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

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Abstract

We show how instant payment systems may constrain liquidity transformation and exacerbate risk-taking by banks. Using payment data from Brazil's Pix and a novel instrument, we find that instant payments increased banks' liquid asset holdings and the share of subprime lending. These effects arise because instant payments eliminate banks' ability to delay and net payment flows, which incentivizes them to set aside more liquid assets to meet payment shocks. Greater liquid holdings, in turn, lead to more risk-taking in loan provisions. Our findings have important implications for instant payment adoption and CBDC design.

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

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1 Introduction

In recent years, the global banking and payment landscape has undergone significant changes. Among these, instant payment systems have attracted considerable attention from academics and policymakers, owing to their integration with the banking system and their shared functionalities with CBDCs. While both arrangements enable the instantaneous transfer of deposited funds, instant payment systems differ in that the backing assets remain on commercial bank balance sheets rather than being shifted to central bank balance sheets. As a result, instant payment systems are often regarded as a favourable option: they improve payment convenience while avoiding the risk of crowding out bank funding.

While instant payments allow assets to remain on banks' balance sheets, they affect banks' liability side by altering the functionality of bank deposits. Without instant payments, banks can defer settlement of transfer requests until the end of the day or even several days later. [1] With instant payments, however, customers gain the ability to transfer deposits across banks instantaneously. Instant payments therefore do not merely accelerate transactions; rather, they eliminate banks' discretion over the timing of outflows. This raises the question of how the banking system, which relies on deposits as a key source of stable funding, can adapt to this change. Can banks still perform liquidity transformation and extend credit to the real economy in the same way as before?

In this paper, we find that instant payments may have the unintended consequence of constraining liquidity transformation and amplifying risk taking by banks. 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 riskier loans. We confirm that the observed relationship is causal by constructing a novel instrument based on passive payment timeouts.

Economically, our findings arise because the immediacy of payments implies a loss in banks' ability to decide on the timing of their payment flows. In particular, banks can no longer delay outgoing payments to net them with incoming ones within the same day, which translates into more volatile payment shocks. In response, banks hold a larger proportion of liquid asset buffers and a smaller fraction of illiquid assets, effectively becoming "narrower". Larger liquid asset holdings also

[1] In the U.S., for example, Fedwire transfers must be made before the end of the day, while ACH can be delayed for several business days without an expedited processing fee. In Brazil, before the implementation of the instant payment system Pix, transfers can be delayed until the end of the day under TED and the next day under DOC.

induce bank equity holders to take on more credit risk when investing in illiquid assets like loans. Thus, instant payments may lead to narrower banks with riskier loan books.

Our analysis highlights the importance of considering the effect of instant payments on the banking sector. While instant payment systems undoubtedly bear many benefits for consumers, the instant means of payments–deposits–are ultimately provided by banks, and banks rely on the same deposits for stable funding. Therefore, amidst the surge in adopting instant payments around the world, e.g., FedNow in the U.S., Pix in Brazil, and UPI in India, 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 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 bank balance sheet and income statement data from the BCB (COSIF).

We first measure the extent of 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. While the vast majority of banks adopted Pix right away following its November 2020 implementation, the extent to which Pix was used at different banks varied widely. The average Pix usage for banks in the first and fourth quartile of Pix usage was 0.07% and 42.66%, respectively, during our sample period. We will use this cross-sectional variation in banks' exposure to Pix to estimate the effect on various outcome variables.

We show that, the overlap between daily gross Pix sent and received that determines Pix usage also represents payment flows that would have been nettable with end-of-day rather than instant settlement. Thus, Pix usage also reflects the potential loss of nettable payments per unit bank size due to instant payments. The volume of nettable payments is economically significant. For the median bank in the average month, 71.26% of total payment flows would have been nettable absent instant instant payments. These nettable payments are also sizable relative to banks' liquid asset holdings, which suggests that the loss of payment netting is economically relevant and may impact banks' demand for liquid assets and other balance sheet decisions.

We then uncover three novel stylized facts about the response of the Brazilian banking system to

the introduction of instant payments. 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.

On the liability side, we 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.

Zooming in on banks' loan portfolios, we find that banks with more Pix usage take on more credit risk. Banks with higher Pix usage had a disproportionate increase in the ratio of subprime loans, default loans, and loan loss provisions. In contrast, their ratio of prime loans decreased.

To rationalize our stylized facts, 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 demandable deposits, time deposits, and equity. We assume the bank's equity ratio is exogenous, consistent with the substantial costs associated with adjusting bank equity. On the asset side, the bank 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 being more likely to default but earning higher realized returns absent default, representing a risk premium.

Depositors with unpredictable payment needs allocate their funds between demandable deposits, which can be used to make payments, and time deposits, which provide higher returns but cannot be directly used for payments. Absent instant payments, banks can delay depositors' payment requests for a given amount of time and thereby net outgoing payments with incoming ones. With instant payments, banks are required to settle payment requests without delay and can no longer net payment flows over time. Therefore, instant payments render demandable deposits more attractive for depositors but at the expense of banks' ability to delay and net payment flows.

Our model sheds new light on the effect of instant payment systems on banks. First, as instant payments remove banks' ability to delay payments, they also expose banks to greater uncertainty in deposit flows. Banks, in turn, choose to set aside more liquid assets to reduce the potential sell-off of illiquid loans when hit with payment shocks. In other words, the instant nature of payments increases banks' own demand for liquidity, which constrains their capacity for liquidity transformation and

ultimately results in a "narrower" bank. A related prediction is that the proportion of demandable deposits relative to time deposits increases because instant payments render demandable deposits more attractive for depositors.[2]

As banks hold larger liquid buffers, equity holders are incentivized to take greater risks in their loan portfolios. We show that increased liquid asset holdings provide the bank with more protection against default, reducing the sensitivity of equity holders' payoffs to downside risks. Consequently, banks choose loans with higher default risk to gamble for higher returns under the instant payment system. This risk-taking effect is more pronounced when capital ratios are lower, which exacerbates agency conflicts. One concern may be that increased payment processing under instant payments improves loan outcomes through better monitoring and screening, thereby reducing risk-taking. To address this, we allow loan returns to vary with payment volume and show that risk-taking still increases with instant payments as long as the sensitivity of loan returns to payment processing is not too high.

