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 Brazil's 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). 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 Bartik-style 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 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. 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. First, we use transaction-level Pix data to measure the extent of Pix usage for each bank. This data also records 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 Central Bank of Brazil (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 liqudidity 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 anjoy 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.

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.

Finally, 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 reflect an increase in the riskiness of banks' loan books consistent with our model. Nevertheless, we acknowledge that there could be a silver lining. For example, it could be that loans are given out to new borrowers without credit ratings, fostering financial inclusion. It could also be that banks charge a fair price for their riskier loans. These 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 central bank digital currencies (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).[1] Three recent studies examine instant payment systems. Dubey and Purnanandam (2023) 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

[1] 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).

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 paymen 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' payment processing and lending.[2] 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

[2] 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).

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.[3]

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 Central Bank of Brazil, 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 Central Bank of Brazil 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.[4]

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

[3] See https://fastpayments.worldbank.org/resources#block-homenav.

[4] 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.

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.[5]

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 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 utilize 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

[5] See here.

banks and credit unions, as these institutions engage in both deposit-taking and lending.[6]

Together, these data provide a comprehensive view of the banking sectors following Pix's implementation. Our dataset spans January 2018 to March 2023, with the primary analysis focused on the period from Pix's 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 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, "Transferência Eletrônica Disponível". 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

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

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 are 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.

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 1. 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%, whle 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 5.2, 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 Effects on 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 3a 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 3b further confirms that the trend in Figure 3a 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 deposits—particularly in checking deposits—may 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 Effects on Asset Composition

We proceed to examine how banks adjust their asset composition. In particular, we focus on banks' liquid asset holdings, which can be more readily converted to cash to meet payment demands on short notice.

In Figure 4a, 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 4b. One likely interpretation is that government bonds serve as liquid assets that banks can pledge in repo transactions, including with the Central Bank of Brazil, 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 Pix's implementation, as seen in Figure 4c. 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 Pix's 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 Effects on 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 5a and 5b 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 5c 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.[7]

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.

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 crytallize the underlying economic channels. For detailed proofs, please refer to Appendix A.

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. 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.[8] Time deposits, on the other hand, accrue a positive interest rate $r > 0$ which is realized at date T but cannot be used

[7]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.

[8]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 Central Bank of Brazil.

for payments before maturity at T. We also assume that both demandable and time deposits are insured.[9]

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).[10] 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, 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

[9]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.

[10]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.

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,

$$\widetilde{R} = \begin{cases} R(p)\theta & \text{with probability } p\,, \\ 0 & \text{with probability } 1-p\,, \end{cases} \tag{4.3}$$

where $R(p)$ is decreasing in p to reflect a positive risk premium, θ captures aggregate uncertainty, which for simplicity follows a standard uniform distribution betweem $[0,1]$, and the bank chooses p. 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 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

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

$$\max_{\{x_{j,0};p\}} E\left[\Pi_{j,T}\right]\,, \tag{4.4}$$

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

$$\Pi_{j,T} = \max\{\underbrace{x_{j,T} + p y_{j,T} R}_{\text{gross revenue}} - \underbrace{(1-\eta)(1+(1-\alpha)r)}_{\text{debt expenses}}, 0\}\,, \tag{4.5}$$

subject to the law of motion for the liquid asset

$$x_{j,t+1} = \begin{cases} x_{j,t} - \alpha(1-\eta)(\pi_{j,t} - \pi_{-j,t}) & \text{if } x_{j,t} \geq \alpha(1-\eta)(\pi_{j,t} - \pi_{-j,t})\,, \\ 0 & \text{if } x_{j,t} < \alpha(1-\eta)(\pi_{j,t} - \pi_{-j,t})\,, \end{cases} \tag{4.6}$$

as well as that for the illiquid loan

$$y_{j,t+1} = \begin{cases} y_{j,t} & \text{if } x_{j,t} \geq \alpha(1-\eta)(\pi_{j,t} - \pi_{-j,t})\,, \\ \max\{y_{j,t} - \frac{\alpha(1-\eta)(\pi_{j,t}-\pi_{-j,t})-x_{j,t}}{1-\phi}, 0\} & \text{if } x_{j,t} < \alpha(1-\eta)(\pi_{j,t} - \pi_{-j,t})\,. \end{cases} \tag{4.7}$$

