The Effect of Instant Payments on the Banking System: Liquidity Transformation and Risk-Taking*

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Abstract

Instant payment systems have received considerable attention because of their integration with the banking system and their shared functionalities with CBDCs. We show that instant payments may have the unintended consequences of increasing the banking sector's demand for liquidity and risk-taking incentives. Using administrative banking data and transaction-level payment data from Brazils Pix, one of the most widely adopted instant payment systems, we find that banks increased their liquid asset holdings and lent out more subprime and defaulting loans after the adoption of instant payments. We establish the causal relationship by constructing a novel instrument based on passive payment timeouts. These findings arise because the convenience of instant payments to consumers comes at the expense of banks ability to delay and net payment flows. The inability to delay payments increases banks demand for holding liquid assets over transforming illiquid ones. Banks' increased holding of liquid and safe assets in turn exacerbates their risk-taking incentives in choosing illiquid assets. Our findings bear important financial stability implications in light of the global surge in adopting instant payment systems, e.g., FedNow in the US.

Keywords: Payments, banking, financial stability, liquidity, FedNow

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1 Introduction

A fundamental role of deposits is to provide a means of payment. Bank deposits form the backbone of payment systems that facilitate transactions between households, merchants, and firms. In recent years, the global landscape of banking and payments has been undergoing significant changes due to innovations in payment technology. In particular, instant payment systems have drawn considerable attention from academics and policymakers because of their integration with the banking system and their shared functionalities with CBDCs (e.g., Brunnermeier, James and Landau, 2019, Duffie, 2019).[1] In the U.S., for example, the Federal Reserve has rolled out FedNow since July 2023, which enables all US banks to provide their customers with 24/7 instant payment services for the first time. Thus, instant payments offer the capability to transfer deposited funds more rapidly and thereby enhance the convenience value for depositors.

At the same time, deposits are a liability of the banking system, and banks value deposits as an important source of stable funding in providing loans to the real economy. When deposits become a more convenient means of payment that can be transferred from one bank to another without delay, what are the implications for the banking sector?

In this paper, we provide the first evidence that instant payments may have the unintended consequence of increasing the banking sectors' liquidity demand and risk-taking. Using administrative data on Brazil's Pix, one of the most widely and successfully adopted instant payment systems, we document that the use of instant payments positively correlates with banks' disproportionate allocation towards liquid assets and an increased share of subprime loans. We confirm that the observed relationship is causal by constructing a novel instrument based on passive payment timeouts. Our timeout instrument leverages the payment network structure to capture the variation in a bank's unsuccessful payments that arise from the technological failure of its counterparty banks.

Economically, our findings arise because depositors benefit from immediate payments, but this convenience inadvertently implies a loss in banks' autonomy in managing the timing of their payment flows. As our model shows, the reduced capacity to delay and net payments leaves banks more exposed to the volatility of payment shocks, which induces them to hold a larger proportion of liquid asset buffers and a smaller fraction of illiquid assets. That is, banks are

[1]The key difference between CBDCs and instant payments is that CBDCs are backed by assets on central banks' balance sheets while instant payment systems are operated through commercial banks. Some CBDCs, such as Brazil's DREX may also embed smart contract functions.

effectively becoming "narrower". Because of banks' increased holding of liquid and safe assets, they also become more incentivized to take on credit risk when investing in illiquid assets such as loans. The effect of this risk taking on loan outcomes further interacts with the level of lending technology. Thus, financial stability risks may not become necessarily lower despite a lower level of liquidity transformation.

Our analysis highlights the importance of understanding the costs and benefits of instant payments from the perspective of the banking sector. After all, unless instant payments are provided via CBDCs, banks own the assets that are ultimately backing the means of payments, i.e., deposits, that are used in instant payment systems like Pix and FedNow. Therefore, amidst the surge in adopting instant payments around the world, it is crucial to monitor and ensure that banks' new role in facilitating payment convenience does not impede their capacity to engage in liquidity and credit transformation for the economy.

Our empirical analysis mainly leverages two administrative datasets from the Central Bank of Brazil (BCB). First, we use transaction-level Pix data to measure the extent of Pix usage for each bank. This data also record transactions that are unsuccessful and whether these transaction failures were due to the sending or receiving bank. We use this information on failed transactions to construct an instrument for Pix usage in our empirical analysis. Second, we use monthly balance sheet and income statement data for commercial banks and credit unions from the BCB (COSIF), the Brazilian counterpart of Call Reports.

We uncover several novel stylized facts about the response of the Brazilian Banking system to the introduction of instant payments. We measure Pix usage by calculating the overlap between a bank's daily gross Pix sent and received, summed over each month, and divided by the bank's total assets for that month. This measure captures Pix payment turnover relative to bank size, reflecting how actively bank customers use Pix. The overlap between daily gross Pix sent and received also represents payment flows that would have been nettable with end-of-day rather than instant settlement. Thus, Pix usage also reflects the monthly loss of nettable payments per unit bank size.

The volume of nettable payments is economically substantial. For the median bank, nettable payments account for over 57% of total payments throughout our sample period. There is also considerable cross-sectional variation in banks' exposure to the loss of nettable payments relative to bank size. The average Pix usage in the first and fourth Pix usage quartiles is 0.08% and

43.21%, respectively. This indicates that while the average bank is significantly exposed to the loss of payment netting capacity due to the introduction of Pix, the degree of exposure varies widely across banks.

Sorting banks into quartiles of Pix usage, we first find that banks with higher Pix usage experienced a rise in the ratio of demandable deposits. This finding is consistent with Pix making demandable deposits more attractive because they can be used in instant payments without the liquidity restrictions that time deposits impose. From the perspective of the bank, however, a rise in the share of demandable deposits coupled with depositors' ability to send payments without delay may imply a rise in funding volatility.

On the asset side, we find that banks with more Pix usage also increased their ratio of liquid assets by more, especially in the form of government bonds. One likely interpretation is that banks set aside these government bonds as precautionary liquidity buffers to be pledged as collateral in repo transactions or to sell in secondary markets in the case of unanticipated payment shocks. Banks with large Pix usage experience an initial increase and subsequent volatility in cash holdings, consistent with cash being set aside ahead of time and then being deployed to meet more volatile payment shocks.

Finally, we find that banks with more Pix usage take on more credit risk in their portfolios. Our results on risk-taking are reflected in a disproportionate increase in the ratio of subprime loans, default loans, and loan loss provisions for banks with higher Pix usage. In contrast, the ratio of prime loans decreased for these banks. Our model uncovers an intricate connection between Pix usage and risk-taking, where banks' larger holdings of safe and liquid asset buffers following the introduction of instant payments incentivizes their risk-taking in illiquid assets, i.e., loans.

To rationalize our stylized facts and to provide testable predictions, we present a simple banking model that relates the role of deposits as a means of payment to bank lending. In the model, a representative bank finances its assets with deposits, wholesale funding, and equity. We assume the bank's equity ratio is exogenous, consistent with the substantial costs associated with adjusting bank equity. For given deposit and wholesale funding rates, the bank then chooses between a portfolio of risk-free liquid assets, which return a standardized rate of one, and riskier, but more productive, illiquid loans. Critically, the bank decides the extent of credit risk in its lending, with riskier loans offering higher expected returns.

On the liability side, deposits are a means of payment for depositors, subjecting the bank to random deposit flows. Specifically, depositors with unpredictable payment needs may choose to deposit their funds with the bank and enjoy payment services or invest in an outside option for higher returns without payment services. Without instant payments, banks can choose to delay depositors' payment requests for a given amount of time and, thereby, net incoming and outgoing payments. With the introduction of an instant payment system, bank are required to settle payments without delays and can no longer net payment flows over time. Consequently, the bank provides greater payment convenience for its depositors at the expense of forgoing the ability to delay and net payment flows.

Our model makes three main predictions about the effects of instant payment systems on banks' liquidity transformation and risk-taking behavior. First, as instant payments improve the convenience of deposits through removing banks' ability to delay payments, they also expose banks to greater uncertainty in deposit flows.

Second, in response to the higher volatility in deposit funding, the bank strategically increases its liquid asset holdings ahead of time to reduce the potential sell off of illiquid loans when hit with payment shocks. In other words, the instant nature of payments increases the bank's own demand for liquidity, which constrains its capacity for liquidity transformation, and ultimately results in a narrower bank.

Third, as the bank transforms less liquidity and holds more liquid buffers, equity holders are incentivized to take greater risks in the loan portfolio. This unintended consequence of instant payments on risk-taking may seem surprising, but it is reminiscent of the ideas of Acharya and Naqvi (2012) and Diamond, Hu, and Rajan (2020), which suggest that higher liquidity holdings reduce banks' incentives to screen and monitor risky loans. Specifically, bank equity is penalized in a loan default only if the bank experiences a significant liquidity shortfall. The increased pool of liquidity buffers resulting from instant payments gives the bank a larger buffer against default, reducing the sensitivity of bankers payoffs to downside risks and encouraging risk-taking. Consequently, the bank takes higher risk in lending to harvest a higher risk premium, leading to higher risk-taking under the instant payment system. This risk-taking is exacerbated by agency conflicts between banks' equity and deposit holders so the effect of instant payments on bank risk taking is larger at banks with lower capital ratios.

Our model further predicts that the implications of risk-taking varies with lending technology. If banks are more efficient at selecting and monitoring borrowers when instant payments are introduced, their risk-taking is more likely to generate a higher risk premium. If lending technology is efficient enough, the increase in risk premia may even compensate the drop in loan ratios to increase loan income ber unit assets. These results highlight that risk-taking and lending technology from instant payments jointly influence loan outcomes.

To verify the model predictions in the data, we need to overcome the identification challenge that Pix usage may be correlated with observable and unobservable bank characteristics, which also affect the composition of their balance sheets. To this end, we construct a novel instrument for Pix usage using transaction timeouts. The basic idea is that the availability of Pix is only relevant if Pix payments are successfully sent by the sending bank and then successfully received by the receiving bank. If either the sending bank or the receiving bank fail to process the payment within 40 seconds, the payment attempt is unsuccessful and deemed as "timeout" by the Pix system. The convenience of Pix payments is lost in the event of a timeout. Therefore, banks that experience more frequent timeouts are likely to see reduced Pix usage due to the increased inconvenience experienced by their customers.

Although timeouts are for the most part driven by unexpected technical issues, banks may still have some control over the speed and ability to resolve timeouts at their own bank. To this end, we construct our timeout instrument for a given bank i in month t only using the variation in timeouts induced by other banks. This includes timeouts due to receiving banks if bank i is the sending bank in the transaction as well as timeouts due to sending banks if bank i is the receiving bank in the transaction. In both cases, the attractiveness of bank i's Pix service is reduced, but bank i cannot actively fix the timeouts induced by technical issues at other banks. Formally, we define the timeout instrument for bank i in month t as the weighted passive timeout probability, stemming from both its sending and receiving banks. The weights are the fractions of transactions that bank i sends to and receives from each counterparty bank. The identifying assumption is that, for each bank i, these passively induced timeouts from other banks do not influence bank i's decisions regarding its balance sheet composition through channels other than its customers' Pix usage over time.

After confirming that our timeout instrument is indeed negatively affecting Pix usage in the first stage, we instrument for Pix usage and estimate the causal effect of Pix usage on banks' liability structure, asset composition, and risk-taking. Our sample period is from November 2020 to March 2023. We control for bank characteristics like asset size, capital, and the number of branches. We also include bank and time fixed effects.

Our estimates confirm the model predictions. First, we find that a one-standard-deviation increase in Pix usage leads to a 12.7 ppts increase in the ratio of demandable deposits, consistent with the instant payments making demandable deposits especially attractive. As our model shows, this increased convenience to depositors comes at the expense of banks losing their ability to delay payments, which exposes banks to unexpected funding shocks.

Our empirical estimates also confirm that Pix usage increases the proportion of liquid asset buffers. A one-standard-deviation increase in Pix usage causes a 15.4 ppts increase in the ratio of liquid assets. Echoing our earlier results, this increase in liquid assets primarily comes from government bond holdings. At the same time, Pix usage also causes a drop in the ratio of loans on bank balance sheets, consistent with instant payments constraining bank liquidity transformation.

Further, we show that higher Pix usage exacerbates risk-taking in lending, as our model predicts. We find that a one-standard-deviation increase in Pix usage causes the ratio of prime loans to decrease by 21.8 ppts and the ratio of sub-prime loans to increase by 18.6 ppts. In line with the disproportionate lending to riskier borrowers, banks with more Pix usage also set aside more loan loss reserves and eventually experience a higher ratio of defaulting loans. These results are amplified by lower capital ratios, consistent with agency conflicts exacerbating risk-taking incentives in our model.

Finally, we show that lending technology is such that banks' increased risk-taking increases loan risk premia but decreases loan income per unit assets because the lower ratio of loans over bank assets dominates. In this regard, we acknowledge that our results are focused on the short- and medium-term effects and that the implications may differ in the long term. For example, it could be that loans are given out to new borrowers without credit ratings, fostering financial inclusion in the long run. These long-term benefits should be considered alongside the costs of a riskier loan book to determine the welfare implications of banks' increased risk-taking. We leave this important question for future research.

Related Literature. Our paper contributes to the understanding of instant payments, which is among the most promising next-generation payment systems that include fast payment systems, stablecoins, and CBDCs, as discussed by Brunnermeier, James and Landau (2019) and Duffie (2019). Most papers in this burgeoning literature have focused on the effect of new payment technologies on consumers' consumption, investment, and default decisions (e.g. Jack and Suri, 2014, Muralidharan, Niehaus, and Sukhtankar, 2016, Higgins, 2020, Ghosh, Vallee, and Zeng, 2022).[2] Several recent studies examine instant payment systems. Dubey and Purnanandam (2023) and Alok, Ghosh, Kulkarni, and Puri (2024) show the benefits of instant payments for financial inclusion in the context of India's UPI, Sarkisyan (2023) analyzes the effects of instant payments on deposit competition in the context of Brazil's Pix, while Liang, Sampaio and Sarkisyan (2024) show that the increased deposit competition from instant payments amplifies monetary policy transmission. Our paper is the first to examine how instant payment systems affect the fundamental roles of the banking system in terms of liquidity and credit intermediation. We uncover that instant payments may have the unintended consequence of increasing banks' demand for liquidity and risk-taking incentives, which have far-reaching implications for the central banks' supply of liquid assets and monitoring of bank stability.

Our result that instant payments increase banks' demand for liquid assets also relates to the literature on the optimal supply of liquid assets for the banking sector. Following studies on disruptions and liquidity shortages in interbank payments (e.g., McAndrews and Potter, 2002, Bech and Garratt, 2003, Afonso, Kovner and Schoar, 2011, Afonso and Shin, 2011, Iyer, Peydro, da-Rocha-Lopes and Schoar, 2014), a recent set of papers explores how reserve scarcity contributed to delays in interbank payments and disruptions in repo funding in September 2019 (Copeland, Duffie and Yang, 2020, Correa, Du and Liao, 2020, d'Avernas and Vandeweyer, 2020, Afonso, Duffie, Rigon and Shin, 2022). More generally, Acharya and Rajan (2023) and Lopez-Salido and Vissing-Jorgensen (2023) show the effects of quantitative easing (QE) and quantitative tightening (QT) on the banking sector's demand for liquidity, and Afonso, Gianonne, La Spada and Williams (2020) show that the liquidity needs of the banking sector are state-contingent. Our findings highlight the introduction of instant payment systems as a new contributing factor to the liquidity demand of the banking sector. One implication is that the supply of liquid assets for the banking sector may have to increase following the introduction of instant payment systems to meet the increased demand for liquid asset buffers and to prevent fragility arising from liquidity shortages.

Finally, our paper contributes to the literature that explores the interaction between banks'

[2] Another strand of the literature examines the effects of digital deposits on banks (e.g., Benmelech, Yang, and Zator, 2023, Erel, Liebersohn, Yannelis, and Earnest, 2023, Jiang, Yu, and Zhang, 2023, Koont, 2023, Koont, Santos, and Zingales, 2023).

payment processing and lending.[3] In the process of creating liquidity, banks naturally embody both roles as the circulation of deposits as a means of payment facilitates loan repayments (Donaldson, Piacentino and Thakor, 2018). However, Parlour, Rajan and Walden (2020) demonstrate that the necessity for banks to settle interbank payments using liquid assets gives rise to a liquidity externality that limits their capacity to lend. Consistent with this notion, Bolton, Li, Wang, and Yang (2020) and Jermann and Xiang (2023) model deposits as obligations with random maturity and as non-maturing debt, respectively, analyzing their impact on bank investments and default risks. Using Fedwire data, Li and Li (2021) empirically find that more volatile payment flows lead to increased funding risk and reduced loan growth, especially for undercapitalized banks. In contrast to these studies, our work highlights the impact of instant payment systems. We show that instant payment systems remove banks' ability to delay and net payments, which ultimately results in more volatile payment flows, a larger demand for liquidity, and an increase in risk-taking due to lower profitability. Thus, our findings further shed light on instant payments as a constraint to bank liquidity transformation (Diamond and Dybvig, 1983, Diamond and Rajan, 2005, Goldstein and Pauzner, 2005).

2 Institutional Setting and Data

2.1 Instant Payment Systems and Pix

Instant payment systems represent a global evolution in financial transactions, functioning as broadly accessible Real-Time Gross Settlement (RTGS) bank-railed systems that operate 24/7. This infrastructure enables instantaneous transactions between individuals across any day or time, provided their banks grant interoperable access to these systems. Unlike traditional payment technologies, instant payment systems facilitate instant transfers between parties at any time, provided their banks are interconnected through these platforms. They are pivotal in updating the mechanics of payments to align with the immediate transaction needs demanded by the digital economy. Various central banks also view instant payments as a building block for the modernization of the financial ecosystem. About 100 jurisdictions have introduced instant payments, and several others have announced plans to go live soon.[4]

[3] Another strand of literature delves into bank liquidity management amidst uncertainty, asymmetric information, or counterparty risks (e.g., Caballero and Krishnamurthy, 2008, Allen, Carletti and Gale, 2009, Acharya and Skeie, 2011, Gale and Yorulmazer, 2013, Heider, Hoerova and Holthausen, 2015).