Increased liquid asset holdings and risk-taking from instant payments jointly influence loan outcomes. Interestingly, we find that loan income per unit asset unambiguously decreases, even though loans make up a smaller share of bank assets as liquid asset holdings increase. This result arises because equity holders do not fully internalize the impact of risk-taking in adverse states of the world. Nevertheless, total income per unit asset, which includes both loan and liquid asset income, may still increase if the marginal returns from taking on riskier loans are sufficiently high to compensate for the greater share of lower-yielding liquid assets.

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 based on payment timeouts, which we uniquely construct from the administrative data. 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 so that frequent timeouts reduce the perceived attractiveness of Pix for customers and decreases their Pix usage.

[2]Nevertheless, note that banks' increased liquid assets are not simply because demandable deposits become more convenient and increase in volume. Rather, banks increase their liquid asset holdings under instant payments even for a given ratio of demandable versus time deposits, due to their lost ability to delay and net payments.

Although timeouts are mostly driven by unexpected technical issues, one may worry that banks still have some control over the speed or ability to resolve timeouts at their own institution. To address this concern, we construct our timeout instrument for a given bank i in month t as the probability of timeouts induced by other banks. This includes timeouts due to receiving banks when bank i is the sender, as well as timeouts due to sending banks when bank i is the receiver. In both cases, the attractiveness of bank i's Pix service is reduced, but bank i cannot actively resolve the timeouts caused by other banks. The identifying assumption is that timeouts induced by other banks affect bank i only through their impact on its customers' Pix usage, and not through any direct influence on bank i's balance sheet composition.

After confirming that our timeout instrument reduces 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's predictions. First, we find that Pix usage increases the proportion of liquid asset buffers. Echoing our earlier results, this increase in liquid assets primarily comes from government bond holdings. At the same time, Pix usage causes a drop in the ratio of loans on bank balance sheets, confirming that instant payments constrain bank liquidity transformation. We also find that Pix usage increases the ratio of demandable deposits, consistent with our model prediction that demandable deposits become more attractive with instant payments.

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 Pix usage decreases loan income per unit asset, corroborating the liquidity asset channel of risk-taking in our model. In contrast, total income per unit asset increases with Pix usage in our sample period, which is consistent with the higher returns from riskier loans compensating for the smaller fraction of loans on bank balance sheets. In the data, Pix usage also increases service fee income generated by customers setting up bank accounts, which contributes to the increase in total income per unit assets.

Related Literature. Our paper contributes to the understanding of instant payment systems, which, together with stablecoins and CBDCs, are among the most promising advances in payment technologies (Brunnermeier, James and Landau, 2019, Duffie, 2019). Most papers in the literature on modern payment technologies have focused on how they affect consumption, investment, credit access, and consumer default (e.g., Jack and Suri, 2014, Muralidharan, Niehaus, and Sukhtankar, 2016, Higgins, 2020, Ghosh, Vallee, and Zeng, 2022, Berg, Fuster, and Puri, 2022, Dubey and Purnanandam, 2023, Alok, Ghosh, Kulkarni, and Puri, 2024). A few papers have examined how instant payments affect the banking system: Sarkisyan (2023) analyzes the effects on deposit competition, while Liang, Sampaio and Sarkisyan (2024) show that increased deposit competition improves monetary policy transmission. Most closely related to usis Parlour, Rajan and Walden (2022), who also focus on the unintended consequences of payment convenience on bank lending. They demonstrate that the settlement of interbank payments using liquid assets gives rise to a liquidity externality that limits banks' lending capacity, and that this liquidity externality is exacerbated when payment frictions are reduced. Focusing on the loss of payment delays, our paper is the first to examine how instant payment systems affect banks' demand for liquid assets and risk-taking activities. We highlight that instant payment systems are not merely providing more convenient and faster payments, but they fundamentally remove banks' ability to delay and net outgoing payments with incoming ones, which ultimately constrains liquidity transformation and amplifies risk-taking by banks.

More generally, our findings shed light on the interaction between banks' liabilities and assets. A large literature has shown how the risk of runs on demandable deposits limits banks' illiquid asset holdings (e.g. Diamond and Dybvig, 1983, Calomiris and Kahn, 1991, Goldstein and Pauzner, 2005). Volatility in bank funding constrains lending even in the absence of runs. Bolton, Li, Wang, and Yang (2020) and Jermann and Xiang (2023) model deposits as obligations with random maturity and non-maturing debt, respectively, analyzing their impact on bank investment and default risks. Empirically, Supera (2021) shows that the rise of demandable deposits constrain banks' ability to extend loans. Using Fedwire data, Li and Li (2021, 2023) find that banks with more volatile flows experience reduced loan growth. Another set of papers highlight the complementarity between liquid deposits and lending. Kashyap et al. (2002) argue that complementarity results when deposit withdrawals and commitment takedowns are not correlated. Donaldson, Piacentino and Thakor (2018) show that the circulation of deposits as a means of payment facilitates loan repayments, while Parlour, Rajan and Zhu (2022) analyze how information gathered from payments influence bank lending decisions. Our work complements these studies. We focus on the effect of instant payment systems and show

that they increase banks' liquid assets holdings over illiquid loans by reducing banks' capacity for payment netting.

We further find that banks' increased liquid asset holdings induce riskier lending. This result is closely related to Acharya and Naqvi (2012), who show that higher liquid asset holdings reduces monitoring incentives and results in excessive and risky lending. Relatedly, Diamond, Hu, and Rajan (2020) show that expectations of more liquid markets in the future discourages investment in pledgeable assets, which increases risk ex ante.

Finally, our results relate to the literature on the demand and supply of liquid assets by 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 tighting (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.

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 BCB in November 2020, 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.[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 small businesses in Brazil utilize Pix, and the volume of transactions is substantial. 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

[3] See here.

[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.

[5] See here.

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.[6]

Together, these data provide a comprehensive view of the banking sector 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.