(4.5) 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 (4.6) 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 (4.7) 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

$$\max_{\{\alpha_j\}} E\left[\sum_t \pi_{j,t} c_t\right]\,, \tag{4.8}$$

where

$$c_{j,t} = \begin{cases} \alpha & \text{if } 1 \leq t \leq T-1\,, \\ (1-\alpha)(1+r) & \text{if } t = T\,. \end{cases} \tag{4.9}$$

(4.9) 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:

$$\max_{\{x_{j,0};p\}} E\left[\Pi_{j,T}\right] , \tag{4.10}$$

where the date-T bank profit accrued to bank equity is the same as that in (4.5) while subject to a different law of motion for the liquid asset

$$x_{j,t+1} = \begin{cases} x_{j,t} & \text{if } t \leq \kappa\,, \\ x_{j,t} - \alpha(1-\eta)(\pi_{j,t-\kappa} - \pi_{-j,t-\kappa}) & \text{if } t \geq \kappa+1 \text{ and } x_{j,t} \geq \alpha(1-\eta)(\pi_{j,t} - \pi_{-j,t})\,, \\ 0 & \text{if } t \geq \kappa+1 \text{ and } x_{j,t} < \alpha(1-\eta)(\pi_{j,t} - \pi_{-j,t})\,, \end{cases} \tag{4.11}$$

and that for the illiquid loan

$$y_{j,t+1} = \begin{cases} y_{j,t} & \text{if } t \leq \kappa\,, \\ y_{j,t} & \text{if } t \geq \kappa+1 \text{ and } x_{j,t} \geq \alpha(1-\eta)(\pi_{j,t} - \pi_{-j,t})\,, \\ \max\{y_{j,t} - \frac{\alpha(1-\eta)(\pi_{j,t-\kappa} - \pi_{-j,t-\kappa}) - x_{j,t}}{1-\phi}, 0\} & \text{if } t \geq \kappa+1 \text{ and } x_{j,t} < \alpha(1-\eta)(\pi_{j,t} - \pi_{-j,t})\,. \end{cases} \tag{4.12}$$

Compared to the bank's problem (4.4) under the instant payment system, the laws of motion (4.11) and (4.12) 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 (4.11). Additionally, the time buffer created by the delay helps the bank to partially mitigate the illiquidity associated with the underlying loans, as shown in (4.12). 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

$$\max_{\{\alpha_j\}} E\left[\sum_t \pi_{j,t} u(c_t)\right], \tag{4.13}$$

where

$$c_{j,t} = \begin{cases} \delta^{\kappa}\alpha & \text{if } 1 \leq t \leq T-\kappa\,, \\ \delta^{T-t}\alpha & \text{if } T-\kappa+1 \leq t \leq T-1\,, \\ (1-\alpha)(1+r) & \text{if } t = T\,. \end{cases} \tag{4.14}$$

Thus, (4.14) 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.

Having detailed the problems faced by banks and households, we now compare the equilibrium outcomes between the two payment systems.

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 (4.6) and (4.11) 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 (4.7) and (4.12) 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.

Finally, we show that the liquidity demand effect directly implies more risk-taking by the bank under the instant payment system.