[4] See here.

The adoption and economic impact of these systems vary worldwide, with Pix standing out for its notable success. Pix, the instant payment system introduced by the BCB, enables instant, around-the-clock payments between individuals, businesses, and government entities without the fees commonly associated with traditional banking services. Pix's success is largely attributed to its real-time banking infrastructure and user-friendly design, which includes an innovative alias resolution service. This feature allows users to make payments using simple identifiers, such as phone numbers, significantly simplifying and enhancing the user experience for daily financial activities. Moreover, the BCB mandated that all financial and payments institutions with more than 500,000 opened accounts offer access to Pix through applications that adhere to common standards, promoting universal access and integration within the Brazilian financial ecosystem.[5] Within just two years of its launch, Pix saw an adoption rate unparalleled by any other payment system, with more than 150 million users in its first year alone. Currently, nine out of ten small businesses in Brazil utilize Pix, and the volume of transactions continues to grow. For example, on July 5th, 2024 alone, PIX transactions amounted to BRL 119 billion, which is about 1% of annual GDP.[6]

2.1.1 Comparison to the US: Fedwire and FedNow

In the U.S., Fedwire has been the most commonly used RTGS for interbank payments before the launch of FedNow in July 2023. Fedwire allows for bank discretion in payment timing, where a bank may voluntarily delay submitting a payment order received from a customer. As a result, Fedwire can be viewed as an analogy to the pre-Pix interbank payment system in Brazil.

The current landscape of instant payment systems features both RTP and FedNow. While RTP, a private-sector service, has seen relative success in specific, mainly business-related services among a subset of banks, FedNow, launched by the Federal Reserve, aims for broader accessibility to retail bank customers. Comparatively, FedNow has yet to attain the extensive adoption observed in Brazil or India. Despite FedNow becoming available to all banks in 2023 and enrolling 400 banks by January 2024, broad-based adoption, especially among the largest banks, remains limited. The decentralized approach to adopting fast payment services in the U.S., without substantial regulatory directives, contrasts with the strategies that fueled the rapid

[5] The regulation refers to eligible accounts, i.e., savings, checking (demand deposits) and prepaid accounts, where prepaid accounts are only offered by payment institutions. PIX adoption by smaller participants is voluntary but widespread. See more here.

[6] See here.

spread of Pix in Brazil. Nevertheless, the potential for FedNow to reach wider adoption remains large, given the prevalent use of bank deposits as a means of payment in the US.

2.2 Data

Our analysis draws on several regulatory datasets from the Brazilian Central Bank. First, we employ transaction-level Pix data to quantify Pix usage at the bank level and to construct our timeout instrument. For each transaction, we observe details such as timestamp, amount, and both the sending and receiving banks. Importantly, failed transactions (timeouts) are also recorded, including indicators identifying whether the timeout was due to the sending or receiving bank. We will use the data on failed transactions to develop our instrument for Pix usage.

Second, we incorporate monthly bank balance sheet and income statement data from COSIF. We use the conglomerate-level version to account for banks that manage loans and other assets through specific subsidiaries within the conglomerate. Our sample comprises of commercial banks and credit unions, as these institutions engage in both deposit-taking and lending.[7]

Together, these data provide a comprehensive view of the banking sector following Pixs implementation. Our dataset spans January 2018 to March 2023, with the primary analysis focused on the period from Pixs implementation in November 2020 through March 2023. Table 1 presents summary statistics of the main variables in our analysis.

3 Stylized Facts

We first show several novel stylized facts about the variation in Pix usage and the banking sector's response.

3.1 Pix Usage and Nettable Payments

Although the vast majority of banks in Brazil adopted Pix, their exposure to the adoption differed by the extent to which their customers utilized Pix in making payments. We proxy for a bank's exposure to Pix using $PixUsage_{it}$, which is the overlap between bank i's daily gross Pix sent

[7] We do not include payment institutions because they have a different asset composition and are not engaged in lending.

and received summed over month t divided by its total assets in month t:

$$PixUsage_{it} = \frac{\sum_{d \in t} \min(Outflows_{id}, Inflows_{id})}{TotalAssets_{it}}. \tag{3.1}$$

Pix usage thus represents a turnover ratio. Intuitively, the higher the Pix usage, the more actively a bank's customers send and receive instant payments and the more that bank could become exposed to payment shocks from Pix. We do not consider the gap between Pix sent and received because that may simply be part of general deposit growth at a bank, which is driven by many other factors not directly related to the introduction of Pix.

Further, Pix usage proxies for the loss in a bank's capacity to net payment flows. Prior to Pix, banks had the ability to delay incoming and outgoing payment requests until the end of the business day under PIX's predecessor, "Transferłncia Eletrnica Disponvel". That is, banks could delay processing payment requests until the end of the day so that they can offset outgoing payments with incoming payments within the same business day. This process is known as "netting," where banks could reduce their liquidity needs by only settling the net difference between gross inflows and outflows at the end of each day. On a given day, the overlap between a bank's daily gross Pix sent and received thus represents the payment flows that could have been netted out against each other with end-of-day settlement under the previous payment system. With the introduction of Pix, payments are settled instantaneously so banks lose the ability to delay and net payments within the same day. Pix usage thus reflects the monthly loss of nettable payments per unit size. Higher Pix usage then reflects higher vulnerability to payment shocks due to Pix.

Daily payment netting is important for banks because a large fraction of gross payment flows is nettable within the day. To see this, we calculate the ratio of nettable payments as a proportion of total payments for each bank

$$\frac{2 \sum_{d \in t} \min(Outflows_{id}, Inflows_{id})}{\sum_{d \in t} (Outflows_{id} + Inflows_{id})} \tag{3.2}$$

and plot the p25, p50, and p75 in Figure 2. In Appendix A.1, we provide a detailed derivation showing that the expression (3.2) at the daily level precisely captures the amount of daily nettable payments.

From Figure 2. we observe that 57% to 80% of Pix payments would have been nettable within day for the median bank. In other words, the median bank loses out on flow netting for 57% to

80% of its gross payment flows. For the p25 and p75 bank, the ratio of nettable payments ranged from between 18% to 45% and 73% to 90% over our sample period, which indicates that banks' loss in nettable payments due to instant payments displays significant cross-sectional variation.

There is also significant cross-sectional variation in Pix usage, i.e., banks' loss in nettable payments per unit asset size. We average Pix usage for each bank over our sample period and plot the monthly average Pix usage for each quartile in Figure 3. The figure reveals considerable heterogeneity in Pix usage levels across banks. By the end of the sample period, the average Pix usage for banks in the highest quartile (Q4) exceeded 89.13%, while the average Pix usage for banks in the lowest quartile (Q1) was only about 0.14%.

In the remainder of this section, we show how banks' liabilities, assets, and risk-taking in each Pix usage quartile evolve following the introduction of Pix. We hypothesize that banks' response to the introduction of Pix should vary with Pix usage, i.e., the extent to which they are affected by the loss of payment netting from instant payments. Of course, Pix usage is not randomly distributed and banks with different Pix usage may have other observable and unobservable characteristics that affect the outcome variables we examine. That is why the results in this section only serve as preliminary evidence. In Section 6, we instrument for Pix usage and more formally estimate the causal effect of instant payments on banks' capacity for liquidity transformation and credit intermediation.

3.2 Deposit Structure

We begin by examining how the structure of deposit funding has evolved for banks in response to Pix adoption. Only demandable deposits, including savings and checking deposits, can be directly used for Pix payments without restrictions. In contrast, non-demandable deposits like time deposits cannot be withdrawn before maturity without penalty. They must first be transferred to a checking account before they can be used for Pix transactions. Consequently, we would expect that demandable deposits become more appealing to customers with the availability of Pix.

Figure 4a shows the average ratio of demandable deposits for each Pix usage quartile. Banks in the fourth quartile of Pix usage indeed experience a notably larger increase in their share of demandable deposits compared to banks in lower quartiles. Figure 4b further confirms that the trend in Figure 4a is mostly driven by checking deposits, especially for banks in the fourth quartile. Checking deposits make up the majority of demandable deposits in Brazil. They allow for unrestricted, frequent transactions, making them particularly attractive to Pix users who prioritize immediate access to funds.

These results suggest that Pix usage is positively correlated with depositors' shift toward more liquid accounts. From the bank's perspective, a rise in demandable depositsparticularly in checking depositsmay introduce greater funding volatility. Since depositors can use these deposits to make instant transfers, banks may face more frequent and unpredictable deposit outflows, potentially impacting their liquidity management.

3.3 Asset Composition

We proceed to examine how banks adjust their asset composition. In particular, we focus on banks' liquid asset holdings, which includes cash, cash equivalents and government bonds. These assets can be readily converted to cash to meet payment demands on short notice.

In Figure 5a, we observe that the ratio of liquid assets to total assets increases more significantly for banks with higher Pix usage. Notably, this increase in liquid assets is primarily driven by a rise in holdings of government bonds, as shown in Figure 5b. One likely interpretation is that government bonds serve as liquid assets that banks can pledge in repo transactions, including with the BCB, or sell on the secondary market when they face payment shocks. Banks with more Pix usage are more exposed to payment shocks from the loss in payment netting. Their increased holding of government bonds is thus consistent with a higher level of precautionary liquid buffers to manage payment shocks.

Banks holding of cash and cash equivalents shows no clear upward or downward trend after Pixs implementation, as seen in Figure 5c. Cash holdings represent a more dynamic component of liquidity management. In the data, the level of cash depends not only on the ex-ante amount that is set aside but also on how many outgoing and incoming payments have been made at any given time. In fact, banks in the highest Pix usage quartile initially increase their cash holdings in anticipation of Pixs rollout and then experience significant volatility in their cash ratios post-implementation. This pattern suggests that these banks initially set aside more cash in anticipation of Pix and subsequently draw on their cash reserves to meet the more volatile payment demands after the introduction of Pix.

The rise in banks' liquid asset holdings is indicative of their increased exposure to payment shocks under Pix. At the same time, it also implies that Pix may be constraining the banking sector's ability to engage in liquidity transformation.

3.4 Bank Risk-Taking

While Pix usage is associated with a larger share of liquid assets on bank balance sheets, it may be that the characteristics of banks' illiquid assets are changing at the same time. We thus explore how the riskiness of banks' lending to the real economy has evolved with the implementation of Pix.

Figures 6a and 6b show the ratio of loans that are classified as prime and sub-prime over time, respectively. We define prime loans as those classified by banks in the best scoring categories, AA and A, following local regulation "Resolucao' CMN 2,682/1999. We also define as subprime the loans assigned categories B and C. All other, lower ranked categories are considered in default. Banks in the fourth quartile of Pix usage exhibit a notable decline in their prime loan ratio following the implementation of Pix. In place of prime loans, these banks are taking on riskier sub-prime. In contrast, banks in the first two quartiles of Pix usage increase their ratio of prime loans and decrease their ratio of subprime loans over the same period. Banks in the third quartile maintained a relatively stable prime loan ratio after the introduction of Pix. These results suggest that banks more exposed to Pix usage extended riskier loans than banks less exposed to Pix usage.

The shift towards riskier lending practices by high Pix usage banks coincided with a rise in their ratio of loan defaults. Figure 6c displays the average default loan ratio by Pix usage quartile. We observe that defaulting loans at banks in the first two quartiles of Pix usage held steady or declined, while defaulting loans at banks in the third quartile of Pix usage experienced a significant jump around the end of 2021. The timing of the rise in loan defaults is consistent with defaults lagging behind the initial extension of loans. While banks in the highest quartile do show an increase in default ratios, it is more moderate.[8]

The economic connection between Pix usage and bank risk-taking may appear less direct. In the model, we will show that the increase in risk-taking materializes exactly because of the aforementioned increase in banks' liquid asset holdings. While banks increase their liquid asset holdings primarily to prepare for more volatile payment shocks, the liquid asset buffer they set aside also raises their distance to default and thereby incentivizes risk-taking in the illiquid asset.

[8]This trend is driven in part by several credit unions in Q4 which may not only prioritize profit maximization but also have other mandates like member services and community support that influence their lending decisions.

4 Model

In this section, we present a model to shed light on the effect of instant payments on bank liquidity transformation and risk-taking. We keep the baseline model simple to help crystallize the underlying economic channels. For detailed proofs, please refer to Appendix A.2.

4.1 Setup

Time is discrete, $t = 0, 1, 2, ..., T - 1, T$, with $T \geq 3$. There are two banks, denoted as $j \in 1, 2$, each operating in its own distinct market j. Each market hosts a continuum of risk-averse households, details of which are elaborated below. There are two market-specific consumption goods, which are also indexed by j.

Each bank j is risk-neutral and funded through three types of liabilities: equity, demandable deposits, and time deposits. To focus on the composition of deposits, we consider the equity ratio, η, of the two banks as exogenous. As we show below, equity ratio plays an important role in determining bank's risk-taking incentives. Demandable deposits are available for use in payments at any date $1 \leq t \leq T-1$ and yield a normalized interest rate of 0 at T.[9] Time deposits, on the other hand, accrue a positive interest rate $r > 0$ which is realized at date T but cannot be used for payments before maturity at T. We also assume that both demandable and time deposits are insured.[10]

At $t = 0$, the representative household is endowed with an initial wealth of \$1 and makes investment decisions between demandable and time deposits. The household is assumed to be risk-averse and has an intertemporal elasticity of substitution greater than one (i.e., $IES > 1$) as commonly seen in the asset pricing literature (e.g., Nakamura and Steinsson, 2023).[11] Specifically, her per-period utility function satisfies $u'(c) > 0$, $u''(c) < 0$, and $u'(c) + cu''(c) > 0$. We assume that once invested, time deposits cannot be converted into demandable deposits before the maturity date T, and vice versa. She allocates α of her endowment to demandable deposits,

[9] In Brazil, checking deposits do not accrue any interest, whereas the interest rates for savings accounts are regulated by the Brazilian government and tied to the Selic rate, which is the overnight interest rate of the BCB.

[10] Savings, checking and time deposits in Brazil are insured by the Fundo Garantidor de Creditos (FGC). The coverage by the FGC ensures that depositors are protected up to a certain amount, typically 250,000 Brazilian reais per depositor per institution, which provides security against the risk of bank insolvency.

[11] Empirical estimates of the intertemporal elasticity of substitution (IES) range from 0 to 2. It is common in the asset pricing literature to assume an IES greater than 1, as discussed by Nakamura and Steinsson (2023), because otherwise, bad news about future growth would increase stock prices due to an excessively strong desire to save. We adopt this assumption for the same reason: to avoid a counterintuitive mechanism where faster payments would increase household demand for savings deposits due to a similarly strong desire to save.

which will be determined in equilibrium. From $1 \leq t \leq T-1$, households in each market j face idiosyncratic consumption shocks: with probability $\pi_{j,t}$, household i in market j has to consume at time t. For each market j, these probabilities $\pi_{j,t}$ are i.i.d., and sum over time to $\sum_{t=1}^{T-1} \pi_{j,t} = 1$. To focus on the implications of cross-bank payments, we assume that under a consumption shock, households in market j must purchase the consumption good $-j$ produced in the other market, following Freixas, Parigi and Rochet (2000) and Parlour, Rajan and Walden (2020). This transaction requires the withdrawal of demandable deposits from bank j to buy good $-j$, resulting in a net payment request from bank j to bank $-j$ at date t. This setting of cross-market consumption needs captures the economic specialization and the resulting lack of a double coincidence of wants across the two markets, thereby justifying the use of demandable deposits across banks as a means of payment. Note that we abstract away from households in market j purchasing the consumption good j within their own market because this transaction has no impact on cross-bank payments, and thus modeling it would not change the insights of the model.

Also at $t = 0$, the equity holders of each bank j make investment decisions aimed at maximizing the expected value of bank equity at $t = T$. They choose between a liquid, safe asset, such as cash or government bonds, and an illiquid, risky loan. The liquid asset yields a normalized gross return of 1 at any t, while the loan offers a risky gross return of $\widetilde{R}$ at T. We follow Carletti, Leonello, and Marquez (2024) to model the profile of the risky loan and banks' risk-taking activities. Specifically,

$$\widetilde{R} = \begin{cases} R(p)\theta & \text{with probability } p\,, \\ 0 & \text{with probability } 1-p\,, \end{cases} \tag{4.1}$$

where $R(p)$ is decreasing in p to reflect a positive risk premium, θ captures aggregate uncertainty, which follows a standard uniform distribution betweem $[0, 1]$, and the bank chooses p.[12] Intuitively, a bank engages in higher risk-taking when it chooses a lower p, which would allow the bank to capture a higher risk premium at the same time. The loan is also characterized by its illiquidity; only a fraction $1 - \phi$ of the loan value can be recovered if it is liquidated before maturity, i.e., at any $t \leq T$, where $0 < \phi < 1$. Although the liquid asset can be easily carried over from one date to the next, the loan investment can only be made at $t = 0$. At $t = 0$, the bank

[12] We assume a uniform distribution for simplicity but our qualitatative results hold under more general distributions of aggregate uncertainty.

chooses its allocation to the liquid asset, x, allocation to the illiquid loans, y, and the riskiness of its loans, $1-p$.

We analyze symmetric equilibria and explore the effects of two types of payment systems—an instant payment system and a traditional payment system—on banks' demand for liquid assets and risk-taking incentives. Under the instant payment system, banks are required to use the liquid asset to settle any payment balance at any date t immediately, without delays. In contrast, under the traditional payment system, banks can delay settling the payment balance from date t by κ periods to date $\tau = \min\{t+\kappa, T\}$, where $1 \leq \kappa < T$. To reflect the cost of delays to households, we assume that households derive a discounted consumption value of δ^{κ} per dollar processed with a delay of κ dates at date t, where $0 < \delta < 1$.