Figure 1a plots the total assets and deposits of adopting banks during our sample period and shows a steady growth trend both before and after the implementation of Pix in November 2020. This pattern confirms that there were no significant discontinuities in overall bank size coinciding with Pix adoption. The only noticeable jump in assets occurred in early 2020 due to stimulus measures during the Covid-19 crisis, but levels stabilized by late 2020. Figure 1b further shows that the assets of adopting banks accounted for 85% of total bank assets in the first month of adoption and remained steadily between 85% and 88% throughout the sample period, confirming that Pix was widely adopted right from the outset.

3 Stylized Facts

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

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

We begin by documenting several novel facts on the adoption of Pix and the banking sector's response. Specifically, we show (i) how Pix usage varies substantially across banks and proxies for the loss of their ability to net payment flows, (ii) how banks adjust their liability and asset structures in response to Pix, and (iii) how banks' lending portfolios and risk-taking evolve following Pix's implementation. These stylized facts illustrate the channels through which instant payments can affect banks' liquidity management and credit provision, and they provide motivating evidence for the empirical analysis in Section 6.

3.1 Pix Usage and Payment Netting

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.

Although the adoption of Pix was immediate and widespread, the extent to which adopting banks utilized Pix payments displays significant cross-sectional variation. That is, banks differed in their potential loss in nettable payments per unit asset size. To see this, we average Pix usage for each bank over our sample period and plot the monthly average Pix usage for each quartile in Figure 2. 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%.

Economically, note that Pix usage also 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, although the technology to transfer payments between banks itself was instant, 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, banks ahve to settle payments nstantaneously so they lose the ability to delay and net payments within the same day. Pix usage thus reflects the maximum monthly loss of nettable payments per unit size. Higher Pix usage then reflects higher vulnerability to payment shocks due to Pix. In Appendix A.1, we provide a formal derivation showing that (3.1) precisely captures the amount of potential nettable payments per unit of assets.

The ability to net payments is economically significant for banks. To see this, we first calculate the ratio of nettable payments as a proportion of total payments for each bank i in month t:

$$\frac{\sum_{d\in t}\min(Outflows_{id}, Inflows_{id})}{0.5\sum_{d\in t}(Outflows_{id}+Inflows_{id})}. \tag{3.2}$$

For example, if daily inflows are always equal to daily outflows in month t, then the ratio equals 1, whereas if there are only daily inflows or only daily outflows in month t, the ratio equals 0. We then plot the p25, p50, and p75 in Figure 3a and report the summary statistics in Table 2. We observe that nettable payments vary across banks but are overall large. For the median bank in the median month, up to 71.26% of Pix payments would have been nettable within a day in the absence of instant payments. In other words, flow netting is lost for up to 71.26% of gross payment flows for the median bank-month. For the p25 and p75 bank-month, the ratio of nettable payments is also significant at 27.01% and 85.49%, respectively.

We then calculate the ratio of nettable payments as a proportion of liquid assets for each bank i in month t:

$$\frac{\sum_{d\in t}\min(Outflows_{id}, Inflows_{id})}{LiquidAssets_{it}}, \tag{3.3}$$

where $LiquidAssets_{it}$ include cash and government bonds. Then, we plot the p25, p50, and p75 in Figure 3b and show the summary statistics in Table 2. From these results, we observe that nettable payments are also economically significant relative to banks' liquid asset buffers. For the median bank in the median month, nettable payments make up 24.99% of its liquid assets. Taken together, the relationship between nettable payments and banks' liquid assets provides suggestive evidence that

the loss of payment netting may use up a sizable portion of banks' existing liquid assets. In other words, outgoing payment shocks in the absence of payment netting may be large enough to influence banks' demand for liquid asset buffers.

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 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 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 Pix's 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 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 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. We define subprime loans as the ones assigned categories B and C. All other, lower ranked categories are considered in default.[7]

[7]These definitions follow local regulation "Resolucao' CMN 2,682/1999.

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.

4 Model

In this section, we present a model to shed light on the effects of instant payments on bank liquidity transformation and risk-taking. The goal of the model is to provide a framework that connects the stylized facts presented in Section 3, and to guide the subsequent empirical analysis by illustrating the economic mechanisms through which instant payments influence bank business models. 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

[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.

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.[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, 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 (2022). 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 captures the economic specialization and the resulting lack of a double coincidence of wants across the two markets, which justifies 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

[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 reals per depositor per institution.

[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 a strong income effect and 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.

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 $t = T$. The bank chooses its allocation to liquid assets, such as cash or government bonds, x, allocation to illiquid, risky loans, y, and the riskiness of the loans, $1-p$, which we elaborate right below. 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. Following Carletti, Leonello, and Marquez (2024), we let

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

where $R(p)$ is decreasing in p and θ captures aggregate uncertainty that follows a standard uniform distribution betweem $[0, 1]$.[12] Intuitively, when a bank takes more risk by choosing a lower p, the loan is more likely to default, i.e., $1 - p$ increases, but yields higher realized returns in the absence of default, i.e., $R(p)$ increases. The baseline assumption that $R(p)$ decreases in p is natural, since otherwise taking more risk would unambiguously lower expected returns by lowering realized returns. For simplicity, we assume that the credit risk associated with bank lending is not correlated with payment shocks in the baseline model. As we will show, our results remain qualitatively robust when this assumption is relaxed. The loan is also characterized by its illiquidity; only a fraction $1 - \phi$ 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 $t = 0$.

This assumption aligns with the classic notion of bank maturity transformation, which implies that bank assets and liabilities typically have different durations. Similar assumptions have been widely adopted in the literature. For example, Kashyap, Rajan and Stein (2002) assume that the risks associated with deposit withdrawals and credit line drawdowns are not perfectly correlated.

We analyze symmetric equilibria and explore the equilibrium outcomes of banks' demand for liquid assets and risk-taking incentives under two types of payment systems, an instant payment system and a traditional payment system. Under the instant payment system, banks are required to use the liquid asset to settle any payment balance at any date t without delay. 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

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

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 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; 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 at t to meet payment requests if it runs out of liquid assets in that period.

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.

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 payment 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

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

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, effectively discounting the consumption value.

4.2.1 The Effect of Instant Payments on Bank Liquidity Transformation

We begin by examining how instant payments affect banks' liquidity transformation. Specifically, we consider both sides of the bank's balance sheet: on the asset side, how much liquidity banks choose to hold to support their liabilities, and on the liability side, how households allocate between demandable and savings deposits.