Proposition 3. [BANK RISK-TAKING EFFECT]*: given any* $\alpha > 0$, $p^*_{ins} < p^*_{tra}$*, that is, banks take higher risk 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. We call this effect the risk-taking effect, which is a direct implication of Proposition 2 and the underlying liquidity demand effect. To understand this 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:

$$\max_p E\left[x + (1-x)pR(p)\theta - (1+(1+\alpha)r) | x + (1-x)R(p)\theta - (1+(1+\alpha)r) > 0\right], \tag{4.15}$$

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

$$p^* = R^{-1}\left(\frac{1+(1+\alpha)r - x}{1-x}\right), \tag{4.16}$$

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. Consequently, as shown in (4.16), 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 (4.15) to the bank's initial portfolio decisions and noticing that the bank effectively chooses p^* and x^* sequentially.

5 Empirical Analysis

In this Section, we formally estimate the effect of Pix usage on the deposit funding structure, asset composition, and risk-taking of the banking sector. To estimate the causal effect, we construct a novel instrument for Pix usage based on payment timeouts. Overall, our findings in this Section are consistent with and corroborate our preliminary evidence in Section 3 and our model predictions in Section 4.

5.1 Estimation Strategy

To understand the effects of Pix usage on different outcome variables, we estimate

$$OutcomeVar_{it} = \beta PixUsage_{it} + Controls_{it} + \eta_i + \omega_t + \epsilon_{it}, \tag{5.17}$$

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 in all specifications to ensure reliable inference.

Although 5.17 controls for bank characteristics and fixed effects, readers may still worry that there are other unobserved bank characteristics that simultaneously affect their Pix usage and the composition of their balance sheets over time. To this end, we further repeat our estimation using an instrumental variable approach to isolate plausibly exogenous variation in Pix usage.

The basic idea of our instrument 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 without delay. If either bank fails to process the payment within the allotted time, the payment attempt 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 Central Bank of Brazil 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, which cannot be easily anticipated. 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 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 to its customers is lowered, reducing its equilibrium level of Pix usage. However, because these timeouts arise from counterparty banks rather than from bank i's 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:

$$Timeout_{it} = \sum_{j \in J, j \neq i} \frac{PixReceived_{ijt}}{PixReceived_{it}} SenderTimeout_{ij} + \sum_{j \in J, j \neq i} \frac{PixSent_{ijt}}{PixSent_{it}} ReceiverTimeout_{ij}, \tag{5.18}$$

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. The identifying assumption is that these passively induced timeouts due to other banks do not affect bank i's decisions over its balance sheet composition through channels other than bank i's Pix usage.

For our timeout instrument to be relevant, it must have a negative and statistically significant effect on Pix usage. To check the relevance condition, we estimate the specification

$$PixUsage_{it} = Timeout_{it} + Controls_{it} + \eta_i + \omega_t + \epsilon_{it}, \tag{5.19}$$

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.

From these 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 5.17. That is, we estimate

$$OutcomeVar_{it} = \beta \widehat{PixUsage}_{it} + Controls_{it} + \eta_i + \omega_t + \epsilon_{it}. \tag{5.20}$$

The estimated coefficients from this second stage provide plausibly causal estimates of the effect of Pix usage on bank asset composition, liability structure, and risk-taking.

5.2 Estimation Results

In this section, we present our estimation results. We focus on the IV estimates and show the corresponding OLS results in Appendix B.

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 model's 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. 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 predictions regarding the effect of instant payments on banks' liquid asset holdings. 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.

Finally, we shed light on the effect of Pix usage on bank risk-taking. From Table 5, we observe that Pix usage decreases the ratio of prime loans and increases the ratio of sub-prime and default loans. 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.

While our results establish an increase in the realized and expected riskiness of bank loans, we remain agnostic about the normative prediction about whether such risk-taking is good or bad for welfare. For example, it could be that banks are charging a fair risk premium for the riskier loans they give out. It could also be that these loans are given out to borrowers that were previously not part for the formal financial system. Extending loans to these borrowers may increase default risk in the short run but lead to improved financial inclusion and credit access in the long run. We leave these considerations for future research.

6 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, which eventually leads to a rise in the ratio of defaulting loans.