4.2 Equilibrium Analysis: Instant vs. Traditional Payments

We first consider the equilibrium under the instant payment system. Specifically, bank j's problem is given by:

$$\max_{\{x_{j,0};p\}} E\left[\Pi_{j,T}\right] , \tag{4.2}$$

where the date-T bank profit accrued to bank equity is given by

$$\Pi_{j,T} = \max\{\underbrace{x_{j,T} + py_{j,T}R}_{\text{gross revenue}} - \underbrace{(1-\eta)(1+(1-\alpha)r)}_{\text{debt expenses}}, 0\} , \tag{4.3}$$

subject to the law of motion for the liquid asset

$$x_{j,t+1} = \begin{cases} x_{j,t} - \alpha(1-\eta)(\pi_{j,t} - \pi_{-j,t}) & \text{if } x_{j,t} \geq \alpha(1-\eta)(\pi_{j,t} - \pi_{-j,t}) , \\ 0 & \text{if } x_{j,t} < \alpha(1-\eta)(\pi_{j,t} - \pi_{-j,t}) , \end{cases} \tag{4.4}$$

as well as that for the illiquid loan

$$y_{j,t+1} = \begin{cases} y_{j,t} & \text{if } x_{j,t} \geq \alpha(1-\eta)(\pi_{j,t} - \pi_{-j,t}) , \\ \max\{y_{j,t} - \frac{\alpha(1-\eta)(\pi_{j,t}-\pi_{-j,t})-x_{j,t}}{1-\phi}, 0\} & \text{if } x_{j,t} < \alpha(1-\eta)(\pi_{j,t} - \pi_{-j,t}) . \end{cases} \tag{4.5}$$

(4.3) indicates that the bank remains solvent only if the gross revenue is sufficient to cover the expected debt expenses, including interest on time deposits; otherwise, the bank defaults at $t = T$ and bank equity receives nothing. The law of motion for the liquid asset (4.4) suggests that, without the ability to delay payment requests, the bank must deploy its liquid assets to satisfy any net outgoing payment requests at t until the liquid assets are depleted. Additionally, the law of motion for the illiquid asset (4.5) implies that the bank may need to liquidate its illiquid assets prematurely to meet payment requests if it runs out of liquid assets at t.

At the same time, the problem for the representative household in market j is given by

$$\max_{\{\alpha_j\}} E\left[\sum_t \pi_{j,t} c_t\right] , \tag{4.6}$$

where

$$c_{j,t} = \begin{cases} \alpha & \text{if } 1 \leq t \leq T-1 \,, \\ (1-\alpha)(1+r) & \text{if } t = T \,. \end{cases} \tag{4.7}$$

(4.7) indicates that under a consumption shock, the instant payment system processes the household's payment from bank j to $-j$ instantaneously. This allows the household to access the consumption value of their demandable deposits immediately without delay. At the end, when $t = T$, households also enjoy the principal and interest paid on their time deposits. Note that deposit insurance guarantees the preservation of deposit values including both demandable and time deposits, regardless of whether the bank defaults or not at any date t.

Having described the instant payment system, we now illustrate how the traditional payment system operates within our framework. Under the traditional payment system, the problem faced by bank j is as follows:

$$\max_{\{x_{j,0};p\}} E\left[\Pi_{j,T}\right] , \tag{4.8}$$

where the date-T bank profit accrued to bank equity is the same as that in (4.3) while subject to a different law of motion for the liquid asset

$$x_{j,t+1} = \begin{cases} x_{j,t} & \text{if } t \leq \kappa\,, \\ x_{j,t} - \alpha(1-\eta)(\pi_{j,t-\kappa} - \pi_{-j,t-\kappa}) & \text{if } t \geq \kappa+1 \text{ and } x_{j,t} \geq \alpha(1-\eta)(\pi_{j,t} - \pi_{-j,t})\,, \\ 0 & \text{if } t \geq \kappa+1 \text{ and } x_{j,t} < \alpha(1-\eta)(\pi_{j,t} - \pi_{-j,t})\,, \end{cases} \tag{4.9}$$

and that for the illiquid loan

$$y_{j,t+1} = \begin{cases} y_{j,t} & \text{if } t \leq \kappa\,, \\ y_{j,t} & \text{if } t \geq \kappa+1 \text{ and } x_{j,t} \geq \alpha(1-\eta)(\pi_{j,t} - \pi_{-j,t})\,, \\ \max\{y_{j,t} - \frac{\alpha(1-\eta)(\pi_{j,t-\kappa}-\pi_{-j,t-\kappa})-x_{j,t}}{1-\phi}, 0\} & \text{if } t \geq \kappa+1 \text{ and } x_{j,t} < \alpha(1-\eta)(\pi_{j,t} - \pi_{-j,t})\,. \end{cases} \tag{4.10}$$

Compared to the bank's problem (4.2) under the instant payment system, the laws of motion (4.9) and (4.10) indicate that the ability to delay payments under the traditional system allows the bank to defer fulfilling households' payment requests. This capability enables banks to net incoming and outgoing payment flows over a period of κ periods as shown in (4.9). Additionally, the time buffer created by the delay helps the bank to partially mitigate the illiquidity associated with the underlying loans, as shown in (4.10). Moving forward, we demonstrate that these two effects significantly influence the bank's portfolio choices, and subsequently, its profitability and risk-taking incentives.

The problem for the representative household in market j is now given by

$$\max_{\{\alpha_j\}} E\left[\sum_t \pi_{j,t} u(c_t)\right]\,, \tag{4.11}$$

where

$$c_{j,t} = \begin{cases} \delta^{\kappa}\alpha & \text{if } 1 \leq t \leq T-\kappa\,, \\ \delta^{T-t}\alpha & \text{if } T-\kappa+1 \leq t \leq T-1\,, \\ (1-\alpha)(1+r) & \text{if } t = T\,. \end{cases} \tag{4.12}$$

Thus, (4.12) indicates that under a consumption shock, the traditional payment system may subject the household's payment from bank j to bank $-j$ to potential delays depending on the size of payments, effectively discounting the consumption value.

4.2.1 The Effect of Instant Payments on Bank Liquidity Transformation

Having detailed the problems faced by banks and households, we now compare the equilibrium outcomes between the two payment systems. We first examine how instant payments affect bank liquidity transformation.

Proposition 1. [DEPOSIT PAYMENT CONVENIENCE EFFECT]*: Given any* $x > 0$ *and* $p > 0$*,* $\alpha^*_{ins} > \alpha^*_{tra}$*, that is, households demand more demandable deposits under the instant payment system compared to the traditional system.*

Proposition 1 explores the household demand for demandable deposits and suggests that households increasingly favor demandable deposits following the introduction of the instant payment system. Intuitively, the relative convenience of demandable deposits compared to time deposits is enhanced by instant payments, effectively increasing the consumption value per unit of demandable deposit.

Proposition 2. [BANK LIQUIDITY DEMAND EFFECT]*: Given any* $\alpha > 0$*,* $x^*_{ins} > x^*_{tra}$*, that is, banks demand more liquid buffers under the instant payment system compared to the traditional system when* ϕ *is sufficiently large and* η *is sufficiently small.*

Proposition 2 implies that, compared to the traditional payment system, the introduction of the instant payment system prompts banks to maintain larger liquid buffers. Intuitively, a comparison of the laws of motion (4.4) and (4.9) demonstrates that the requirement to process payment requests instantaneously eliminates the banks' ability to net incoming and outgoing payments. Furthermore, a comparison between the laws of motion (4.5) and (4.10) suggests that instant payments expose banks to higher liquidity risks, as they are more likely to be forced to liquidate their illiquid loans. In response, banks optimally increase their liquid buffers following the implementation of the instant payment system, thereby raising the overall liquidity demand within the banking sector.

4.2.2 The Effect of Instant Payments on Bank Risk-Taking

Next, we show how instant payments affect banks' risk-taking activities. Importantly and perhaps surprisingly, we find that the instant payment system, despite making banks "narrower" in that it encourages banks to transform less liquidity to accomodate more volatile payment needs, at the same time leads banks to take more risk in their illiquid assets.

Proposition 3. [Bank Risk-Taking Effect]*: Given any $\alpha > 0$, $p^*_{ins} < p^*_{tra}$, that is, banks choose riskier illiquid assets under the instant payment system compared to the traditional system.*

Proposition 3 implies that, compared to the traditional payment system, the introduction of the instant payment system prompts banks to lend out riskier loans while the share of lending over bank assets is decreasing. We call this effect the risk-taking effect, which is an implication of Proposition 2 and the underlying liquidity demand effect.

To better understand the risk-taking effect, it is useful to express the bank's problem of optimal risk-taking under a terminal portfolio of $(x, 1-x)$ as follows:

$$\max_p E\left[x + (1-x)pR(p)\theta - (1-\eta)(1+(1+\alpha)r) | x + (1-x)R(p)\theta - (1+(1+\alpha)r) > 0\right], \tag{4.13}$$

where the expectation is taken over θ. Solving the problem yields the bank's optimal risk-taking decision

$$p^* = R^{-1}\left(\frac{(1-\eta)(1+(1+\alpha)r) - x}{1-x}\right), \tag{4.14}$$

which is, in turn, decreasing in x. Intuitively, bank equity retains residual claims of the bank subject to a limited liability constraint. Bank equity is only penalized in the event of a loan default if the bank faces a significant liquidity shortfall. As Proposition 2 indicates, the increased liquidity from instant payments provides a larger buffer against default. This gives the bank more distance from default in any aggregate state, reducing the sensitivity of bankers payoffs to downside risks and encouraging risk-taking, reminiscent of the ideas of Acharya and Naqvi (2012) and Diamond, Hu, and Rajan (2020). Consequently, as shown in (4.14), the bank optimally takes more risk to harvest a higher risk premium under the instant payment system. Proposition 3 then immediately follows by linking the problem in (4.13) to the bank's initial portfolio decisions and noticing that the bank effectively chooses p^* and x^* sequentially.

A natural implication of Proposition 3 is that the increase in risk-taking following the introduction of instant payment systems can vary depending on the severity of agency conflicts. Specifically, the increased risk-taking due to instant payment system is amplified for banks with lower equity ratios. Formally, we state this implication in the following corollary:

Corollary 1. [Bank Risk-Taking and Agency Issues]*: Given any $\alpha > 0$, the difference $p^*_{tra} - p^*_{ins}$ increases as the bank's equity ratio decreases.*

[#This subsection is newly added.]

4.2.3 Instant Payments, Lending Technology, and Risk-Taking

So far, we have established that instant payments encourage bank risk-taking, and that such risk-taking is partly driven by agency issues, suggesting the presence of inefficiencies. However, the implications of risk-taking also depend on banks' lending technology. Recent studies highlight that improvements in payment processing capabilities have enhanced banks lending technologies by enabling more effective borrower screening and loan monitoring (e.g., Berg, Fuster, and Puri, 2022, Ghosh, Vallee, and Zeng, 2022). Moreover, emerging evidence shows that instant payment systems, such as Indias UPI, have helped expand credit access for traditionally underserved borrowers, supporting both consumption and firm growth, outcomes indicative of improved lending performance (Dubey and Purnanandam, 2023, Alok, Ghosh, Kulkarni, and Puri, 2024).

To account for this possibility, we augment our baseline model by introducing a channel through which payment processing may endogenously influence lending technologies. Specifically, we consider the total gross payments processed by bank j between $1 \leq t \leq T$, denoted by Z_j, which will be endogenously determined in equilibrium. Instead of modeling the realized return on the risky loan, $R(p)$, solely as a decreasing function of p, we extend it to a function $R(p, \rho Z)$, where $R(p, \rho Z)$ continues to decrease in p but now is also increasing and concave in Z. The parameter $\rho \geq 0$ captures the extent to which gross payment processing enhances the lending technology.

Intuitively, this augmented setup parsimoniously captures the idea that greater payment processing activity provides the bank with improved information flows or monitoring capacity, thereby increasing expected loan returns at any given level of risk-taking (e.g., Berlin and Mester, 1999, Norden and Weber, 2010, Puri, Rocholl, and Steffen, 2017). It is important to note that the associated benefits are not exclusive to instant payment systems. Rather, under any payment system, a bank may realize these gains simply by processing more gross payments. As a benchmark, we normalize $R(p)$ in the baseline model to $R(p, 0)$; that is, the baseline model is a special case of the extended model with $\rho = 0$.

Using p^{**} to denote the equilibrium level of risk-taking in the extended model, we present the following result:

Proposition 4. [BANK RISK-TAKING EFFECT REVISITED]*: Given any* $\alpha > 0$, $p^{**}_{ins} < p^{**}_{tra}$, *that is, banks choose riskier illiquid assets under the instant payment system compared to the traditional system.*

Proposition 4 is particularly useful because it enables a decomposition of risk-taking behavior into two components: one driven by agency frictions, as highlighted earlier, and the other arising from the improved lending technology introduced in the extended model. To see this more clearly, note that

$$p_{ins}^{**} = R^{-1}(x_{ins}^{**}, \rho Z_{ins}^{**}) < R^{-1}(x_{ins}^{**}, \rho Z_{tra}^{**}) < R^{-1}(x_{tra}^{**}, \rho Z_{tra}^{**}) = p_{tra}^{**} ,$$

where the second inequality holds because $x_{ins}^{**} > x_{tra}^{**}$, reflecting increased risk-taking due to the agency friction emphasized in Proposition 3. Meanwhile, the first inequality holds because $Z_{ins}^{**} > Z_{tra}^{**}$, capturing the additional increase in risk-taking due to improved lending technology resulting from greater gross payment volume.

Figure 1 further illustrates this decomposition. After the introduction of the instant payment system, the effect of agency frictions on risk-taking is represented by movement along the curve $R^{-1}(x, Z_{tra}^{**})$, while the effect of improved lending technology is captured by the upward shift from the curve $R^{-1}(x, Z_{tra}^{**})$ to $R^{-1}(x, Z_{ins}^{**})$.

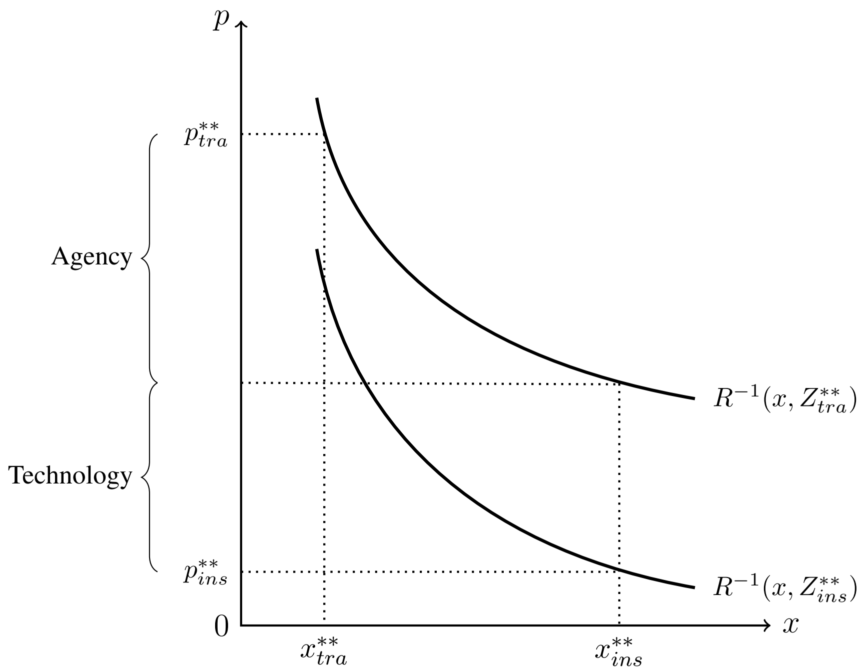

Figure 1: Decomposition of Risk-Taking

The proof of Proposition 4 reduces to showing the two key inequalities stated above: $Z^{**}_{ins} > Z^{**}_{tra}$ and $x^{**}_{ins} > x^{**}_{tra}$. Intuitively, these inequalities imply that even in the extended model where gross payment processing enhances lending technology banks still optimally process more gross payments under the instant payment system compared to the traditional system. To understand this, first note that under the instant payment system, the newly introduced lending technology channel does not alter how the bank processes payments or manages liquidity. This is because the bank is already required to fulfill all payment requests without delay, regardless of the lending benefit. As a result, the bank passively captures the technological benefits of gross payment processing, which, in turn, encourages greater risk-taking. In contrast, under the traditional payment system, the bank retains some flexibility to delay and net payments. In the extended model, the bank has an incentive to delay fewer payments to actively reap the benefits of improved lending technology from processing more gross payments. However, fully mimicking the instant payment systems level of gross payment processing would forgo the liquidity risk-reducing benefits of netting and delay. That is, even though increasing payment processing improves lending outcomes, the bank still chooses to process fewer gross payments than under the instant system, in order to preserve liquidity buffers and reduce the risk of default. Therefore, the bank under the traditional system still ends up with both lower gross payment processing (Z^{**}_{tra}) and lower liquid asset holdings (x^{**}_{tra}) in equilibrium.

Similarly, Proposition 4 also implies that the increase in risk-taking following the introduction of instant payments can vary depending on the extent to which payment processing improves lending technology. Beyond the relatively unintended consequence of agency-issue-induced risk-taking highlighted in Proposition 3, our result in this subsection offers a more comprehensive and nuanced perspective. It helps reconcile our new findings with the broader literature that emphasizes the benefits of introducing fast payment systems.

Corollary 2. [BANK RISK-TAKING AND TECHNOLOGY IMPROVEMENT]*: Given any* $\alpha > 0$*, the difference* $p^{**}_{tra} - p^{**}_{ins}$ *increases as* ρ*, the extent to which gross payment processing enhances lending increases.*

[#This subsection is unchanged but needs revision afterward.]