Proposition 1 (Bank Liquidity Demand Effect)**.** *Suppose ϕ is sufficiently large and η is sufficiently small. Then banks hold larger liquidity buffers under the instant payment system than under the traditional payment system, i.e., $x^*_{ins} > x^*_{tra}$ given any $\alpha > 0$.*

Proposition 1 implies that the instant payment system prompts banks to increase their liquid asset holdings relative to the traditional payment system. This result is intuitive. Comparing the laws of motion (4.4) and (4.9), we see that the requirement to process payments instantaneously eliminates banks' ability to net incoming and outgoing payments. Without the ability to net payment flows, banks become more exposed to payment shocks. Further, comparing (4.5) and (4.10), we find that instant payments raise banks' exposure to liquidity risk, as they are more likely to be forced to liquidate illiquid assets prematurely. In response, banks optimally choose to hold larger liquidity buffers, increasing the demand for liquid assets by banks. In other words, instant payment systems may render the banking system narrower and less engaged in liquidity transformation than under the traditional payment system.

Proposition 2 (Deposit Payment Convenience Effect)**.** *Households demand more demandable deposits under the instant payment system than under the traditional payment system, i.e.,* $\alpha^*_{ins} > \alpha^*_{tra}$ *given any* $x > 0$ *and* $p > 0$*.*

Proposition 2 highlights that households increase their demand for demandable deposits under the instant payment system, taking banks' assets as given. Intuitively, instant payments enhance the relative payment convenience of demandable deposits by increasing the marginal consumption value per unit deposit. When the intertemporal elasticity of substitution is sufficiently large as specified in the model, this substitution effect dominates the income effect, leading households to allocate more toward demandable deposits to better facilitate consumption.

It is important to note that banks' increased demand for liquid assets in Proposition 1 is not caused directly by the increase in demandable deposits in Proposition 2. Rather, in Proposition 1, banks are incentivized to set aside more liquid assets under instant payments in order to prepare for liquidity shocks that arise once they can no longer delay outgoing payments to net them against incoming ones. While the improvement in payment convenience and households' increased use of demandable deposits may further raise banks' liquid asset holdings, the direct first-order effect of instant payments on banks' liquidity demand comes from the loss of netting ability.

4.2.2 The Effect of Instant Payments on Bank Risk-Taking

Next, we examine how instant payments affect banks' risk-taking behavior.

Proposition 3 (Bank Risk-Taking Effect: Liquidity Channel)**.** *The banks choose riskier loans under the instant payment system compared to the traditional payment system, i.e.,* $p^*_{ins} < p^*_{tra}$*. Particularly, the difference* $p^*_{tra} - p^*_{ins}$ *increases as bank equity ratio* η *decreases.*

Proposition 3 implies that banks originate riskier loans that are more likely to default under the instant payment system compared to the traditional payment system. We refer to this result as the risk-taking effect, which stems from Proposition 1 and the underlying liquidity demand mechanism.

To better understand the drivers of the risk-taking effect, we first express the bank's problem of optimal risk-taking under a terminal portfolio of $(x, 1-x)$:

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

where the expectation is taken over θ. We then solve for the bank's optimal risk-taking decision

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

where debt obligations D are

$$D = (1-\eta)(1+(1+\alpha)r).$$

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 1 implies, the increased liquid asset holdings under instant payments provide a larger buffer against default. When payment shocks are not correlated with credit risks, larger liquid asset holdings increase the bank's distance to default and reduces the sensitivity of bankers' payoffs to downside risks. Consequently, bank equity optimally takes more risk under the instant payment system, as shown in (4.14) which is decreasing in x.

Further, note that the extent of the risk-taking effect depends on the severity of agency frictions. Specifically, risk taking is amplified when banks' equity ratio is lower and they face stronger conflicts between debt and equity holders. This is also evident from (4.14) , where p^* is increasing in bank equity η.

It is worth noting how the liquidity channel of risk-taking relates to the assumption that payment shocks are not correlated with credit risks. This assumption effectively allows the bank to consider its liquidity holdings and risk-taking choices sequentially, where endogenously higher liquidity buffers lead to endogenously greater risk-taking. Mathematically, Proposition 3 follows by linking the bank's problem in (4.13) to its initial portfolio decisions and observing that the bank effectively chooses x^* and p^* in sequence. In Appendix A.3, we show that our results remain qualitatively robust when the assumption is relaxed to allow for some, but not perfect, correlation between credit risk and liquidity shocks. In practice, perfect correlation is unlikely because the factors that drive depositors' short-term payment needs differ from those that determine borrowers' long-term investment outcomes. Moreover, payment shocks realize at much higher frequencies compared to lending decisions, particularly in the context of instant payments.

4.2.3 The Effect of Instant Payments on Bank Income

So far, we have established that instant payments encourage banks to hold more liquid assets, lend less, yet simultaneously take more risk in lending. In this section, we further examine how these

changes in bank balance sheets affect bank income. Understanding how various measures of bank income are affected, and the conditions under which they rise or fall, offers important insights into how instant payments shape bank business models. Our predictions on how income measures should change with instant payments also help guide our later empirical analysis in confirming the liquidity channel of bank risk-taking.

We first define several bank income measures:

Definition 1 (Bank Income Measures)**.** *We define the following measures of bank income:*

(i). Loan income per lunit oan: $\Gamma_l = \frac{(1-x)pR(p)}{1-x} = pR(p)$ *;*

(ii). Liquid asset income per unit asset: $\Gamma_x = \frac{x}{x+(1-x)} = x$ *;*

(iii). Loan income per unit asset: $\Gamma_o = \frac{(1-x)pR(p)}{x+(1-x)} = (1-x)pR(p)$ *;*

(iv). Asset income per unit asset: $\Gamma_a = \frac{x+(1-x)pR(p)}{x+(1-x)} = x + (1-x)pR(p)$ *.*

The first measure, loan income per unit loan, Γ_l, captures the expected return per dollar initially lent in risky loans, reflecting the risk premium from risky lending. The second measure, liquid asset income per unit of bank assets, Γ_x, is simply equal to x in our framework. The third measure, loan income per unit asset, Γ_o, captures the expected loan return per unit of bank assets and reflects the contribution of risky lending to the bank's overall portfolio return. Finally, total income per unit asset, Γ_a, captures the total expected return per unit of bank assets, incorporating returns from both liquid assets and loans.