Taken together, our findings highlight that in addition to the many benefits of instant payments to consumers, another consequence may be a riskier financial 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 1: 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. The sample period is from November 2020 to March 2023.

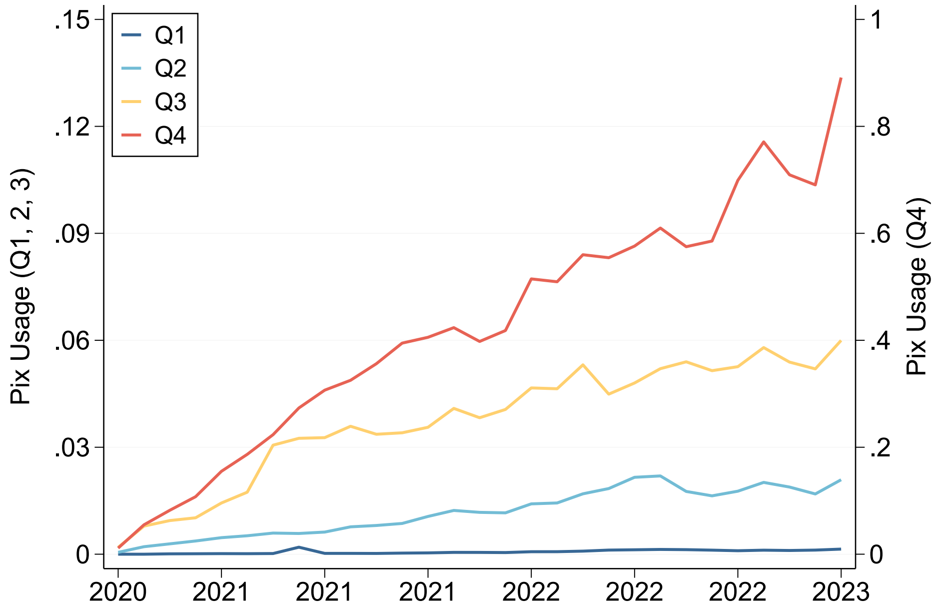


Figure 2: Nettable Payments Ratio

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.

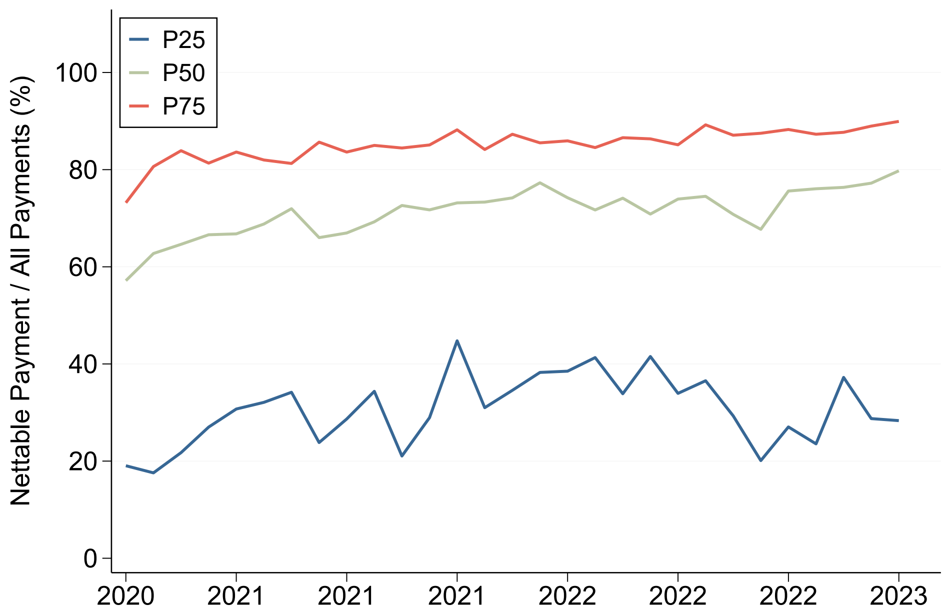
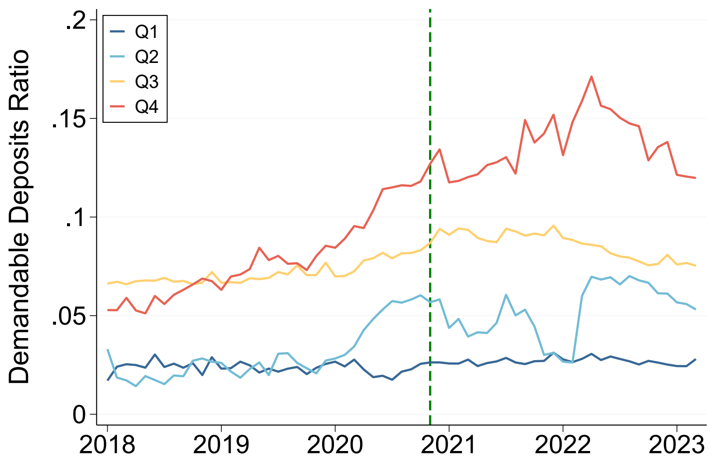