4.2.4 Instant Payments and Bank Lending Technology

So far, we have established that instant payments encourage bank risk-taking and that such risk-taking is in part driven by agency issues. The implication of risk taking, however, depends on banks' lending technology. Indeed, recent studies suggest that enhanced payment processing capabilities have improved banks' lending technologies by enabling better borrower selection and loan monitoring (e.g., Berg, Fuster, and Puri, 2022, Ghosh, Vallee, and Zeng, 2022). The natural question then is how lending technology interacts with agency-driven risk-taking to influence banks' expected loan outcomes and what banks' expected loan outcomes reveal about their lending technology.

We first characterize the notion of lending technology in our setting:

Definition 1. [LENDING TECHNOLOGY]*: Loan technology is captured by* $R(p)$*, where banks with better loan technology realize a larger* $R(p)$ *when they take more risks by decreasing* p*.*

In other words, we think of lending technology as the efficiency at which banks can take risks. With improved information to select and monitor borrowers, banks' risk-taking can be more efficiently transformed into eventual returns In contrast, risk-taking with low-technology translates into realized returns by less.

We use loan outcomes to shed light on the efficiency of banks' lending technology. To this end, we define two distinct yet related measures of lending outcomes:

Definition 2. [LOAN OUTCOME]*: We define two notions of loan outcome:*

(i) The loan income per loan is defined as $\Gamma_l = pR(p)$*.*

(ii) The loan income per asset is given by $\Gamma_a = x + (1 - x)pR(p)$*.*

These two measures capture loan income relative to different benchmarks, each providing insights into banks' lending technology. Loan income per loan reflects the expected lending payoff relative to each dollar lent, effectively capturing the risk premium associated with bank lending. Loan income per asset captures the expected payoff relative to every dollar invested, including both loans and liquidity holdings. A higher loan income per asset thus implies an improved overall asset return from loans, indicating an even stronger lending technology.

We formally state the following proposition, which characterizes the conditions for lending technology under which instant payments improve loan outcomes. If we observe loan outcomes, these conditions also shed light on the extent of banks' lending technology under instant payment system.

Proposition 5. [BANK LENDING TECHNOLOGY]*: Given any $\alpha > 0$, the following results hold:*

(i) If $pR(p)$ is strictly decreasing in p, that is, if riskier loans consistently carry a sufficiently high risk premium, then $\Gamma^*_{l,ins} > \Gamma^*_{l,tra}$. In other words, banks achieve higher loan income per loan under the instant payment system compared to the traditional system.

(ii) Moreover, if $R(p)$ further satisfies the condition

$$-R'(p)(1-p) > R(p)\left(R(p)-1\right),$$

which means that not only does $pR(p)$ strictly decrease in p, but also the risk premium increases sufficiently rapidly as loans become riskier, then we additionally have $\Gamma^*_{a,ins} > \Gamma^*_{a,tra}$. That is, banks achieve higher total loan income per asset under the instant payment system compared to the traditional system.

Proposition 5 offers new insights into how the introduction of an instant payment system might reshape bank business models. Recall that $R(p)$ reflects banks' lending technology. The baseline assumption that $R(p)$ decreases in p is natural, since otherwise increased risk-taking would necessarily reduce profitability. Now, part (i) of Proposition 5 implies that if banks' lending technology is sufficiently high such that riskier loans offer higher risk premia, then instant payments will lead to improved lending outcomes in terms of a higher loan income per loan.

Following a similar logic, part (ii) implies that with even better lending technology where riskier loans not only carry a higher risk premium, but where this risk premium increases sufficiently to outweigh the shrinking share of lending on bank balance sheets, instant payments will further yield a higher loan income per asset.

We note that if the adoption of instant payments also facilitates better screening and monitoring, the conditions underlying part (i) and (ii) are more likely satisfied, thereby improving lending outcomes. Importantly, the condition for part (ii) is strictly stronger than that for part (i). Thus, in practice, we might observe that instant payments lead to higher loan income per loan without necessarily increasing loan income per asset. Observing such patterns in the data would shed light on the extent of lending technology under instant payment systems and how instant payment systems influence loan outcomes in the presence of risk-taking.

5 Estimation Strategy

In this section, we formally outline our empirical approach to estimating the impact of Pix adoption on banks' deposit funding structure, asset composition, and risk-taking behavior.

To estimate the effects of Pix usage on various outcomes, we consider the following baseline specification:

$$OutcomeVar_{it} = \beta PixUsage_{it} + Controls_{it} + \eta_i + \omega_t + \epsilon_{it}, \tag{5.1}$$

where $PixUsage_{it}$ captures banks' loss of payment netting due to Pix, as defined in Equation (3.1). We control for banks' time-varying asset size, capital, and number of branches. We further include time fixed effects (ω_t) to control for aggregate shocks and bank fixed effects (η_i) to account for unobserved bank-specific characteristics. All right-hand-side variables are standardized to have a unit standard deviation. The sample period ranges from November 2020 to March 2023. Robust standard errors clustered by bank are used throughout.

Although (5.1) controls for bank characteristics and fixed effects, readers may still worry that there are other unobserved bank characteristics that simultaneously affect banks' Pix usage and the composition of their balance sheets over time. Thus, we further adopt an instrumental variable approach to isolate plausibly exogenous variation in Pix usage.

Our instrument leverages the insight that Pix's attractiveness relies on Pix payments being successfully sent by the sending bank and then successfully received by the receiving bank without delay. If either bank fails to process the payment within a specified timeframe, the paymentattempt is unsuccessful and marked as a "timeout" by the Pix system. In the event of a timeout, the sender is notified and prompted to retry the payment later. Even if successful on a later attempt, the instantaneous and convenient feature of Pix payments is lost to both the sender and receiver. Pix is therefore less attractive at banks with more frequent timeouts and these banks should consequently experience lower Pix usage.

We use variation in timeouts to construct our instrument. What drives the variation in timeouts? Our conversations with the Pix operations team at the BCB reveal that timeouts are, for the most part, driven by technical and communication errors in banks' payment interface, including proprietary apps used to initiate the Pix, unrelated to customer or bank strategies. Nevertheless, the speed at which banks can resolve these errors varies. For example, banks with larger and more skilled IT teams may more promptly address instabilities.

One may still worry that the exlcusion restriction is violated because a bank's own timeouts are correlated with bank characteristics that affect both its Pix usage and balance sheet characteristics over time. To address this concern, we construct our timeout instrument for a given bank i in month t, $Timeout_{it}$, only using variation in timeouts induced by other banks $j \neq i$. This includes timeouts by receiving banks if bank i is the sending bank and timeouts by sending banks if bank i is the receiving bank in the transaction. In both cases, the attractiveness of bank i's Pix service is lowered so that bank i's customers are less inclined to use Pix relative to other forms of payments, which reduces bank i's equilibrium level of Pix usage. However, because these timeouts arise from counterparty banks rather than from bank is own operations, bank i cannot directly control or mitigate them. Also, note that these counterparty banks are not actively chosen by bank i to transact with itself. Rather, banks i's exposure to timeouts at different counterparty banks depends on the time-varying payment flows that bank i's customers receive from and send to customers at counterparty banks at each point in time. This design helps to ensure that our instrument is exogenous to bank i's unobservable characteristics that may also influence its balance sheet decisions.

Formally, the timeout instrument for bank i in month t, $Timeout_{it}$, constructed as the weighted sum of passively induced timeout probabilities arising from the banks that send payments to i and the banks that receive payments from i:

$$Timeout_{it} = \sum_{j \in J, j \neq i} \frac{PixReceived_{ijt}}{PixReceived_{it}} SenderTimeout_{ij} + \sum_{j \in J, j \neq i} \frac{PixSent_{ijt}}{PixSent_{it}} ReceiverTimeout_{ij}, \tag{5.2}$$

where $PixReceived_{ijt}$ is the amount of Pix payments received by bank i from bank j in month t, $PixReceived_{it}$ is the total amount of Pix payments received by bank i from all other bank js in month t, and $SenderTimeout_{ij}$ is the proportion of payments received by bank i from bank j that timed out due to the sending bank j. Similarly, $PixSent_{ijt}$ is the amount of Pix payments sent by bank i to bank j in month t, $PixSent_{it}$ is the total amount of Pix payments sent by bank i to all other bank js in month t, and $ReceiverTimeout_{ij}$ is the proportion of payments sent by bank i to bank j that timed out due to the receiver, bank j.

For our timeout instrument to be relevant, it must have a negative and statistically significant effect on Pix usage. We evaluate instrument relevance by estimating the following first-stage regression:

$$PixUsage_{it} = Timeout_{it} + Controls_{it} + \eta_i + \omega_t + \epsilon_{it}, \tag{5.3}$$

where we include the same set of controls and fixed effects as in our baseline specification before. The first stage results are shown in Table 2. We see that higher probabilities of passive timeouts, i.e., a larger timeout instrument, indeed correspond to lower Pix usage. The coefficients are economically significant and their statistical significance is generally above the 1% level. The specification is also overall significant with F statistics ranging between 59.9 and 70.0.

Figure 7 further illustrates this relationship by plotting the timeout instrument against Pix usage, residualized by the same bank fixed effects, time fixed effects and controls as in equation (5.3). The histogram shows the distribution of the residualized timeout instrument . The solid line represents a local linear regression, evaluated at 1,000 evenly spaced intervals from -0.01 to 0.01 with a bandwidth of 0.005. The shaded region denotes the 95% confidence interval. The figure demonstrates a clear negative association between the timeout instrument and Pix usage, reinforcing the instrument's relevance. Specifically, cases with higher values of the timeout instrument are linked to lower predicted Pix usage, consistent with the underlying mechanism that Pix payments disruptions from counterparts banks reduce a bank's Pix usage.

From the first stage results, we obtain the predicted value of $\widehat{PixUsage}_{it}$. In the second stage, we use these predicted values to instrument for $PixUsage_{it}$ in equation (5.1). That is, we estimate

$$OutcomeVar_{it} = \beta \widehat{PixUsage}_{it} + Controls_{it} + \eta_i + \omega_t + \epsilon_{it}. \tag{5.4}$$

For the estimated coefficients from this second stage to provide plausibly causal estimates of the effect of Pix usage on bank balance sheets, the instrument needs to satisfy the exclusion restriction. The exlusion restriction requires that the timeout instrument impacts bank i's balance sheet decisions solely through its effect on Pix usage, with no direct influence through alternative channels. The main rationale is that because we only use timeouts that arise from counterparty banks rather than from bank i's own operations, bank i cannot directly control or mitigate them. Further, the the payment volumes with counterparty banks are not actively chosen by bank i

but depend on the time-varying payment flows that bank i's customers receive from and send to customers at counterparty banks at each point in time.

Although there is no direct test for the exclusion restriction, we provide supporting evidence by showing how our timeout instrument varies with key observable covariates. If our timeout instrument captures quasi-exogenous variation, it should not systematically correlate with observable characteristics of bank i. Specifically, we estimate

$$Covariate_{it} = \alpha^b + \beta^b Timeout_{it} + \eta_i^b + \omega_t^b + \nu_{it}^b, \tag{5.5}$$

where $Covariate_{it}$ includes bank i's own timeouts, total assets, core capital, number of branches, number of service stations, and intangible assets. Bank i's own timeouts is the proportion of Pix payments initiated or received by bank i that fail due to bank i itself.

Figure 8 presents the coefficient estimates β^b along with their corresponding 95% and 99% confidence intervals. The coefficients are small in magnitude, and their confidence intervals generally overlap with zero, indicating that there is no statistically significant correlation between the instrument and these covariates. Notably, our instrument that captures bank i's timeouts due to its counterparys banks does not correlate with bank i's own timeouts.

6 Estimation Results

In this section, we present our empirical results testing the propositions and implications of the model in Section 4. We focus on the IV estimates and show the corresponding OLS results in Appendix B. Overall, our findings in this section are consistent with and corroborate our preliminary evidence in Section 3 and our model predictions in Section 4.

6.1 Effect of Pix on Bank Liquidity Transformation

Table 3 presents our estimation results for the effect of Pix usage on bank deposit ratios. The results in the first four columns show that Pix usage increases the proportion of checking deposits and demandable deposits. The coefficients are statistically significant at 1%. This finding aligns with our models prediction that the convenience of using demandable deposits for instant payments enhances their attractiveness to depositors, particularly for checking deposits that have fewer withdrawal restrictions (Proposition 1). The economic magnitude is substantial: a one-standard-deviation increase in Pix usage leads to an increase in the ratio of demandable deposits by 12.7 ppts. Most of this effect comes from checking deposits, as evident from the relative size and statistical significance of the coefficients for checking deposits and savings deposits. This is in part because in Brazil, all banks have checking deposits, but only a fraction of banks have savings deposits, which reduces the available variation in the ratio of savings deposits.

On the asset side, the results in Table 4 validate our model's predictions regarding the effect of instant payments on banks' liquid asset holdings (Proposition 2). In the first two columns, the coefficients for Pix usage on the liquid asset ratio are positive and significant at the 1% level. A one-standard-deviation increase in Pix usage results in a 15.4 ppt increase in the ratio of liquid assets. This increase is mainly driven by higher government bond holdings, as shown in columns (5) and (6). The coefficient for cash holdings, while positive, is much smaller in magnitude. These findings align with our earlier observations that banks with more Pix usage mainly set aside government bonds as a buffer for potential future liquidity needs while actively using cash to meet the more volatile payment shocks from Pix usage. These findings also confirm our model prediction that banks choose to hold a larger ratio of liquid assets when instant payments remove their ability to net payments and expose them to more volatile funding shocks. Similarly, our model also predicts that the ratio of illiquid assets falls. Indeed, columns (7) and (8) show that Pix usage leads to a lower ratio of loans to bank assets in an economically and statistically significant way, which highlights the side effect of instant payments in constraining banks' capacity for liquidity transformation.

6.2 Effect of Pix on Bank Risk Taking

We then shed light on the effect of Pix usage on bank risk-taking. Consistent with Proposition 3 that predicts more risk-taking with instant payment systems, we observe that Pix usage decreases the ratio of prime loans and increases the ratio of sub-prime and default loans inTable 5. From the last two columns, we also see that Pix usage increases the ratio of loan loss provisions, which is an ex-ante measure of anticipated credit risk. This result indicates that banks anticipate higher credit risk and set aside reserves for their riskier loan portfolios.The economic impact is significant: a one-standard-deviation increase in Pix usage results in a 21.8 ppts decrease in the ratio of prime loans, which is mostly accounted for by a 18.6 ppts increase in the ratio of sub-prime loans. A one-standard-deviation increase in Pix usage also increases the ratio of default loans by 2.7

ppts. These findings jointly confirm the model's predictions that instant payments increase the risk-taking incentives of banks.

Corollary 2 further predicts that banks' risk-taking is exacerbated by agency conflicts. To test this prediction, we assess how the impact of Pix on bank risk-taking varies with banks' ex ante capital ratios. Specifically, we estimate

$$OutcomeVar_{it} = \beta_1 \widehat{PixUsage}_{it} + \beta_2 \widehat{PixUsage_{it} \times HighCapRatio_i} + Controls_{it} + \eta_i + \omega_t + \epsilon_{it}, \tag{6.1}$$

where $HighCapRatio_i$ is an indicator variable equal to 1 if a bank's core capital-to-risk-weighted assets (RWA) ratio before Pix adoption is above the median in our sample. Pix usage and the interaction term $PixUsage_{it} \times HighCapRatio_i$ are instrumented using the timeout instrument and its interaction with $HighCapRatio_i$.

The first-stage results are reported in Table 13, and the second-stage (2SLS) results are presented in Table 6. From Table 6, we observe that the coefficient on the interaction term $PixUsage_{it} \times HighCapRatio_i$ is of the opposite sign as that for $PixUsage_{it}$ for prime loan and sub-prime loan ratios. In other words, the impact of Pix on risk-taking is amplified at less capitalized banks, which implies is consistent with risk-taking arising through agency issues that are worse at banks with low capital ratios.

Finally, we examine how the effect of Pix usage on loan outcomes is augmented by bank lending technology. Recall from Proposition 5 that the effect of risk taking on loan outcomes vary with the efficiency at which banks can generate returns from riskier loans. From Table 7, we observe that Pix usage significantly increases the loan income per loan, suggesting that banks' lending technology is sufficiently high to generate a higher expected return per unit loan following the introduction of instant payments, implying that condition (i) of Proposition 5 is satisfied. Magnitude wise, a one-standard-deviation increase in Pix usage results in an approximately 2.75 ppts increase in loan income per unit loan,

However, we find that Pix usage negatively impacts the loan income ratio per unit bank asset, reducing it by around 0.17 ppts for a one-standard-deviation increase in Pix usage. This result implies that the stronger condition for lending technology in part (ii) of Proposition 5, which requires the risk premium on riskier loans to be sufficiently large to compensate for the reduction in loan ratios as a proportion of bank assets. These findings provide novel insights into bank lending technology and broad business models post-Pix adoption, highlighting that although banks can generate higher risk premiums from risk-taking, bank lending technology is not yet sufficient to generate higher incomes from a smaller loan portfolio per unit asset size following the introduction of Pix.

7 Conclusion

Using novel data from Brazil's Pix, we show that the introduction of instant payments has important implications for the banking system. While instant payments allow depositors to transfer funds without delay, it is precisely the inability to delay payments that subjects banks to unexpected payment shocks and a more volatile deposit funding base. In response, banks increase their holdings of liquid asset buffers, while becoming more reluctant to lend to the real economy. Higher levels of liquid asset buffers, however, also trigger banks to take on more risk in their lending decisions.

Taken together, our findings highlight that in addition to the many benefits of instant payments to consumers, another consequence may be a riskier banking sector that is less engaged in liquidity transformation. Regulators should pay close attention to these potential side effects when introducing instant payment systems going forward.