Before proceeding, we highlight an important distinction between the first two and the last two measures. The first two measures, Γ_l and Γ_x, pertain to either risk-taking p or liquidity holdings x, but not both. In contrast, the last two measures, Γ_o and Γ_a, depend on both p and x, and are therefore shaped by the equilibrium relationship between risk-taking and liquidity holdings that is central to the liquidity-driven risk-taking mechanism described in Proposition 3. Hence, the effect of instant payments depend on how the various economic forces play out in equilibrium and may differ across income measures.

We now formally characterize the effect of instant payments on each bank income measure:

Proposition 4 (Bank Income)**.** *Under Definition 1, the following results hold:*

(i). Loan income per unit loan is higher under the instant payment system, i.e., $\Gamma^*_{l,\text{ins}} \geq \Gamma^*_{l,\text{tra}}$*, if* $pR(p)$ *is decreasing in* p*, and, equivalently,*

$$-R'(p) \geq \frac{R(p)}{p}\,. \tag{4.15}$$

(ii). Liquid asset income per unit asset is higher under the instant payment system, i.e., $\Gamma^*_{x,\text{ins}} > \Gamma^*_{x,\text{tra}}$.

(iii). Loan income per unit asset is lower under the instant payment system, i.e., $\Gamma^*_{o,\text{ins}} < \Gamma^*_{o,\text{tra}}$.

(iv). Asset income per unit asset is higher under the instant payment system, i.e., $\Gamma^*_{a,\text{ins}} \geq \Gamma^*_{a,\text{tra}}$, *if* $R(p)$ *satisfies*

$$-R'(p) \geq \frac{R(p)\left(R(p)-1\right)}{1-p}\,. \tag{4.16}$$

Proposition 4 offers new insights into how instant payments affect bank income measures. First, part (i) shows that loan income per unit loan, Γ_l, improves with instant payments if riskier loans yield higher expected lending returns. Recall that riskier loans have a higher default probability but generate higher realized returns when they do not default. For riskier loans to also have higher expected returns, the condition in part (i) requires the marginal lending return from risk-taking to be sufficiently high to exceed the average return per unit of risk-taking.

Second, part (ii) shows that liquid asset income per unit asset, Γ_x, is unambiguously higher under the instant payment system. This result follows directly from Proposition 1, which states that banks increase their liquid asset holdings under instant payments to compensate for the lost ability to delay and net payment flows.

Importantly, part (iii) shows that loan income per unit asset, Γ_o, is unambiguously lower under the instant payment system. To understand this subtle result, note that the effect of instant payements on $\Gamma_o = (1-x)\Gamma_l$ hinges on two counteracting forces—changes in the liquid asset share x and the loan income per unit loan Γ_l. On the one hand, a higher liquid asset share, x, unambiguously decreases Γ_o. On the other hand, loan income per unit loan increases if condition (4.15) holds, which increases Γ_o. One might therefore expect the effect on Γ_o to depend on which of the two forces dominates.

However, the liquidity channel of risk-taking underlying Proposition 3, which pins down the equilibrium relationship between liquidity holdings x and risk-taking p, offers a sharper prediction. Specifically, (4.14) implies that

$$\Gamma_o = (1-x)pR(p) = (D-x)p\,, \tag{4.17}$$

in which both $(D-x)$ and p decrease under instant payments, as shown in Propositions 1 and 3, respectively. As a result, Γ_o is unambigeously lower with instant payments.

To better understand this result, note that the agency problem between debt and equity implies that bank equity chooses an equilibrium level of risk such that, when the risky project succeeds in the

best aggregate state of the world, the realized bank cash flow just meets its debt obligations:

$$x + (1 - x)R(p) = D\,. \tag{4.18}$$

In any state worse than the best, bank equity does not internalize the externality of its risk-taking on debt holders. This leads to condition (4.17). In other words, bank equity takes risk precisely to the point where the expected loan income covers the expected repayment shortfall $(D - x)p$ in the best aggregate state of the world. Because the expected repayment shortfall declines as x increases and p decreases with instant payments, the expected loan income per unit asset, Γ_o, must also decrease with instant payments.

Finally, part (iv) suggests that instant payments can improve overall bank performance as measured by asset income per unit asset, Γ_a, if the marginal realized return from risk-taking is sufficiently high. Intuitively, the larger share of liquid assets and the smaller share of loans under instant payments exert a negative effect on Γ_a. At the same time, increased risk-taking may raise expected loan returns, which has a positive effect on Γ_a. If the increase in expected returns from riskier loans is large enough to offset the higher share of liquid assets with lower returns, then instant payments will also improve total asset income per unit asset.

4.2.4 Lending Technology Improvement, Risk Taking, and Lending Outcomes

So far, we have established that instant payments encourage bank risk-taking through the liquidity channel. However, instant payments also bring about increased payment activity that may enhance banks' capacity for loan screening and monitoring (e.g., Berlin and Mester, 1999, Norden and Weber, 2010, Puri, Rocholl, and Steffen, 2017). In this section, we account for the possibility that payment processing may enhance banks' lending outcome to shed light on the net effect of instant payments on bank risk taking.

We augment our baseline model by letting the lending return function $R(p)$ depend on the total payments processed by bank j between $1 \leq t \leq T$, Z_j, which is determined in equilibrium. Specifically, we assume that $R(p, \lambda Z)$ is decreasing in p as in the baseline model and increasing in λZ. The parameter $\lambda \geq 0$ governs the extent to which payment processing improves lending outcomes, with loan returns benefiting more from payment-enhanced screening and monitoring when λ is higher.