Figure 3: Deposits Ratios by Pix Usage

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

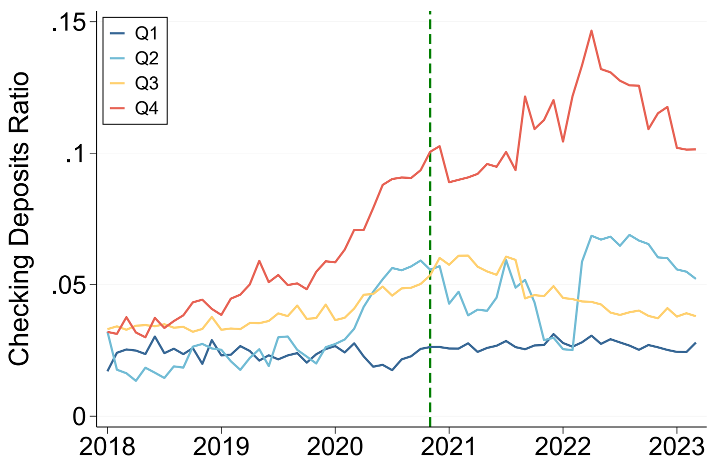
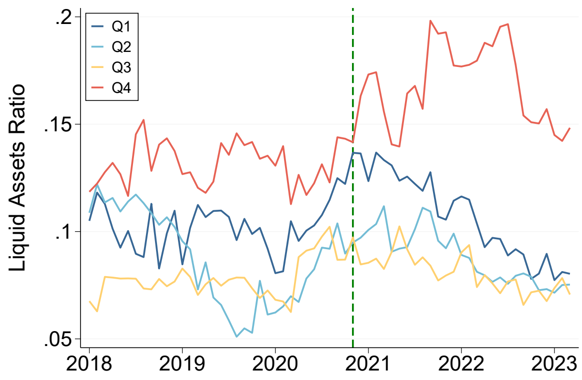


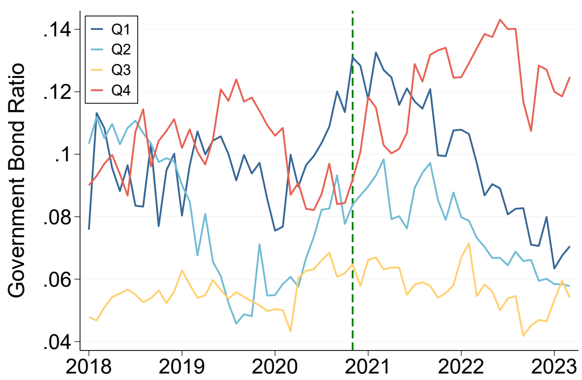
Figure 4: Liquid Assets Ratios by Pix Usage