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A Figures and Tables

Figure 2: Nettable Payments Ratio

The figure shows Q1, Q2, and Q3 of the nettable payments ratio from November 2020 to March 2023. The nettable payments ratio is the proportion of payments that would be nettable at the end of each day without instant payments relative to all Pix payments, averaged monthly.

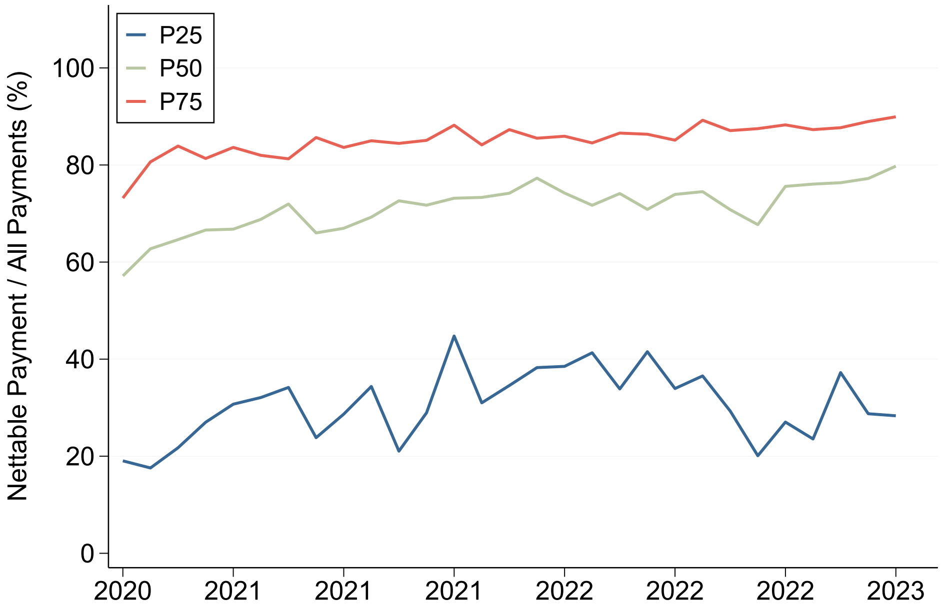


Figure 3: Pix Usage by Quantile

This figure shows the average Pix usage for each Pix usage quartile over time. Pix usage is defined in Equation (3.1). Pix usage quartiles are defined by the mean Pix usage of each bank over the sample period.

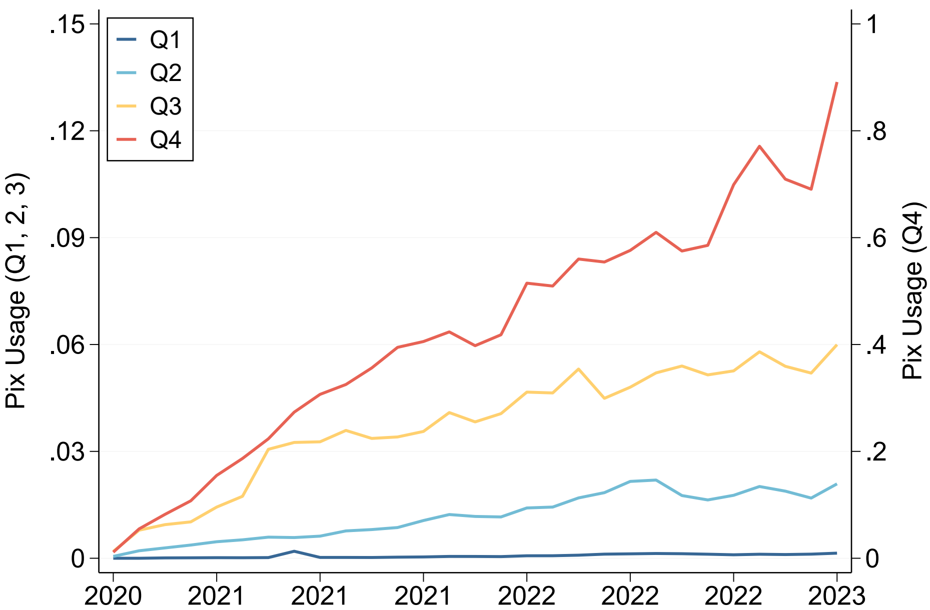
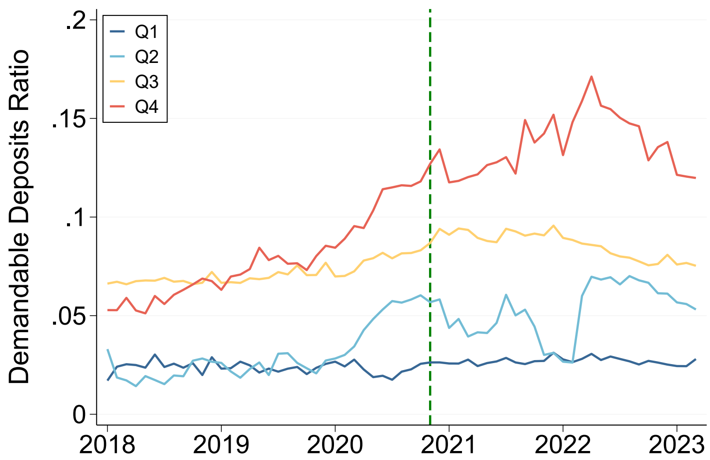


Figure 4: Deposits Ratios by Pix Usage

Panel (a) shows the average ratio of demandable deposits to total bank assets for each Pix usage quartile over time. Demandable deposits are comprised of savings and checking deposits. Panel (b) shows the average ratio of checkings deposits to total bank assets for each Pix usage quartile over time. Pix usage quartiles are defined by the mean Pix usage of each bank over the sample period.

(a) Demandable Deposits Ratio



(b) Checking Deposits Ratio

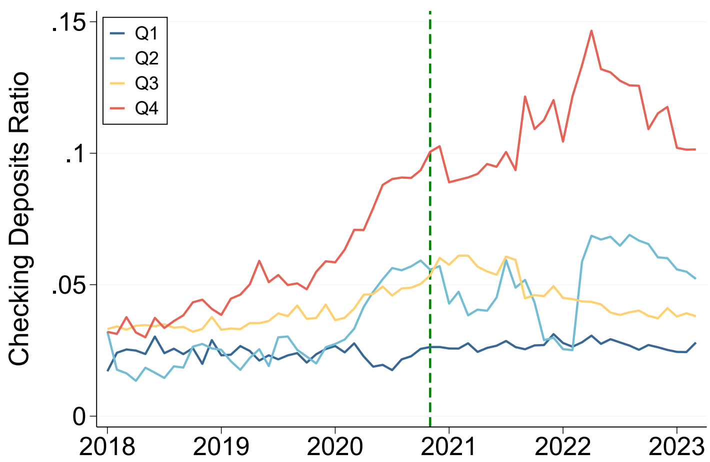
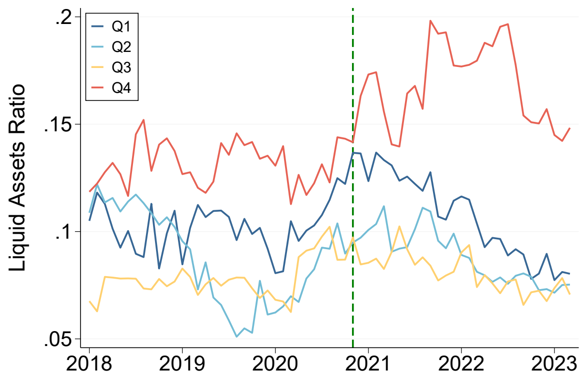


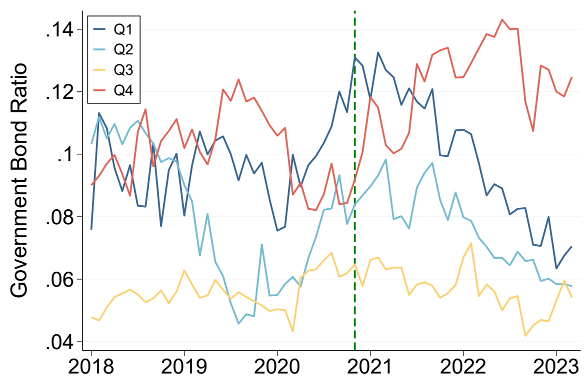
Figure 5: Liquid Assets Ratios by Pix Usage

Panel (a) shows the average ratio of liquid assets to total bank assets for each Pix usage quartile over time. Liquid assets are comprised of cash and government bonds. Panel (b) shows the average ratio of government bonds to total bank assets for each Pix usage quartile over time. Panel (c) shows the average ratio of cash to total bank assets for each Pix usage quartile over time. Pix usage quartiles are defined by the mean Pix usage of each bank over the sample period.

(a) Liquid Assets Ratio



(b) Government Bond Ratio



(c) Cash Ratio

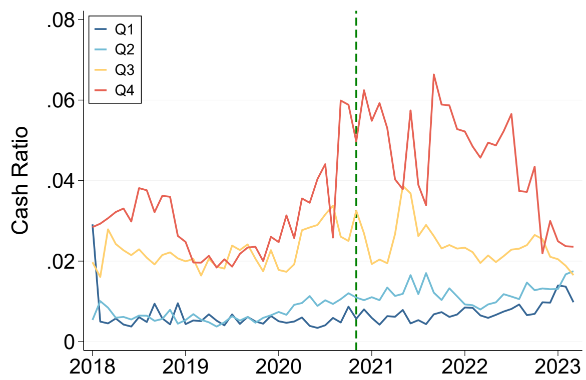
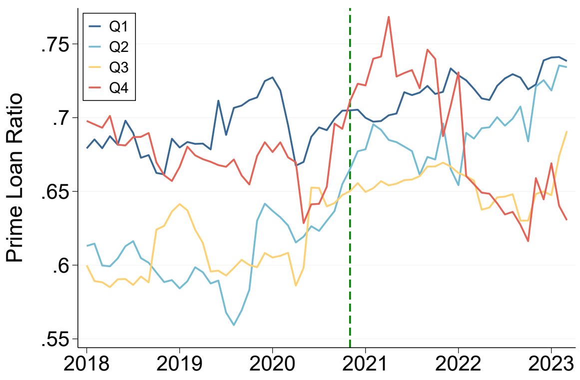


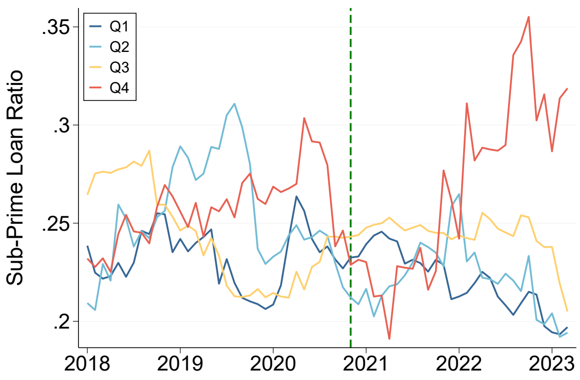
Figure 6: Prime, Subprime, and Default Loan Ratios by Pix Usage

Panel (a) shows the average ratio of prime loans to total loans for each Pix usage quartile over time. Panel (b) shows the average ratio of sub-prime loans to total loans for each Pix usage quartile over time. Panel (c) shows the average ratio of default loans to bank total loans for each Pix usage quartile over time. Pix usage quartiles are defined by the mean Pix usage of each bank over the sample period.

(a) Prime Loan Ratio



(b) Subprime Loan Ratio



(c) Default Loan Ratio

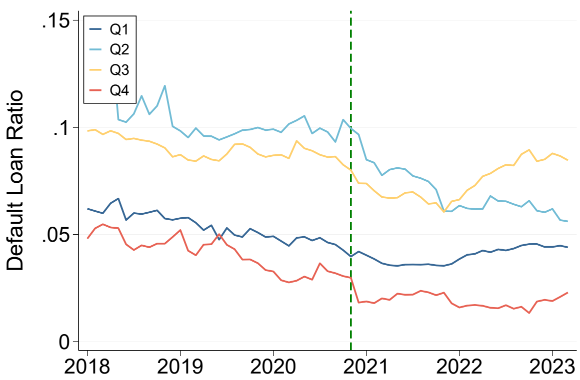


Figure 7: Variation in the Timeout Instrument and Pix Usage

This figure shows the distribution of the timeout instrument against Pix usage. Both the instrument and Pix usaged are residualized by bank fixed effects, time fixed effects and controls. The histogram represents the fraction of the sample across different values of the instrument from -0.01 to 0.01. The solid line indicates a local linear regression of Pix usage on the timeout instrument and the dashed lines represent the 95% confidence intervals.

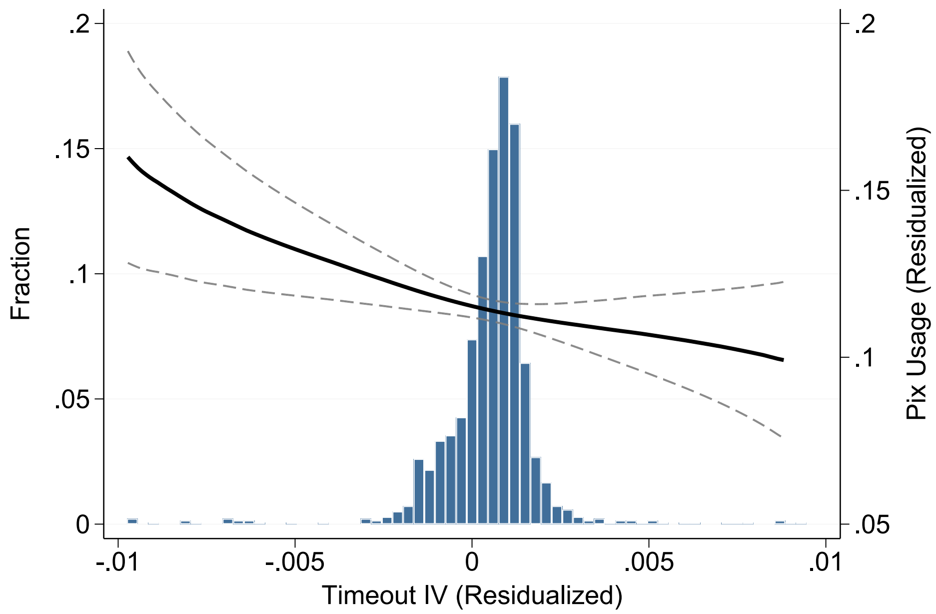


Figure 8: Relationship between the Timeout Instrument and Bank Covariates

This figure presents the estimated coefficients from regressions of the timeout instrument on various bank characteristics, including banks' own timeout, total assets, core capital, number of branches, number of service stations, and intangible assets. All variables are standardized. The plotted coefficients represent β^b from equation (5.3), which includes bank and time fixed effects. Horizontal bars represent 95% and 99% confidence intervals. Standard errors are clustered at the bank level.

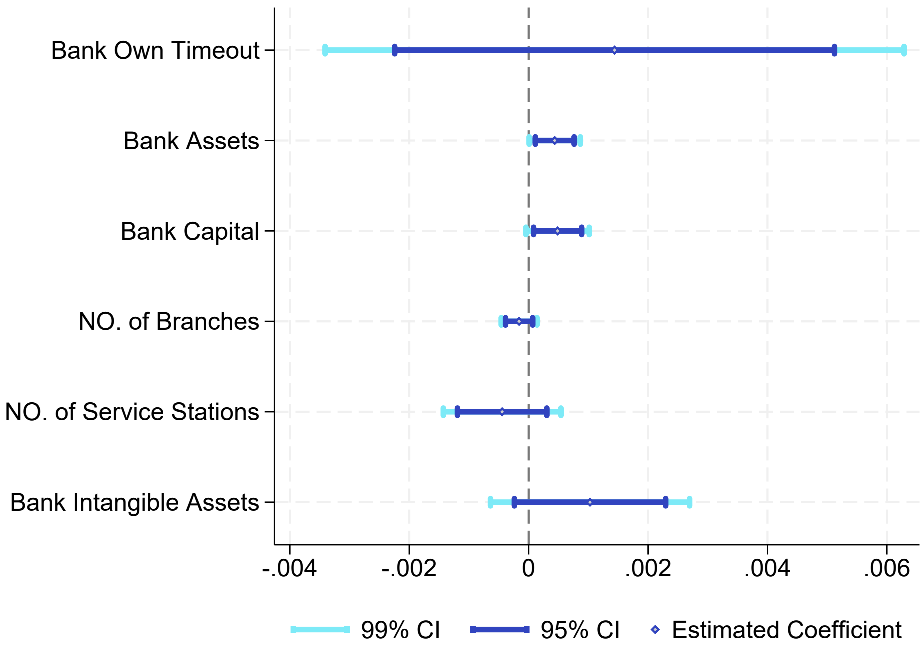


Table 1: Summary Statistics

This table shows summary statistics of our main variables and control variables. Deposit ratios, asset ratios, and loan income ratio are expressed as a fraction of bank assets. Demandable deposits comprise checking and savings deposits. The prime loan ratio, subprime loan ratio, default loan ratio, loan loss provision ratio, and loan income rate are expressed as a fraction of total loans. All main variables are expressed in percent. For control variables, bank assets represent the value of bank assets in billions, bank capital is the value of bank core capital in billions, and No. of branches indicates the number of bank branches.

