending: the nonlinear effects of bank capital**

The dependent variable is the 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. $\mathbf{1}$(Regulatory capital $\leq$ 3pctl) is a dummy variable that takes the value of 1 when a bank's U.S. leverage ratio is below the cross-sectional 3rd percentile level in a given quarter and zero otherwise. $\mathbf{1}$(3pctl $<$ Regulatory capital $\leq$ 5pctl) and $\mathbf{1}$(5pctl $<$ Regulatory capital $\leq$ 7pctl) are similarly defined. $Flow\ volatility$ 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 3. 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×$\mathbf{1}$(Regulatory capital $\leq$ 3pctl)	-0.0151*	-0.0361***		
	(-1.93)	(-3.33)		
Flow volatility×$\mathbf{1}$(3pctl $<$ Regulatory capital $\leq$ 5pctl)	-0.0079*	-0.0140**		
	(-1.71)	(-2.54)		
Flow volatility×$\mathbf{1}$(5pctl $<$ Regulatory capital $\leq$ 7pctl)	0.0053	-0.0009		
	(0.92)	(-0.16)		
Counterparty HHI×$\mathbf{1}$(Regulatory capital $\leq$ 3pctl)			-0.0171***	-0.0370***
			(-2.76)	(-3.93)
Counterparty HHI×$\mathbf{1}$(3pctl $<$ Regulatory capital $\leq$ 5pctl)			-0.0076*	-0.0143***
			(-1.97)	(-3.10)
Counterparty HHI×$\mathbf{1}$(5pctl $<$ Regulatory capital $\leq$ 7pctl)			0.0012	-0.0038
			(0.25)	(-0.78)
Flow volatility	-0.0136***	-0.0037		
	(-4.11)	(-1.46)		
Counterparty HHI			-0.0242***	-0.0142***
			(-4.66)	(-2.94)
$\mathbf{1}$(Regulatory capital $\leq$ 3pctl)	-0.0063	0.0006	-0.0055	0.0004
	(-1.26)	(0.12)	(-1.28)	(0.09)
$\mathbf{1}$(3pctl $<$ Regulatory capital $\leq$ 5pctl)	0.0017	0.0009	0.0014	0.0008
	(0.57)	(0.30)	(0.55)	(0.34)
$\mathbf{1}$(5pctl $<$ Regulatory capital $\leq$ 7pctl)	-0.0032	-0.0034	-0.0012	-0.0020
	(-1.06)	(-1.07)	(-0.47)	(-0.75)
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	0.140	0.224	0.143	0.225
N of Obs.	92528	92449	92528	92449

Table 11: **Payment risk and monetary policy transmission**

The dependent variable is the 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 3. 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 12: **Payment risk and deposit rate**

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. 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, as defined in Table 3. 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)
Liquidity ratio	-0.0175	-0.0258	-0.0675**	-0.0726**	-0.0336	-0.0408
	(-0.33)	(-0.49)	(-2.13)	(-2.32)	(-1.02)	(-1.26)
Loan ratio	0.2241***	0.2259***	0.0290	0.0319	-0.0066	-0.0022
	(3.87)	(3.98)	(0.85)	(0.95)	(-0.19)	(-0.07)
Trading ratio	-1.3439	-1.5540	-0.4856	-0.5442	-1.4613	-1.5655
	(-0.32)	(-0.37)	(-0.15)	(-0.17)	(-0.92)	(-0.96)
Capital ratio	0.5837***	0.5777***	0.2474***	0.2406***	0.2111***	0.1989***
	(3.32)	(3.32)	(3.33)	(3.30)	(3.01)	(2.93)
Deposit ratio	0.1752***	0.1726***	0.0895***	0.0878***	0.0832***	0.0805***
	(4.89)	(4.84)	(4.41)	(4.39)	(4.75)	(4.66)
Return on asset	1.9775*	1.8461	1.0972	1.0388	1.9860***	1.9113***
	(1.79)	(1.67)	(1.50)	(1.41)	(3.64)	(3.51)
log(Size)	0.0108	0.0484	-0.0641*	-0.0374	-0.0180	0.0192
	(0.24)	(1.03)	(-1.86)	(-1.11)	(-0.66)	(0.72)
$(\log(\text{Size}))^2$	-0.0008	-0.0019	0.0021	0.0014	0.0004	-0.0007
	(-0.48)	(-1.11)	(1.62)	(1.08)	(0.35)	(-0.69)
Number of states	-0.0083**	-0.0082**	-0.0054*	-0.0053*	-0.0007	-0.0006
	(-2.09)	(-2.07)	(-1.75)	(-1.74)	(-0.32)	(-0.28)
State $\times$ Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Type $\times$ 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