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

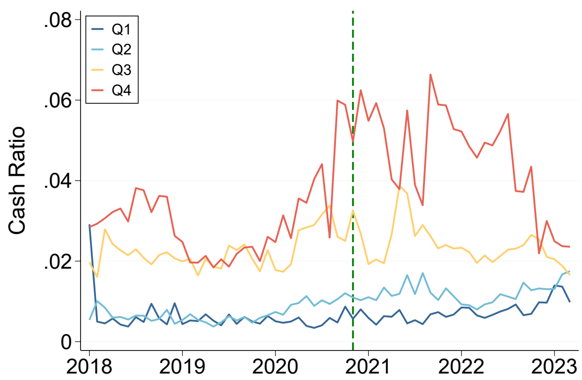
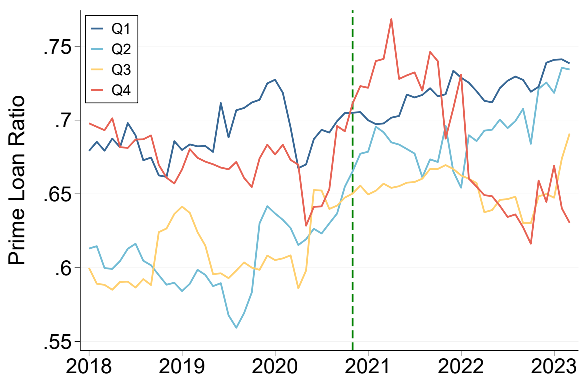


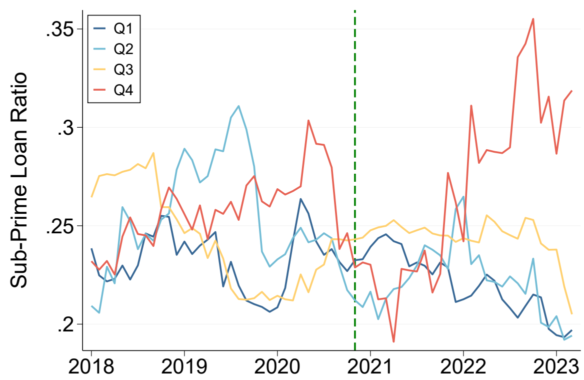
Figure 5: Prime, Subprime, and Default Loan Ratios by Pix Usage

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

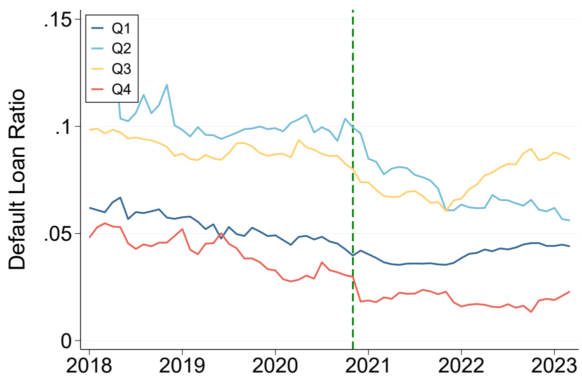


Table 1: Summary Statistics

This table shows the summary statistics of our main variables and control variables. Deposits and assets ratios are expressed as a fraction of bank assets. The prime loan ratio, subprime loan ratio, default loan ratio, and loan loss provision ratio are expressed as a fraction of total loans. All main variables are expressed in percent. For control variables, bank assets is the value of bank assets expressed in billions, Bank capital is the value of bank core-capital in billions, and No. of branches is 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
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 (5.20). 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 (5.20). 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 (5.20). 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

Appendix

A Omitted Proofs

Proof of Proposition 1: Consider first the household's portfolio choice problem under the instant payment system. We have:

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

As a result, the household's expected utility under the instant payment system is given by:

$$U_{ins}=E\left[\sum_{t}^{T-1}\pi_{j,t}u(c_{j,t})+u(c_{j,T})\right]=u(\alpha)+u((1-\alpha)(1+r))\,,$$

with the first-order condition with respect to α:

$$u'(\alpha^*_{\text{ins}})-(1+r)u'((1-\alpha^*_{\text{ins}})(1+r))=0\,. \tag{A.21}$$

Then, consider the household's portfolio choice problem under the traditional payment system. We have:

$$u(c_j,t)=\begin{cases}u(\delta^{\kappa}\alpha)\,, & 1\le t\le T-\kappa\,,\\ u(\delta^{T-t}\alpha)\,, & T-\kappa+1\le t\le T-1 \text{ and } \kappa\ge 2\,,\\ u((1-\alpha)(1+r))\,, & t=T\,,\end{cases}$$

which implies that

$$E[\pi_{j,t}u(c_{j,t})]=\begin{cases}\dfrac{u(\delta^{k}\alpha)}{2(T-2)}\,, & 1\le t\le T-\kappa\,,\\ \dfrac{u(\delta^{T-t}\alpha)}{2(T-2)}\,, & T-\kappa+1\le t\le T-2 \text{ and } \kappa\ge 3\,,\\ \dfrac{u(\delta\alpha)}{2}\,, & t=T-1\,.\end{cases}$$

As a result, the household's expected utility under the traditional payment system is given by:

$$
\begin{aligned}
U_{tra} &= E\left[\sum_{t}^{T-1} \pi_{j,t} u(c_{j,t}) + u(c_{j,T})\right] \\
&= \frac{(T-\kappa)u(\delta^\kappa \alpha)}{2(T-2)} + \mathbf{1}_{\kappa\geq 3} \sum_{\tau=2}^{\kappa-1} \frac{u(\delta^\tau \alpha)}{2(T-2)} + \frac{u(\delta\alpha)}{2} + u((1-\alpha)(1+r)) \, .
\end{aligned}
$$

Similarly, taking the first-order condition with respect to α yields:

$$
\frac{(T-\kappa)\delta^\kappa u'(\delta^\kappa \alpha_{\text{tra}})}{2(T-2)} + \mathbf{1}_{\kappa\geq 3} \sum_{\tau=2}^{\kappa-1} \frac{\delta^\tau u'(\delta^\tau \alpha_{\text{tra}})}{2(T-2)} + \frac{\delta u'(\delta \alpha_{\text{tra}})}{2} - (1+r)u'((1-\alpha_{\text{tra}})(1+r)) = 0 \tag{A.22}
$$

We now compare the two first-order conditions (A.21) and (A.22). Let $f(x) = xu(x)$. Because $f'(x) = u(x) + xu'(x) > 0$, $f(x)$ increases in x. Hence, $f(\alpha_{\text{tra}}) > f(\delta^\tau \alpha_{\text{tra}})$ for any τ, implying that $u'(\alpha_{\text{tra}}) > \delta^\tau u'(\delta^\tau \alpha_{\text{tra}})$ for any τ. Therefore, (A.22) implies that:

$$
\begin{aligned}
0 &< \frac{(T-\kappa)u'(\alpha_{\text{tra}})}{2(T-2)} + \mathbf{1}_{\kappa\geq 3} \sum_{\tau=2}^{\kappa-1} \frac{u'(\alpha_{\text{tra}})}{2(T-2)} + \frac{u'(\alpha_{\text{tra}})}{2} - (1+r)u'((1-\alpha_{\text{tra}})(1+r)) \\
&= u'(\alpha_{\text{tra}}) - (1+r)u'((1-\alpha_{\text{tra}})(1+r)) \, .
\end{aligned}
$$