	Mean	SD	P25	P50	P75	N
Pix Usage (%)	9.25	20.01	0.21	1.99	6.35	1501
Timeout IV (%)	0.60	2.57	0.35	0.47	0.54	1471
Demandable Deposits Ratio (%)	7.13	8.88	0.64	3.33	10.46	1501
Checking Deposits Ratio (%)	5.13	7.66	0.47	2.39	6.96	1501
Savings Deposits Ratio (%)	1.99	5.15	0.00	0.00	0.00	1501
Liquid Assets Ratio (%)	10.78	8.23	5.03	9.12	13.89	1501
Cash Ratio (%)	1.79	3.14	0.14	0.73	1.72	1501
Gov Bond Ratio (%)	8.99	8.36	3.01	7.01	12.34	1501
Loan Ratio (%)	33.68	23.46	11.06	33.94	50.14	1501
Prime Loan Ratio (%)	69.71	23.53	56.31	74.68	88.61	1397
Sub-Prime Loan Ratio (%)	23.05	20.51	6.13	18.03	34.08	1397
Default Loan Ratio (%)	5.04	6.37	1.19	3.04	6.00	1397
Loan Loss Ratio (%)	5.97	7.21	1.71	4.29	6.81	1237
Loan Income / Loans (%)	2.56	16.10	1.06	1.50	2.24	1392
Loan Income / Assets (%)	0.66	0.62	0.10	0.52	0.94	1496
Bank Assets (Billion)	175.07	471.73	1.23	6.93	46.29	1501
Bank Capital (Billion)	13.48	35.78	0.14	0.75	4.43	1501
No. of Branches	299.37	918.96	2.00	6.00	21.00	1497

Table 2: The Effect of Timeouts on Pix Usage

This table shows the effect of the timeout instrument on Pix usage. Pix usage is defined in Equation (3.1). Timeout IV is the timeout instrument that captures the proportion of failed Pix transactions due to other banks. The sample period is from November, 2020 to March, 2023. Time fixed effects and bank fixed effects are included in both specifications. Robust standard errors clustered by bank are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	Pix Usage	
	(1)	(2)
Timeout IV	-0.013***	-0.013***
	(0.002)	(0.002)
Bank Assets		-0.329
		(0.200)
Bank Capital		-0.083
		(0.169)
No. of Branches		0.174
		(0.236)
Bank FE	Yes	Yes
Time FE	Yes	Yes
Observations	1471	1467
Adjusted R^2	0.9	0.9
Kleibergen-Paap F	68.9	59.9
Montiel-Pflueger F	70.0	60.8

Table 3: The Effect of Pix Usage on Deposits Ratios

This table shows the effect of instrumented Pix usage on the ratio of demandable deposits, savings deposits, and checking deposits based on the IV specification in (5.4). Demandable deposits are comprised of savings and checking deposits. Pix usage is defined in Equation (3.1). We instrument for Pix usage with the timeout instrument, which captures the proportion of failed Pix transactions due to other banks. Control variables include bank assets, core capital, and the number of bank branches. Time fixed effects and Bank fixed effects are included in all specifications. The sample period is from November, 2020 to March, 2023. Robust standard errors clustered by bank are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	Demandable Deposits Ratio		Checking Deposits Ratio		Savings Deposits Ratio	
	(1)	(2)	(3)	(4)	(5)	(6)
Pix Usage	0.127***	0.127***	0.124***	0.125***	0.004**	0.003*
	(0.016)	(0.017)	(0.015)	(0.016)	(0.002)	(0.002)
Bank Assets		-0.041		0.023		-0.064*
		(0.047)		(0.030)		(0.036)
Bank Capital		0.020		-0.002		0.022
		(0.042)		(0.033)		(0.022)
No. of Branches		-0.047		-0.024		-0.023
		(0.048)		(0.036)		(0.022)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1471	1467	1471	1467	1471	1467

Table 4: The Effect of Pix Usage on Asset Ratios

This table shows the effect of instrumented Pix usage on the ratio of liquid assets, cash, government bonds, and loans based on the IV specification in (5.4). Liquid assets are comprised of cash and government bonds. Pix usage is defined in Equation (3.1). We instrument for Pix usage with the timeout instrument, which captures the proportion of failed Pix transactions due to other banks. Control variables include bank assets, core capital, and the number of bank branches. Time fixed effects and Bank fixed effects are included in all specifications. The sample period is from November, 2020 to March, 2023. Robust standard errors clustered by bank are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	Liquid Assets Ratio		Cash Ratio		Gov Bond Ratio		Loan Ratio	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pix Usage	0.152***	0.154***	0.029***	0.030***	0.123***	0.124***	-0.279***	-0.284***
	(0.021)	(0.022)	(0.011)	(0.011)	(0.016)	(0.017)	(0.029)	(0.032)
Bank Assets		0.034		0.007		0.028		-0.140**
		(0.035)		(0.013)		(0.027)		(0.061)
Bank Capital		0.020		0.004		0.016		0.004
		(0.033)		(0.007)		(0.029)		(0.036)
No. of Branches		-0.012		-0.004		-0.007		0.032
		(0.042)		(0.011)		(0.034)		(0.053)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1471	1467	1471	1467	1471	1467	1471	1467

Table 5: The Effect of Pix Usage on Bank Risk-Taking

This table shows the effect of instrumented Pix usage on the ratio of prime, subprime, and default loans based on the IV specification in (5.4). It also shows the effect of instrumented Pix usage on the ratio of banks' loan loss reserves. All ratios are denoted relative to total loans. Pix usage is defined in Equation (3.1). We instrument for Pix usage with the timeout instrument, which captures the proportion of failed Pix transactions due to other banks. Control variables include bank assets, core capital, and the number of bank branches. Time fixed effects and Bank fixed effects are included in all specifications. The sample period is from November, 2020 to March, 2023. Robust standard errors clustered by bank are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	Prime Loan Ratio		Sub-Prime Loan Ratio		Default Loan Ratio		Loan Loss Ratio	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pix Usage	-0.216***	-0.218***	0.186***	0.186***	0.025***	0.027***	0.119**	0.123**
	(0.035)	(0.037)	(0.030)	(0.032)	(0.007)	(0.008)	(0.061)	(0.059)
Bank Assets		-0.016		0.011		0.004		0.051
		(0.050)		(0.042)		(0.015)		(0.044)
Bank Capital		0.006		-0.034		0.029*		0.029
		(0.037)		(0.027)		(0.016)		(0.027)
No. of Branches		0.066*		-0.056		0.001		-0.008
		(0.037)		(0.035)		(0.022)		(0.037)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1371	1367	1371	1367	1371	1367	1216	1212

Table 6: The Effect of Pix Usage on Bank Risk-Taking: Agency Conflict

This table shows the effect of instrumented Pix usage and its interaction with "High Cap Ratio", which is a dummy variable equal to 1 if a bank's core capital-to-risk-weighted assets (RWA) ratio prior to Pix adoption is above the median in the sample, on the ratio of prime, subprime, and default loans based on the IV specification in (6.1). It also shows the effect on the ratio of banks' loan loss reserves. All risk-taking ratios are denoted relative to total loans. Pix usage is defined in Equation (3.1). We instrument for Pix usage and the interaction term with the timeout instrument and the interaction of the timeout instrument with the "High Cap Ratio" dummy. Control variables include bank assets, core capital, and the number of bank branches. Time fixed effects and Bank fixed effects are included in all specifications. The sample period is from November, 2020 to March, 2023. Robust standard errors clustered by bank are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	Prime Loan Ratio		Sub-Prime Loan Ratio		Default Loan Ratio		Loan Loss Ratio	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pix Usage	-0.212***	-0.212***	0.182***	0.180***	0.026***	0.028***	0.123	0.126
	(0.030)	(0.032)	(0.024)	(0.025)	(0.008)	(0.009)	(0.085)	(0.086)
Pix × High Cap Ratio	0.256***	0.262***	-0.256***	-0.258***	0.031	0.026	-0.144	-0.153
	(0.096)	(0.099)	(0.094)	(0.094)	(0.082)	(0.078)	(0.112)	(0.116)
Bank Assets		0.059		-0.064		0.012		0.003
		(0.046)		(0.045)		(0.023)		(0.029)
Bank Capital		-0.013		-0.016		0.027		0.049
		(0.044)		(0.038)		(0.017)		(0.034)
No. of Branches		0.004		0.002		-0.005		0.033
		(0.050)		(0.057)		(0.032)		(0.030)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1352	1348	1352	1348	1352	1348	1200	1196

Table 7: The Effect of Pix Usage on Loan Outcomes

This table shows the effect of instrumented Pix usage on loan income per unit loan and per unit asset based on the IV specification in (5.4). Pix usage is defined in Equation (3.1). We instrument for Pix usage with the timeout instrument, which captures the proportion of failed Pix transactions due to other banks. Control variables include bank assets, core capital, and the number of bank branches. Time fixed effects and Bank fixed effects are included in all specifications. The sample period is from November, 2020 to March, 2023. Robust standard errors clustered by bank are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	Loan Income / Loans (%)		Loan Income / Assets (%)	
	(1)	(2)	(3)	(4)
Pix Usage	2.717***	2.753***	-0.169***	-0.171***
	(0.431)	(0.455)	(0.036)	(0.037)
Bank Assets		0.603		-0.190**
		(0.778)		(0.081)
Bank Capital		0.464		0.102
		(0.665)		(0.069)
No. of Branches		-0.291		-0.051
		(0.991)		(0.088)
Bank FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	1365	1361	1466	1462

Internet Appendix

A Theoretical Appendix

A.1 Pix Usage and Nettable Payments

In this appendix, we provide a detailed derivation to illustrate the precise relationship between Pix usage defined in (3.1) and the notion of nettable payments within a day t. Recall that economically, nettable payments during a day t is defined as

$$Nettable_t = \left|\sum_{\tau=1}^{t} in_\tau\right| + \left|\sum_{\tau=1}^{t} out_\tau\right| - \left|\sum_{\tau=1}^{t} in_\tau - \sum_{\tau=1}^{t} out_\tau\right| ,$$

where τ is the minimal frequency at which a payment may happen intraday, in_τ is the sum of true incoming payments within τ, and out_τ is the sum of true outgoing payments within τ.

Claim: $Nettable_t = 2PixUsage_t$.

Proof of Claim: Without loss of generality, suppose

$$\sum_{\tau=1}^{t} in_\tau > \sum_{\tau=1}^{t} out_\tau.$$

Then,

$$Nettable_t = \left|\sum_{\tau=1}^{t} in_\tau\right| + \left|\sum_{\tau=1}^{t} out_\tau\right| - \left|\sum_{\tau=1}^{t} in_\tau - \sum_{\tau=1}^{t} out_\tau\right| = 2\sum_{\tau=1}^{t} out_\tau ,$$

whereas

$$PixUsage_t = \min\left\{\sum_{\tau=1}^{t} in_\tau, \sum_{\tau=1}^{t} out_\tau\right\} = \sum_{\tau=1}^{t} out_\tau ,$$

concluding the proof. □

A.2 Omitted Proofs

Proof of Proposition 1: We first consider the households portfolio choice under the instant payment system. In this case, consumption is given by

$$u(c_{j,t}) = \begin{cases} u(\alpha), & 1 \le t \le T-1, \\ u((1-\alpha)(1+r)), & t = T\,. \end{cases}$$

Thus, the households expected utility is

$$U_{\text{ins}} = \sum_{t=1}^{T-1} \pi_{j,t}\, u(\alpha) + u((1-\alpha)(1+r)) = u(\alpha) + u((1-\alpha)(1+r))\,,$$

and the first-order condition (FOC) with respect to α is

$$u'(\alpha^*_{\text{ins}}) - (1+r)\, u'\Big((1-\alpha^*_{\text{ins}})(1+r)\Big) = 0\,. \tag{A.1}$$

Next, consider the households portfolio choice under the traditional payment system. Due to payment delays, consumption is now

$$u(c_{j,t}) = \begin{cases} u(\delta^\kappa \alpha), & 1 \le t \le T-\kappa, \\ u(\delta^{T-t}\alpha), & T-\kappa+1 \le t \le T-1 \quad (\kappa \ge 2), \\ u((1-\alpha)(1+r)), & t = T\,. \end{cases}$$

Define the aggregate discounted utility from the delayed consumption as

$$A(\alpha) = \frac{(T-\kappa)u(\delta^\kappa \alpha)}{2(T-2)} + \mathbf{1}_{\{\kappa \ge 3\}} \sum_{\tau=2}^{\kappa-1} \frac{u(\delta^\tau \alpha)}{2(T-2)} + \frac{u(\delta\alpha)}{2}\,.$$

Then, the households expected utility is

$$U_{\text{tra}} = A(\alpha) + u((1-\alpha)(1+r))\,,$$

and the corresponding FOC is

$$\frac{(T-\kappa)\delta^{\kappa}u'(\delta^{\kappa}\alpha^*_{\text{tra}})}{2(T-2)}+\mathbf{1}_{\{\kappa\geq 3\}}\sum_{\tau=2}^{\kappa-1}\frac{\delta^{\tau}u'(\delta^{\tau}\alpha^*_{\text{tra}})}{2(T-2)}+\frac{\delta\, u'(\delta\alpha^*_{\text{tra}})}{2}-(1+r)\,u'\Big((1-\alpha^*_{\text{tra}})(1+r)\Big)=0\,. \tag{A.2}$$

To compare (A.1) and (A.2), define

$$f(x)=x\,u(x)\,.$$

Since

$$f'(x)=u(x)+x\,u'(x)>0\,,$$

the function f is strictly increasing. In particular, because $\delta^{\tau}\alpha^*_{\text{tra}}<\alpha^*_{\text{tra}}$ for any $\tau\geq 1$ (with $\delta<1$), we have

$$f(\alpha^*_{\text{tra}})>f(\delta^{\tau}\alpha^*_{\text{tra}}),$$

which implies that

$$u'(\alpha^*_{\text{tra}})>\delta^{\tau}\,u'(\delta^{\tau}\alpha^*_{\text{tra}})\quad\text{for all }\tau.$$

Thus, the left-hand side of (A.2) is larger than

$$\frac{(T-\kappa)u'(\alpha^*_{\text{tra}})}{2(T-2)}+\mathbf{1}_{\{\kappa\geq 3\}}\sum_{\tau=2}^{\kappa-1}\frac{u'(\alpha^*_{\text{tra}})}{2(T-2)}+\frac{u'(\alpha^*_{\text{tra}})}{2}-(1+r)\,u'\Big((1-\alpha^*_{\text{tra}})(1+r)\Big)\,,$$

so that we obtain

$$u'(\alpha^*_{\text{tra}})-(1+r)\,u'\Big((1-\alpha^*_{\text{tra}})(1+r)\Big)>0\,. \tag{A.3}$$

Comparing (A.3) with (A.1), we deduce

$$u'(\alpha^*_{\text{ins}})-(1+r)\,u'\Big((1-\alpha^*_{\text{ins}})(1+r)\Big)<u'(\alpha^*_{\text{tra}})-(1+r)\,u'\Big((1-\alpha^*_{\text{tra}})(1+r)\Big)\,.$$

Define

$$g(x)=u'(x)-(1+r)u'\Big((1-x)(1+r)\Big)\,.$$

Since

$$g'(x)=u''(x)+(1+r)^2u''\Big((1-x)(1+r)\Big)<0\,,$$

the function g is strictly decreasing, and the inequality above implies

$$\alpha^*_{\text{ins}} > \alpha^*_{\text{tra}} .$$

This completes the proof. $\square$

Proof of Proposition 2: We prove the result for the special case where $\eta = 0$ and $\phi = 1$; the general result follows by continuity.

Case 1 (Instant Payment System): Consider bank j's profit under the instant payment system.

Case 1.1 (Bank remains solvent): If bank j's liquid asset holdings never reach zero during $1 \le t \le T-1$, then at $t = T$ we have

$$\begin{cases} x_{j,T} = x \,, \\ y_{j,T} = 1 - x \,, \end{cases}$$

and the expected profit is

$$\Pi_{j,T} = \begin{cases} x + (1-x)pR - \big[1 + (1+\alpha)r\big], & 0 \le x < 1 - \dfrac{(1-\alpha)r}{pR-1} \,, \\ 0, & 1 - \dfrac{(1-\alpha)r}{pR-1} \le x < 1 \,. \end{cases}$$

Case 1.2 (Bank becomes insolvent): If, at some t with $1 \le t \le T-1$, bank j's liquid assets reach zero, then at $t = T$ we have

$$\begin{cases} x_{j,T} \le 1 \,, \\ y_{j,T} = 0 \,, \end{cases}$$

and consequently, the expected profit is

$$\Pi_{j,T} = \max\Big\{ x_{j,T} + y_{j,T}\, pR - [1 + (1+\alpha)r],\, 0 \Big\} = 0 \,.$$

Define the survival probability function as

$$S(x,t) = \Pr\Big(x > \Delta\pi_1,\ x > \Delta\pi_1 + \Delta\pi_2,\ \ldots,\ x > \sum_{\tau=1}^{t} \Delta\pi_\tau \Big)$$

with $\Delta\pi_\tau = \pi_{j,\tau} - \pi_{-j,\tau}$. Then, combining Cases 1.1 and 1.2, the bank's expected profit at T under the instant payment system can be written as

$$\Pi_{j,T,ins} = \begin{cases} [x + (1-x)pR - (1 + (1+\alpha)r)]\, S(x, T-1)\,, & 0 \le x < 1 - \dfrac{(1-\alpha)r}{pR-1}\,, \\ 0\,, & 1 - \dfrac{(1-\alpha)r}{pR-1} \le x < 1\,. \end{cases}$$

Case 2 (Traditional Payment System): Next, consider bank j's profit under the traditional payment system.