We also assume that $R(p, \lambda Z)$ satisfies the single-crossing property in $(p, \lambda Z)$. This assumption imposes minimal structure for tractability while leaving the flexibility to capture various ways in which payment processing enhances lending outcomes. In particular, it allows for complementarity

between the informational benefits from payment processing and risk-taking, where payment processing can increase the marginal benefit of risk-taking in boosting realized lending returns. For example, $R(p, \lambda Z) = R_2(\lambda Z)/p$ accomodates the possibility that the complementarity is particularly large for the risky segments of lending, that is, when p is small.[13] Alternatively, informational benefits can also increase realized lending returns independently of risk-taking as in $R(p, \lambda Z) = R_1(p) + R_2(\lambda Z)$.

Under this extended model, we have the following result:

Proposition 5 (Bank Risk-Taking Effect Revisited: Liquidity versus Technology Channels)**.** *There exists $\lambda^* \in (0, +\infty]$ such that banks choose riskier loans under the instant payment system compared to the traditional payment system, i.e., $p^*_{ins} < p^*_{tra}$ if and only if $\lambda < \lambda^*$. Moreover, if $\lambda^* < +\infty$, then λ^* increases as bank equity η decreases.*

In words, Proposition 5 states that instant payments increase the riskiness of bank loans, as highlighted in Proposition 3, as long as the technology benefits from payment processing are not too strong. To see the intuition, note that the equilibrium condition for bank risk-taking in Proposition 3 naturally extends to

$$p^* = R^{-1}\left(\frac{D-x}{1-x}, \lambda Z\right), \tag{4.19}$$

where p^* still decreases in x, reflecting the liquidity channel described earlier, but now also increases in λZ, capturing the technology channel. When banks process more payments under the instant payment system than in the traditional system, the resulting enhancement in lending technology enables them to earn a higher realized loan return for any given level of risk-taking. This improvement in expected loan returns reduces banks' incentive to gamble for higher realized returns by choosing riskier loans, all else equal, because greater risk-taking increases the probability of loan default that could wipe out bank equity. In equilibrium, the reduced incentive for risk-taking from the technology channel counteracts the increased incentive to take risk due to the liquidity channel, and the net effect depends on the relative strength of these two forces.

Proposition 5 highlights that the liquidity channel dominates unless the technology channel is sufficiently strong, as captured by a large enough value of λ. Proposition 5 also reveals that the cutoff value for λ, if it exists, decreases in bank equity η. Intuitively, with more pronounced agency conflicts under a smaller η, the liquidity channel is amplified and requires a stronger technology channel to offset it. It is also worth noting that the cutoff λ^* may not exist at all, in which case the liquidity channel always dominates the technology channel of risk-taking. Taken together, the effect of instant

[13] More generally, complementarity can be captured by a simple multiplicative form $R(p, \lambda Z) = R_1(p)R_2(\lambda Z)$, where $R_1(p) > 0$, $R_2(\lambda Z) > 0$, $R_1'(p) < 0$, and $R_2'(\lambda Z) > 0$, which satisfies the single-crossing property.

payments on risk-taking is context-dependent, with risk-taking more likely to increase when banks are poorly capitalized and the benefits from payment processing for loan returns are more limited.

5 Estimation Strategy

In this section, we explain our empirical approach in 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 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. Therefore, banks with more timeouts should have lower Pix usage not only because failed transactions directly reduce Pix usage, but also because, more importantly, frequent timeouts make Pix less attractive to customers and thereby reduce their adoption of the system.

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 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, $Timeout_{it}$, is 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:

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

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 3. 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 with a bandwidth of 0.005 and 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 payment disruptions due to other banks reduce a given 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, for each characteristic of bank i, we estimate

$$Characteristic_{it} = \gamma Timeout_{it} + \eta_i + \omega_t + \epsilon_{it}. \tag{5.5}$$

Observable characteristics 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 of γ 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 observable covariates. Notably, our timeout instrument that captures bank i's timeouts due to its counterparty banks does not correlate with timeouts caused by bank i itself, which suggests that our instrument is unlikely driven by technological similarities between bank counterparties.

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

We first examine the effect of Pix on banks' liquidity transformation. On the asset side, the results in Table 4 validate our model's predictions that instant payments increase banks' liquid asset holdings (Proposition 1). In the first two columns, the coefficients for Pix usage are positive and significant at the 1% level, where 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.

On the liability side, Table 5 presents our estimation results for the effect of Pix on bank deposit ratios. The results in the first two columns show that Pix usage increases the proportion of 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 (Proposition 2). Most of the effect on demandable deposits 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 all banks have checking deposits in Brazil, but only a fraction of banks have savings deposits, which reduces the available variation in the ratio of savings deposits.

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 in Table 6. 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.

Proposition 3 further predicts that banks' risk-taking due to increased liquid asset holdings is exacerbated when agency conflicts are more severe. To test this prediction, we use banks' ex ante capital ratios to proxy for the extent of agency conflict and assess how it influences the impact of Pix on bank risk-taking. 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 ratio before Pix adoption in October 2020 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 $HighCapRatio_i$.

We present the second-stage (2SLS) results in Table 7, with the first-stage results with the new interaction term being reported in Table 13 in the Appendix. From Table 7, we observe that the coefficients on the interaction term $PixUsage_{it} \times HighCapRatio_i$ are of the opposite sign as those 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 is consistent with the liquidity channel of bank risk-taking being amplified by agency issues between bank equity and debt holders.

So far, our findings are consistent with the presence of the liquidity channel of risk-taking, which implies that banks' risk-taking incentives increase with instant payments. In addition to the liquidity channel, our model also considers the possibility that instant payments may improve banks' lending outcomes through enhanced payment processing, which may be especially relevant for riskier loan segments. This technology channel counteracts the liquidity channel and reduces the riskiness of bank lending. Overall, our results in Table 6, which show that Pix usage increases the riskiness of bank loans, coupled with the predictions in Proposition 5, imply that in the empirical context we consider, the liquidity channel dominates the technology channel in terms of bank risk-taking.