Combining with (A.21) then yields:

$$
u'(\alpha_{\text{ins}}) - (1+r)u'((1-\alpha_{\text{ins}})(1+r)) < u'(\alpha_{\text{tra}}) - (1+r)u'((1-\alpha_{\text{tra}})(1+r)) \, . \tag{A.23}
$$

Let

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

It is clear that

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

Thus, (A.23) immediately implies that $\alpha^*_{\text{ins}} > \alpha^*_{\text{tra}}$. This concludes the proof. □

Proof of Proposition 2: We establish the result for the case of $\eta = 0$ and $\phi = 1$, and the general result then follows by continuity. First, consider any bank j's profit under the instant payment system. There are two cases:

CASE 1.1: If bank j's liquid asset holdings have never been exhausted, that is, the bank has been always solvant, during $1 \leq t \leq T-1$, then we have

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

at T, and consequently, bank j's expected profit at T is

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

CASE 1.2: If bank j's liquid assets has ever been exhausted due to payment outflows during $1 \leq t \leq T-1$, that is, the bank has become insolvent during $1 \leq t \leq T-1$, then we have

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

at T, and consequently, bank j's expected profit at T is

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

To proceed, let $S(x,t)$ denote the probability of a bank keeping solvant until t with an initial liquid asset position x:

$$S(x,t) = \text{Prob}(x > \Delta\pi_1, x > \Delta\pi_1 + \Delta\pi_2, ..., x > \sum_{\tau}^{t} \Delta\pi_\tau)\,,$$

where $\Delta\pi_\tau = \pi_{j,\tau} - \pi_{-j,\tau}$.

Using $S(x,t)$ and combining the two cases above, we can now re-write bank j's expected profit at T under the instant payment system as:

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

Then, we consider bank j's profit under the traditional payment system. There are also two cases:

CASE 2.1: If bank j's liquid asset holdings have never been exhausted, that is, the bank has been always solvant, during $1 \le t \le T - \kappa - 1$, then again we have

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

at T, and consequently, bank j's expected profit at T is

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

CASE 2.2: If bank j's liquid assets has ever been exhausted due to payment outflows during $1 \le t \le T - \kappa - 1$, that is, the bank has become insolvent during $1 \le t \le T - \kappa - 1$, then we have

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

at T, and consequently, bank j's expected profit at T is

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

Similarly, using $S(x,t)$ and combining the two cases above, we can now re-write bank j's expected profit at T under the traditional payment system as:

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

Comparing $\Pi_{j,T,\text{ins}}$ and $\Pi_{j,T,\text{tra}}$, we can define $F(x,t)$ such that $F(x,T-1) = \Pi_{j,T,\text{ins}}$ and $F(x,T-\kappa-1) = \Pi_{j,T,\text{tra}}$. Let

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

By the Implicit Function Theorem, we have

$$\begin{aligned}\frac{dx^*}{dt} &= -\frac{F'_t(x,t)}{F'_x(x,t)} \\ &= -\frac{(1-pR)\frac{\partial S(x,t)}{\partial t} + [x+(1-x)pR-(1+(1-\alpha)r)]\,\frac{\partial^2 S(x,t)}{\partial x\partial t}}{2(1-pR)\frac{\partial S(x,t)}{\partial x} + [x+(1-x)pR-(1+(1-\alpha)r)]\,\frac{\partial^2 S(x,t)}{\partial x^2}}\,. \end{aligned} \tag{A.24}$$

Consider $S(x,t)$. By construction, we have

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

As a result, the right-hand-side of (A.24) is strictly positive, implying that x^* increases in t. Notice that

$$x^*_{\text{ins}} = \arg\max F(x,T-1)\,,$$

while

$$x^*_{\text{tra}} = \arg\max F(x,T-\kappa-1)\,,$$

with $\kappa \geq 1$. This immediately implies that $x^*_{\text{ins}} > x^*_{\text{tra}}$. This concludes the proof. □

B Additional Results

Table 6: 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 5.17. 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 7: 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 5.17. 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 8: 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 5.17. 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