Case 2.1 (Bank remains solvent): If bank j remains solvent throughout $1 \le t \le T - \kappa - 1$, then at $t = T$ we have

$$\begin{cases} x_{j,T} = x\,, \\ y_{j,T} = 1 - x\,, \end{cases}$$

and the expected profit is

$$\Pi_{j,T} = \begin{cases} x + (1-x)pR - [1 + (1+\alpha)r], & 0 \le x < 1 - \dfrac{(1-\alpha)r}{pR-1}\,, \\ 0\,, & 1 - \dfrac{(1-\alpha)r}{pR-1} \le x < 1\,. \end{cases}$$

Case 2.2 (Bank becomes insolvent): If bank j becomes insolvent during $1 \le t \le T - \kappa - 1$, then at $t = T$ we have

$$\begin{cases} x_{j,T} \le 1\,, \\ y_{j,T} = 0\,, \end{cases}$$

so that

$$\Pi_{j,T} = \max\Big\{ x_{j,T} + y_{j,T}\, pR - [1 + (1+\alpha)r],\, 0 \Big\} = 0\,.$$

Thus, the bank's expected profit at T under the traditional payment system is

$$\Pi_{j,T,tra} = \begin{cases} [x + (1-x)pR - (1 + (1+\alpha)r)]\ S(x, T-\kappa-1), & 0 \le x < 1 - \dfrac{(1-\alpha)r}{pR-1}, \\ 0, & 1 - \dfrac{(1-\alpha)r}{pR-1} \le x < 1. \end{cases}$$

Define a function $F(x, t)$ such that

$$F(x, T-1) = \Pi_{j,T,ins} \quad \text{and} \quad F(x, T-\kappa-1) = \Pi_{j,T,tra}\,.$$

Let x^* solve

$$x^* = \arg\max_x F(x,t)\,.$$

By the Implicit Function Theorem, we have

$$\frac{dx^*}{dt} = -\frac{\partial F/\partial t}{\partial F/\partial x} = -\frac{(1-pR)\frac{\partial S(x,t)}{\partial t} + [x+(1-x)pR-(1+(1+\alpha)r)]\,\frac{\partial^2 S(x,t)}{\partial x \partial t}}{2(1-pR)\frac{\partial S(x,t)}{\partial x} + [x+(1-x)pR-(1+(1+\alpha)r)]\frac{\partial^2 S(x,t)}{\partial x^2}}\,. \tag{A.4}$$

By construction, we have

$$\frac{\partial S(x,t)}{\partial x} > 0, \quad \frac{\partial S(x,t)}{\partial t} < 0, \quad \frac{\partial^2 S(x,t)}{\partial x^2} < 0, \quad \frac{\partial^2 S(x,t)}{\partial x \partial t} > 0\,.$$

Thus, equation (A.4) implies $\frac{dx^*}{dt} > 0$, indicating the optimal liquid asset level x^* increases with t. Specifically, if we denote

$$x^*_{ins} = \arg\max_x F(x, T-1) \quad \text{and} \quad x^*_{tra} = \arg\max_x F(x, T-\kappa-1), \quad \kappa \geq 1,$$

then we obtain

$$x^*_{ins} > x^*_{tra}\,.$$

This establishes that banks under the instant payment system choose higher liquid asset buffers compared to banks under the traditional payment system. □

Proof of Proposition 3: We first derive the banks solvency threshold θ^*. This threshold is the lowest realization of the uncertainty θ that allows the bank to break even (i.e. yield zero terminal profit). Mathematically, θ^* is defined by the equation

$$x + (1-x)\,p\,R(p)\,\theta^* \;=\; (1-\eta)\left[\,1+(1+\alpha)r\,\right],$$

where x is the fraction of the banks portfolio held in liquid assets, p is the chosen risk level (the success probability of the risky loan portfolio), and $R(p)$ is the gross return on loans (which depends on p). Solving the above equation for θ^* yields an explicit expression for the solvency threshold:

$$\theta^*(x,p) \;=\; \frac{(1-\eta)\left[\,1+(1+\alpha)r\,\right] - x}{(1-x)\;p\,R(p)}\,. \tag{A.5}$$

This θ^* is the cutoff level of the shock θ below which the bank cannot meet its obligations. In other words, the bank remains solvent if and only if $\theta \geq \theta^*(x,p)$, and it defaults (yields zero payoff to equity) if $\theta < \theta^*(x,p)$.

Given a fixed portfolio composition x (chosen liquid asset ratio) at the terminal date T, the bank selects the risk level p of its loans to maximize expected profit. Because the banks equity payoff is truncated at zero in default states ($\theta < \theta^*$), the expected profit can be written as an integral over the solvent region $\{\theta \geq \theta^*\}$. Let $f(\theta)$ denote the probability density function of θ. The banks expected profit is then

$$\Pi(x,p) \;=\; \int_{\theta^*(x,p)}^{\infty} \Big[x + (1-x)\, p\, R(p)\, \theta \;-\; (1-\eta)\, \big(1 + (1+\alpha) r\big) \Big]\, f(\theta)\, d\theta \,,$$

where the integrand $x + (1-x)pR(p)\theta - (1-\eta)[1+(1+\alpha)r]$ is the banks profit in state θ. Under uniform distribution, the expected profit simplifies to

$$\Pi(x,p) \;=\; \int_{\theta^*}^{1} \Big[x - (1-\eta)\big(1 + (1+\alpha) r\big) + (1-x) p R(p)\, \theta \Big] d\theta \,. \tag{A.6}$$

Evaluating the integral in (A.6) yields an explicit objective function in terms of p. Perform the integration term by term:

$$\Pi(x,p) \;=\; \big[x - (1-\eta)(1+(1+\alpha)r)\big]\, (1-\theta^*) \;+\; (1-x)\, p\, R(p)\, \frac{1-(\theta^*)^2}{2} \,,$$

for $\theta^* = \theta^*(x,p)$ given by (A.5). This expression has a clear interpretation: the first term is the net payoff shortfall (liquid assets x minus required payment) times the survival probability $(1-\theta^*)$, and the second term is the expected payoff from loans (of scale $1-x$ and risk p) given survival, which is proportional to the second moment of the tail of the θ distribution above θ^*.

To find the p that maximizes $\Pi(x,p)$, the first-order condition is given by:

$$\frac{\partial \Pi}{\partial p} \;=\; \int_{\theta^*}^{1} (1-x)\, \Big[R(p) + p\, R'(p) \Big]\, \theta\, d\theta \;=\; 0 \,.$$

Since $\theta \geq 0$ on the integration domain, this condition holds if and only if

$$R(p^*) + p^*\, R'(p^*) \;=\; 0 \,. \tag{A.7}$$

Substituting θ^* from (A.5) into the optimality condition, one finds that $p^*(x)$ is characterized by

$$(1-x)\, p^*\, R(p^*) \;=\; (1-\eta)\left[\,1+(1+\alpha)r\,\right]-x\,. \tag{A.8}$$

The left side is the expected payoff from risky loans at the margin of solvency, and the right side is the liquidity shortfall the bank must cover. Equation (A.8) can be rearranged to express the optimal risk in closed form. Dividing both sides by $1-x$ gives

$$p^*\, R(p^*) \;=\; \frac{(1-\eta)\,[\,1+(1+\alpha)r\,]-x}{1-x}\,.$$

Now, provided the function $R(p)$ is strictly monotonic (which is true in our model, as a lower success probability p is associated with a higher loan return R due to risk-return trade-off), we may solve this equation by inverting $R(\cdot)$. In particular, define $y := \frac{(1-\eta)[\,1+(1+\alpha)r\,]-x}{1-x}$. Note that y is a positive number representing the required loan return given x. The optimal p is the value that makes $R(p)=y$. Therefore,

$$p^*(x) \;=\; R^{-1}\!\left(\frac{(1-\eta)\,[\,1+(1+\alpha)r\,]-x}{1-x}\right), \tag{A.9}$$

which is the banks optimal risk-taking choice as a function of its liquid asset holding x.

From the solution (A.9), we can immediately deduce that $p^*(x)$ is decreasing in x. Intuitively, a bank with a larger liquid buffer x faces a smaller chance of insolvency, which means it can afford to require a higher return on its loans (a larger y) to justify taking risk. Because $R(p)$ is a strictly decreasing function of p (riskier loans yield higher returns), it implies that $p^*(x)$ must decline as x increases.

Finally, recall that Proposition 2 established that under the instant payment system a bank will optimally choose a higher liquidity ratio than under the traditional system (formally, $x^*_{\text{ins}} > x^*_{\text{tra}}$). Applying the monotonic relation derived above, we conclude that the corresponding optimal risk choices satisfy

$$p^*_{\text{ins}} \;=\; p^*(\,x^*_{\text{ins}}\,) \;<\; p^*(\,x^*_{\text{tra}}\,) \;=\; p^*_{\text{tra}}\,.$$

In words, when a bank holds a larger buffer of liquid assets (as it does under instant payments), it finds it optimal to lend in riskier projects (lower p). This completes the proof that $p^*_{\text{ins}} < p^*_{\text{tra}}$. □

Proof of Corollary 2: From the derivation in the proof of Proposition 3, the optimal risk parameter p^* is implicitly determined by

$$R(p^*) = \frac{(1-\eta)[1+(1+\alpha)r] - x}{1-x},$$

where $R(\cdot)$ is strictly decreasing in p. Consequently, p^* is strictly decreasing in the liquid asset share x. Proposition 2 shows that the instant payment system induces a higher optimal x (i.e. $x^*_{ins} > x^*_{tra}$); hence,

$$p^*_{ins} = p^*(x^*_{ins}) < p^*(x^*_{tra}) = p^*_{tra}.$$

Moreover, differentiating the implicit relation with respect to the equity ratio η (noting that $D = (1-\eta)[1+(1+\alpha)r]$) shows that

$$\frac{\partial p^*}{\partial \eta} > 0,$$

and that the cross-derivative

$$\frac{\partial^2 p^*}{\partial x\, \partial \eta} > 0.$$

This implies that the sensitivity of p^* to changes in x is greater for banks with lower equity ratios. In other words, the reduction in p^* (and hence the increase in risk-taking) induced by a higher liquid asset share is more pronounced when equity is lower.

Thus, not only do banks choose a lower p^* under the instant payment system, but the risk-taking effect is amplified for banks with a lower equity ratio. $\square$

Proof of Proposition 5: Fix an arbitrary $\alpha > 0$. By Proposition 3, the banks optimal risk choice under instant payments is strictly higher than under the traditional system: $p^*_{\text{ins}} < p^*_{\text{tra}}$. Under the assumption that $pR(p)$ is strictly decreasing in p, a lower success probability p implies a higher value of $pR(p)$. Therefore, substituting the optimal risk levels for each payment system, we obtain

$$\Gamma^*_{l,\text{ins}} \;=\; p^*_{\text{ins}}\, R(p^*_{\text{ins}}) \;>\; p^*_{\text{tra}}\, R(p^*_{\text{tra}}) \;=\; \Gamma^*_{l,\text{tra}},$$

proving part (i).

For part (ii), we need to compare $\Gamma^*_{a,\text{ins}}$ and $\Gamma^*_{a,\text{tra}}$ under the additional condition on $R(p)$. By Proposition 2, the bank holds a larger liquidity share under instant payments: $x^*_{\text{ins}} > x^*_{\text{tra}}$. Thus, under the instant system the bank allocates a smaller fraction $(1 - x^*_{\text{ins}})$ of assets to loans (and conversely under the traditional system). At the same time, by Proposition 3 we have $p^*_{\text{ins}} < p^*_{\text{tra}}$, meaning the instant payment system induces the bank to choose riskier loans with a higher risk premium. To determine the net effect on Γ_a, we utilize the banks break-even condition from the model. In particular, from the proof of Proposition 3 the optimal risk choice satisfies the implicit equation

$$(1 - x^*)\, R(p^*) \;=\; (1 - \eta)\, \big[1 + (1 + \alpha) r\big] \;-\; x^*\,, \tag{A.10}$$

which equates the marginal loan return to the banks required repayment. Denoting the right-hand side of (A.10) by $D \equiv (1-\eta)\,[1+(1+\alpha)r]$ for brevity, we can rewrite (A.10) as $(1-x^*)R(p^*) = D - x^*$. Multiplying both sides by p^* and adding x^* yields an expression for the loan income per asset at the optimum:

$$\Gamma^*_a \;=\; x^* + (1 - x^*)\, p^* R(p^*) \;=\; x^* + p^* \big(D - x^*\big) \;=\; p^*\, D + (1 - p^*)\, x^*\,.$$

This relation holds for both the instant and traditional systems. Now consider the difference in loan income per asset between the two systems:

$$\Gamma^*_{a,\text{ins}} - \Gamma^*_{a,\text{tra}} \;=\; \big(p^*_{\text{ins}} - p^*_{\text{tra}}\big) D \;+\; \big[(1 - p^*_{\text{ins}}) x^*_{\text{ins}} - (1 - p^*_{\text{tra}}) x^*_{\text{tra}}\big]\,.$$

Substituting $p^*_{\text{ins}} < p^*_{\text{tra}}$ and $x^*_{\text{ins}} > x^*_{\text{tra}}$, we see that the first term in this expression is negative (since $D > 0$) while the second term is positive. Intuitively, relative to the traditional system, the instant payment system decreases the term $p^* D$ (because p^*_{ins} is lower) but increases the term $(1 - p^*) x^*$ (because x^*_{ins} is higher). We must show that under the stated condition on $R(p)$, the positive risk-premium effect dominates the negative loan-share effect, making the overall difference $\Gamma^*_{a,\text{ins}} - \Gamma^*_{a,\text{tra}}$ positive.

Claim: Condition (ii) implies that a marginal decrease in p (i.e. taking a slightly riskier loan portfolio) causes Γ_a to increase, once the induced adjustment in x (via the banks optimality condition) is accounted for.

To see this, we differentiate the expression $\Gamma_a = p\, D + (1 - p)x$ implicitly using the relationship (A.10) between x and p. Totally differentiating (A.10) yields

$$\frac{dx}{dp} = -\frac{(1-x)R'(p)}{1-R(p)},$$

which captures how the bank adjusts its liquidity ratio when the loan success probability changes at the optimum. Using this to compute the total derivative of Γ_a with respect to p, we obtain

$$\frac{d\Gamma_a}{dp} = D + (1-p)\frac{dx}{dp} - x = D - \frac{(1-p)(1-x)R'(p)}{1-R(p)} - x\,.$$

Substituting $D = (1-x)R(p) + x$ from (A.10) simplifies this expression to

$$\frac{d\Gamma_a}{dp} = \frac{d}{dp}\left(p\,D + (1-p)x\right) = \frac{1}{1-R(p)}\left(R(p)\big(1-R(p)\big) + \big(p-1\big)R'(p)\right)\,.$$

Crucially, the term in braces is exactly the condition imposed in part (ii). Condition (ii) states that $-R'(p)(1-p) > R(p)\big(R(p)-1\big)$ for all relevant p, which rearranges to

$$R(p)\big(1-R(p)\big) + \big(p-1\big)R'(p) > 0\,.$$

Thus, under condition (ii) we have $\frac{d\Gamma_a}{dp} > 0$. In other words, Γ_a is strictly increasing as the success probability p decreases (loans become riskier), at the margin. Since $p^*_{\text{ins}} < p^*_{\text{tra}}$, moving from p^*_{tra} down to p^*_{ins} (i.e. making the loan portfolio riskier as under instant payments) will raise Γ_a given the above derivative. Formally, integrating the above inequality for $d\Gamma_a/dp$ over the interval $[p^*_{\text{ins}}, p^*_{\text{tra}}]$ gives

$$\Gamma^*_{a,\text{tra}} - \Gamma^*_{a,\text{ins}} = \int_{p^*_{\text{ins}}}^{p^*_{\text{tra}}} \frac{d\Gamma_a}{dp}\,dp < 0\,,$$

which implies $\Gamma^*_{a,\text{ins}} > \Gamma^*_{a,\text{tra}}$. This proves part (ii). □

B Empirical Appendix

B.1 Main OLS Regression Results

Table 8: The Effect of Pix Usage on Deposit Ratios (OLS)

This table shows the effect of Pix usage on the ratio of demandable deposits, savings deposits, and checking deposits based on the baseline specification 5.1. Demandable deposit are comprised of savings and checking deposit. Pix usage is defined in Equation (3.1). Control variables include bank assets, core capital, and the number of bank branches. Time fixed effects and Bank fixed effects are included in all specifications. The sample period is from November, 2020 to March, 2023. Robust standard errors clustered by bank are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	Demandable Deposits Ratio		Checking Deposits Ratio		Savings Deposits Ratio	
	(1)	(2)	(3)	(4)	(5)	(6)
Pix Usage	0.016**	0.015*	0.016**	0.016**	0.000	-0.001
	(0.008)	(0.008)	(0.008)	(0.008)	(0.001)	(0.001)
Bank Assets		-0.079**		-0.013		-0.066*
		(0.038)		(0.015)		(0.037)
Bank Capital		0.011		-0.011		0.022
		(0.028)		(0.020)		(0.022)
No. of Branches		-0.030		-0.008		-0.022
		(0.030)		(0.017)		(0.022)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1501	1497	1501	1497	1501	1497
Adjusted R^2	0.871	0.872	0.841	0.841	0.975	0.978

Table 9: The Effect of Pix Usage on Asset Ratios (OLS)

This table shows the effect of Pix usage on the ratio of liquid assets, cash, government bonds, and loans based on the baseline specification 5.1. Liquid assets are comprised of cash and government bonds. Pix usage is defined in Equation (3.1). Control variables include bank assets, core capital, and the number of bank branches. Time fixed effects and Bank fixed effects are included in all specifications. The sample period is from November, 2020 to March, 2023. Robust standard errors clustered by bank are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	Liquid Assets Ratio		Cash Ratio		Gov Bond Ratio		Loan Ratio	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pix Usage	0.021**	0.022**	-0.003	-0.004	0.025***	0.025***	-0.021**	-0.022**
	(0.010)	(0.011)	(0.004)	(0.004)	(0.009)	(0.009)	(0.009)	(0.010)
Bank Assets		-0.001		-0.005		0.004		-0.053*
		(0.025)		(0.008)		(0.025)		(0.029)
Bank Capital		0.012		0.001		0.011		0.027
		(0.022)		(0.005)		(0.022)		(0.027)
No. of Branches		0.016		0.003		0.014		-0.009
		(0.025)		(0.007)		(0.023)		(0.033)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1501	1497	1501	1497	1501	1497	1501	1497
Adjusted R^2	0.709	0.708	0.614	0.613	0.757	0.757	0.971	0.971