Nevertheless, we acknowledge that the relative strength of the liquidity versus technology channels may vary across different contexts. As Proposition 5 shows, the technology channel is strengthened when lending outcomes benefit more from payment processing, while the liquidity channel is weakened when agency conflicts are less severe. For example, in the context of India's UPI, Alok, Ghosh, Kulkarni, and Puri (2024) find that increased credit to underserved yet creditworthy borrowers does not translate into higher default rates. Our model predictions help to rationalize these results, suggesting that they may arise from two counteracting forces, the liquidity channel and the technology channel, whose relative strength depends on the extent of agency issues and the sensitivity of lending technology to payment processing. The agency friction between bank debt and equity is a unique feature of our framework and has not been considered in prior theoretical studies examining the synergy between payment processing and lending (e.g., Berlin and Mester, 1999, Ghosh, Vallee, and Zeng, 2022).

The interplay between the liquidity and technology channels may also vary in the long run. If banks become better at utilizing payment information in making loan decisions over time, lending outcomes may be further improved as time goes on. At the same time, the strength of the liquidity

channel is influenced by the extent of agency conflicts. Banks' risk taking incentives may thus fluctuate over the business cycle as bank equity buffers vary. The influence of instant payments on bank lending outcomes should thus be continuously monitored and analyzed going forward.

6.3 Effect of Pix on Bank Income

We finally examine the effect of Pix on bank income. We start with banks' loan outcomes in Table 8. Recall from Proposition 4 that the effect of risk-taking on loan outcomes depends on the efficiency with which banks can generate returns from riskier loans. From columns (1) and (2) of Table 8, we observe that Pix usage significantly increases loan income per unit loan, suggesting that banks' lending technology is sufficiently strong to generate higher expected returns per unit loan following the introduction of instant payments. This implies that condition (i) of Proposition 4 is satisfied. In terms of magnitude, a one-standard-deviation increase in Pix usage leads to an increase of about 2.75 ppts in loan income per unit loan.

While the increase in loan income per unit loan from Pix has a positive effect on loan income per unit asset, Pix also exerts a negative effect on loan income per unit asset, as shown in columns (3) and (4) of Table 8. Recall that Pix raises the portfolio share of lower-yielding liquid assets, as documented in Table 4. On net, our model unambiguously predicts that this portfolio share effect dominates the increase in loan income per unit loan, leading to lower loan income per unit asset, as established in part (iii) of Proposition 4. Empirically, we find that Pix usage indeed reduces loan income per unit asset, lowering it by about 0.17 ppts for a one-standard-deviation increase in Pix usage. This finding supports our proposed mechanism in Proposition 3 that instant payments amplify bank risk-taking through increased liquid asset holdings and agency issues. It also underscores that the improved return on riskier lending does not compensate for the smaller share of loans on bank balance sheets following the introduction of Pix.

We then ask how Pix affects banks' total income. Overall, total income per unit asset increases, as evident from columns (1) and (2) of Table 9. Through the lens of our model, this result arises because the increase in expected returns from riskier loans more than offsets the higher share of liquid assets with relatively lower returns, so that condition (iv) in Proposition 4 is satisfied. Note that the higher share of liquid assets with Pix is consistent with Pix usage increasing income from government bonds per unit asset, as shown in columns (3) and (4) of Table 9 and as predicted in part (ii) of Proposition 4. In practice, total income also includes service fee income and wholesale lending income in addition to loan and liquid asset income. Columns (5) through (8) show that service fee income per unit asset

increases, while wholesale lending income per unit asset slightly decreases with Pix usage. Intuitively, Pix may increase service fee income by attracting a larger number of investors to open bank accounts that generate account fees.[14] Therefore, banks' total income-to-asset ratio improves with Pix usage because higher expected loan returns and service fee income dominate the smaller share of loans and the decreased income from wholesale lending.

Taken together, our findings in this section show that risk-taking induced by Pix effectively enhances banks' loan income per unit loan. However, this increase is not sufficient to raise loan income per unit asset but does suffice to increase total income per unit asset, which lends further support to our proposed mechanism that risk taking is partly driven by banks increased holdings of liquid assets and the underlying agency issues.

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.

[14] Using Pix is free for households and of minimal cost for businesses. However, using Pix requires opening a bank account and paying the corresponding account fees, which are called "package fees" in the Brazilian context. These account fees contribute to the increase in service fee income.

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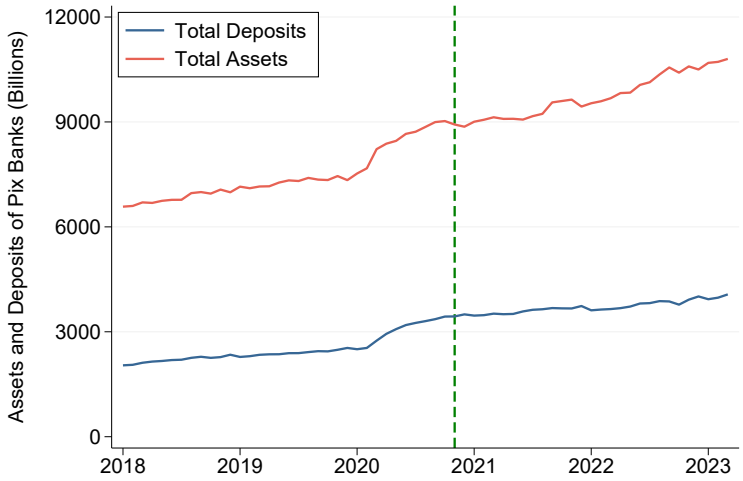
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A Figures and Tables

Figure 1: Assets and Deposits of Pix-Adopting Banks

Panel (a) plots the total assets and deposits (in billions of BRL) of Pix-adopting banks from 2018 to 2023. The green dashed line marks the introduction of Pix in November 2020. Panel (b) shows the share of assets at Pix-adopting banks relative to all banks from November 2020 to March 2023.