Table 10: The Effect of Pix Usage on Bank Risk-Taking (OLS)

This table shows the effect of Pix usage on the ratio of prime, subprime, and default loans based on the baseline specification 5.1. It also shows the effect of Pix usage on the ratio of banks' loan loss reserves. All ratios are denoted relative to total loans. Pix usage is defined in Equation (3.1). Control variables include bank assets, core capital, and the number of bank branches. Time fixed effects and Bank fixed effects are included in all specifications. The sample period is from November, 2020 to March, 2023. Robust standard errors clustered by bank are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	Prime Loan Ratio		Sub-Prime Loan Ratio		Default Loan Ratio		Loan Loss Ratio	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pix Usage	-0.053**	-0.052**	0.056***	0.054***	-0.000	-0.000	0.007	0.007
	(0.024)	(0.024)	(0.014)	(0.014)	(0.005)	(0.005)	(0.006)	(0.007)
Bank Assets		0.035		-0.029		-0.004		-0.001
		(0.026)		(0.025)		(0.013)		(0.015)
Bank Capital		0.022		-0.047*		0.027*		0.025**
		(0.027)		(0.025)		(0.014)		(0.013)
No. of Branches		0.038		-0.034		0.005		0.009
		(0.037)		(0.043)		(0.019)		(0.016)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1397	1393	1397	1393	1397	1393	1236	1232
Adjusted R^2	0.926	0.927	0.926	0.928	0.916	0.917	0.889	0.887

Table 11: The Effect of Pix Usage on Bank Risk-Taking and Agency Issues (OLS)

This table shows the effect of Pix usage and its interaction with "High Cap Ratio" on the ratio of prime, subprime, and default loans. It also shows the effect on the ratio of banks' loan loss reserves. All ratios are denoted relative to total loans. Pix usage is defined in Equation (3.1). The dummy variable "High Cap Ratio" equals 1 if the bank's core capital-to-risk-weighted assets (RWA) ratio before Pix adoption is above the sample median. Control variables include bank assets, core capital, and the number of bank branches. Time fixed effects and Bank fixed effects are included in all specifications. The sample period is from November, 2020 to March, 2023. Robust standard errors clustered by bank are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	Prime Loan Ratio		Sub-Prime Loan Ratio		Default Loan Ratio		Loan Loss Ratio	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pix Usage	-0.028*	-0.027*	0.044***	0.043***	-0.004	-0.004	0.002	0.003
	(0.015)	(0.015)	(0.010)	(0.009)	(0.005)	(0.005)	(0.005)	(0.006)
Pix × High Cap Ratio	-0.065	-0.063	0.030	0.028	0.010	0.010	0.011	0.010
	(0.047)	(0.048)	(0.033)	(0.033)	(0.006)	(0.006)	(0.007)	(0.007)
Bank Assets		0.040*		-0.040*		-0.001		0.001
		(0.022)		(0.022)		(0.013)		(0.015)
Bank Capital		0.026		-0.048**		0.026*		0.024**
		(0.026)		(0.023)		(0.013)		(0.012)
No. of Branches		0.060*		-0.052		0.004		0.007
		(0.035)		(0.041)		(0.018)		(0.015)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1378	1374	1378	1374	1378	1374	1220	1216
Adjusted R^2	0.929	0.930	0.927	0.928	0.917	0.917	0.890	0.888

Table 12: The Effect of Pix Usage on Loan Income (OLS)

This table shows the effect of Pix usage on the loan income rate and loan income ratio based on the baseline specification 5.1. Loan income rate is defined as loan income over loan, and loan income ratio is defined as loan income over asset. Pix usage is defined in Equation (3.1). Control variables include bank assets, core capital, and the number of bank branches. Time fixed effects and Bank fixed effects are included in all specifications. The sample period is from November, 2020 to March, 2023. Robust standard errors clustered by bank are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

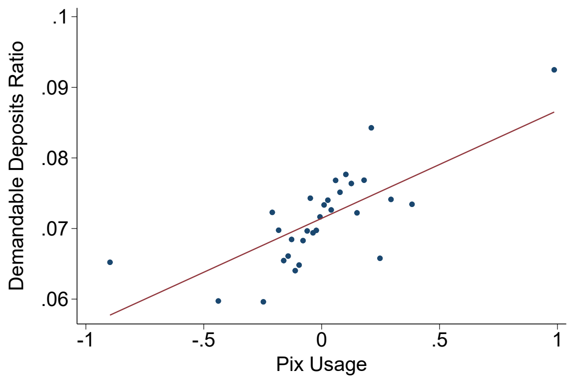
	Loan Income / Loans (%)		Loan Income / Assets (%)	
	(1)	(2)	(3)	(4)
Pix Usage	0.657	0.661	-0.019	-0.019
	(0.577)	(0.583)	(0.020)	(0.021)
Bank Assets		-0.042		-0.145*
		(0.505)		(0.083)
Bank Capital		0.275		0.113
		(0.392)		(0.082)
No. of Branches		0.068		-0.074
		(0.598)		(0.107)
Bank FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	1391	1387	1496	1492
Adjusted R^2	0.586	0.578	0.967	0.967

B.2 Binscatter Plots of the Main OLS Results

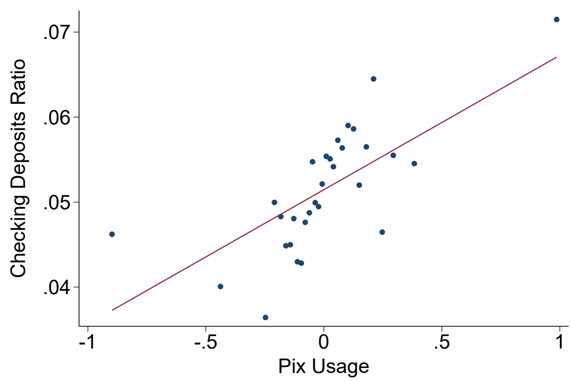
Figure 9: The Effect of Pix Usage on Deposit Ratios

This figure shows the binscatter plots illustrating the relationship between Pix usage (defined in Equation (3.1)) and the ratio of demandable deposits, savings deposits, and checking deposits, based on the baseline OLS specification in Equation (5.1). Demandable deposits consist of savings and checking deposits. All specifications include controls for bank assets, core capital, and the number of bank branches, as well as bank and time fixed effects. The sample covers the period from November 2020 to March 2023. Consistent with the OLS results, there is a positive relationship between Pix usage and the ratio of demandable deposits, primarily driven by checking deposits.

(a) Demandable Deposits Ratio



(b) Checking Deposits Ratio



(c) Savings Deposits Ratio

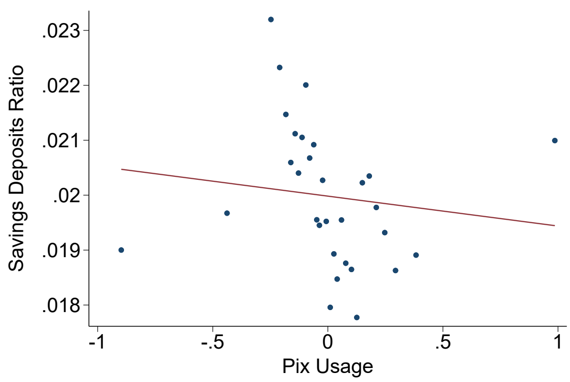
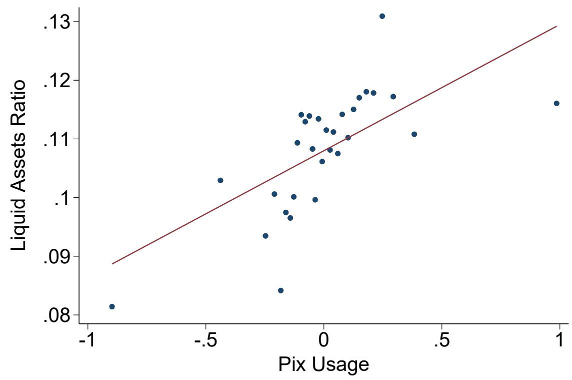


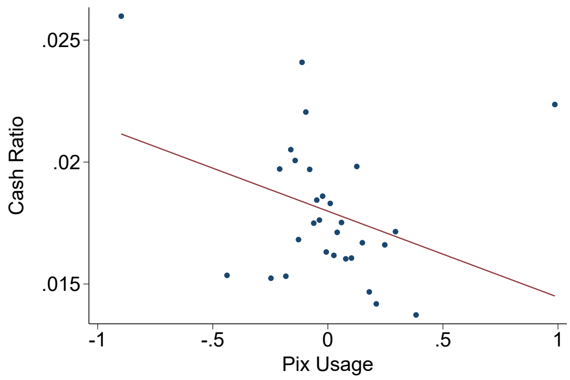
Figure 10: The Effect of Pix Usage on Asset Ratios

This figure presents binscatter plots illustrating the relationship between Pix usage (as defined in Equation (3.1)) and the ratios of liquid assets, cash, government bonds, and loans, based on the baseline OLS specification in Equation (5.1). Liquid assets consist of cash and government bonds. All specifications include controls for bank assets, core capital, and the number of bank branches, along with bank and time fixed effects. The sample period spans from November 2020 to March 2023. Consistent with the OLS results, there is a positive relationship between Pix usage and the ratio of liquid assets, primarily driven by government bonds. Also, there is a negative relationship between Pix usage and the ratio of loans.

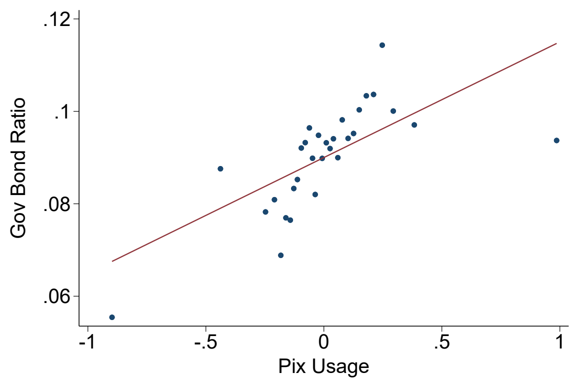
(a) Liquid Assets Ratio



(b) Cash Ratio



(c) Government Bond Ratio



(d) Loan Ratio

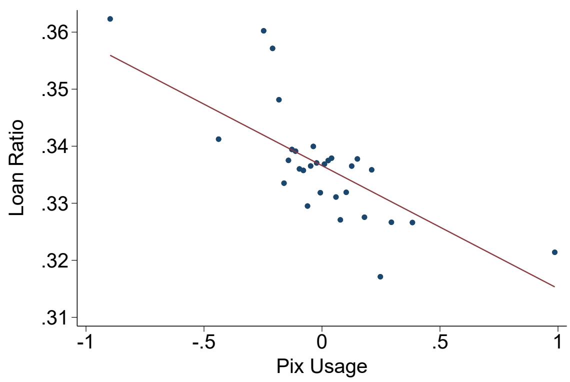
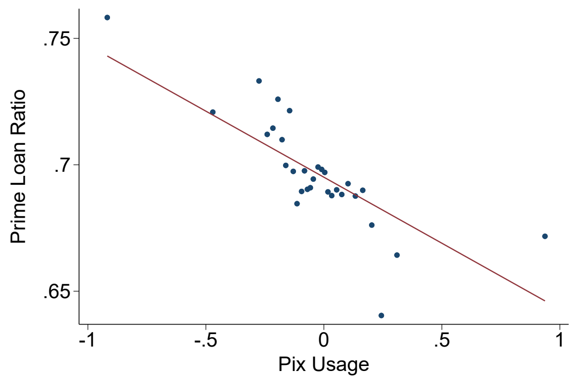


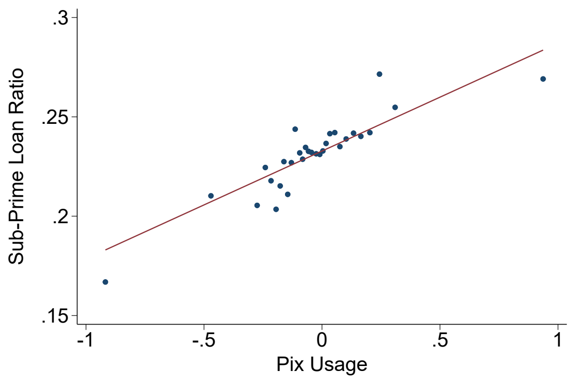
Figure 11: The Effect of Pix Usage on Bank Risk-Taking

Panels (a), (b), (c) and (d) present binscatter plots showing the relationship between Pix usage (as defined in Equation (3.1)) and the ratios of prime, subprime, default loans and loan loss reserves relative to total loans. Results are derived from the baseline OLS specification in Equation (5.1). Control variables include bank assets, core capital, and the number of bank branches. All specifications include bank and time fixed effects. The sample covers the period from November 2020 to March 2023. To mitigate the influence of outliers, panels (e) and (f) show the binscatter plots of default loan ratio and loan loss ratio with the regression discontinuity cutoff being the 2.5th and 97.5th percentile of the residualized pix usage. As shown in the plots, the risk-taking patterns become clearer within this range, as removing outliers reduces noise and makes the breakpoint effect more apparent.

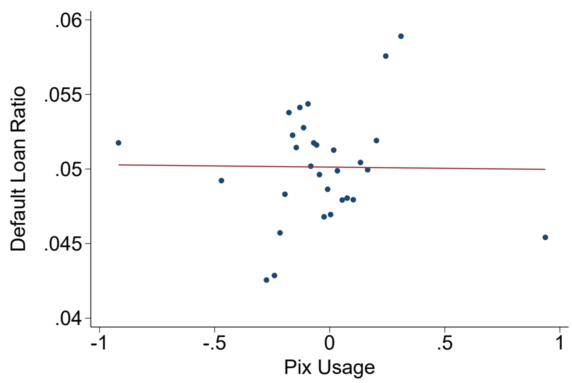
(a) Prime Loan Ratio



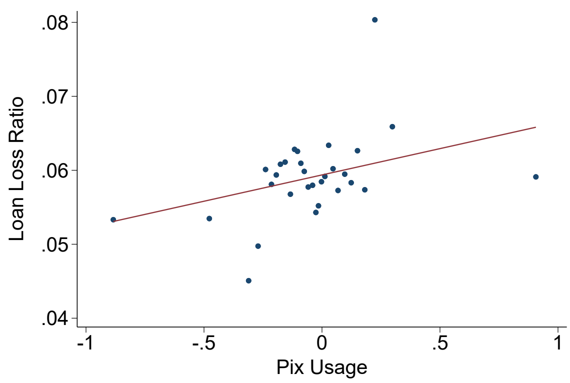
(b) Sub-Prime Loan Ratio



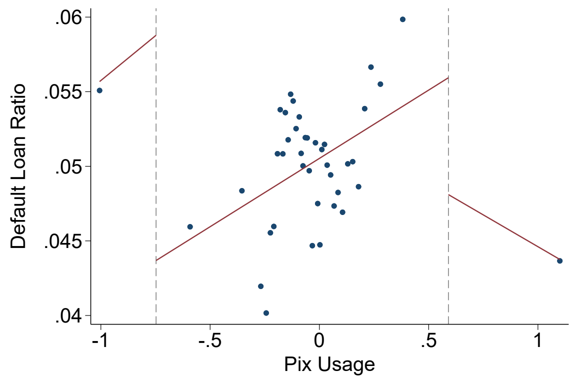
(c) Default Loan Ratio



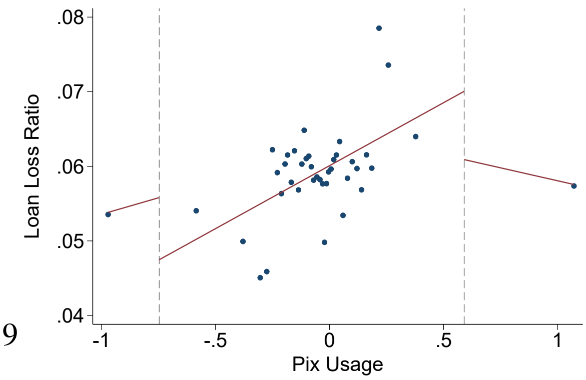
(d) Loan Loss Ratio



(e) Default Loan Ratio, Regression Discontinuity



(f) Loan Loss Ratio, Regression Discontinuity



B.3 First Stage Results with Interaction

Table 13: The Effect of Timeouts on Pix Usage and Interaction with High Cap Ratio

This table shows the effect of the timeout instrument (Timeout IV) and its interaction with "High Cap Ratio" on Pix usage and the interaction term "Pix usage × High Cap Ratio". The dummy variable "High Cap Ratio" equals 1 if the bank's core capital-to-risk-weighted assets (RWA) ratio before Pix adoption is above the sample median. Pix usage is defined as in Equation (3.1). The timeout instrument represents the proportion of failed Pix transactions due to issues originating at other banks. Pix usage and the interaction term is instrumented by Timeout IV and the interaction of Timeout IV and "High Cap Ratio". Controls include bank assets, core capital, and the number of branches. The sample period is from November 2020 to March 2023. Robust standard errors clustered by bank are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	Pix Usage		Pix × High Cap Ratio	
	(1)	(2)	(3)	(4)
Timeout IV	-0.012***	-0.012***	0.001*	0.001*
	(0.001)	(0.001)	(0.001)	(0.001)
Timeout IV × High Cap Ratio	-1.121	-1.117	-1.030	-1.022
	(0.681)	(0.676)	(0.783)	(0.773)
Bank Assets		-0.317		-0.288**
		(0.198)		(0.136)
Bank Capital		-0.074		0.065
		(0.166)		(0.152)
No. of Branches		0.163		0.269
		(0.229)		(0.201)
Bank FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	1452	1448	1452	1448
Adjusted R^2	0.899	0.900	0.933	0.934
Sanderson-Windmeijer F	227.153	196.731	223.305	195.053