(a) Total Assets and Deposits of Pix-Adopting Banks



(b) Asset Share of Pix-Adopting Banks

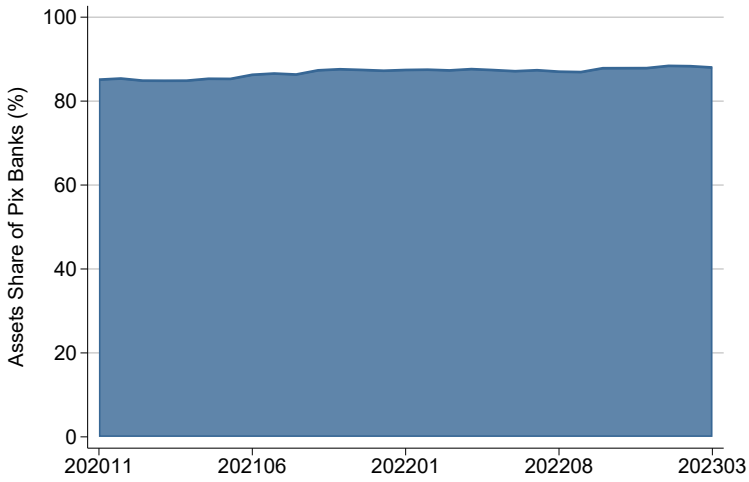


Figure 2: Pix Usage by Quantile

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.

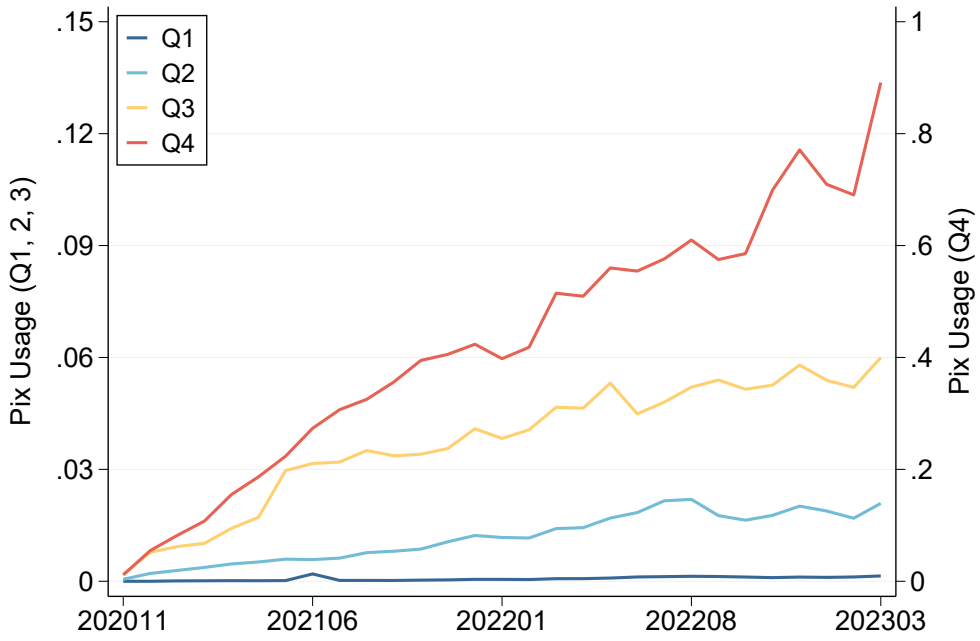
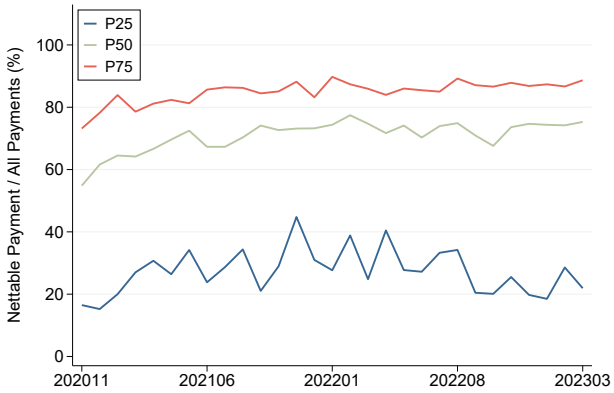


Figure 3: Nettable Payments Ratios

This figure shows the p25, p50, and p75 of monthly average of nettable payment ratios from November 2020 to March 2023. Panel (a) shows the ratio of nettable payments over all payments as defined in Equation (**??**). Panel (b) shows the ratio of nettable payments over liquid assets as defined in Equation (3.3).

(a) Nettable Payments over All Payments



(b) Nettable Payments over Liquid Assets

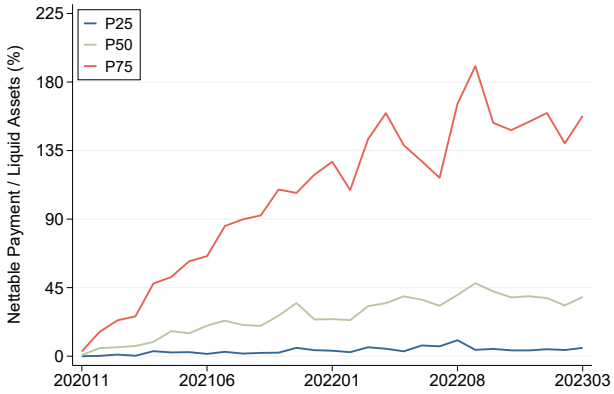
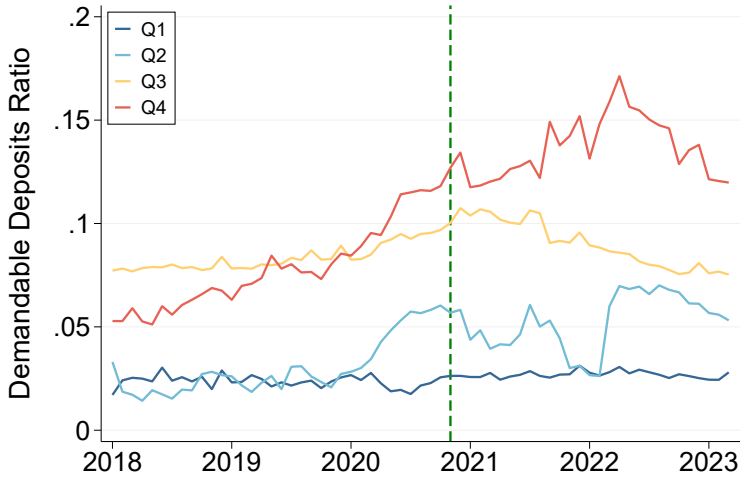


Figure 4: Deposits Ratios by Pix Usage

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

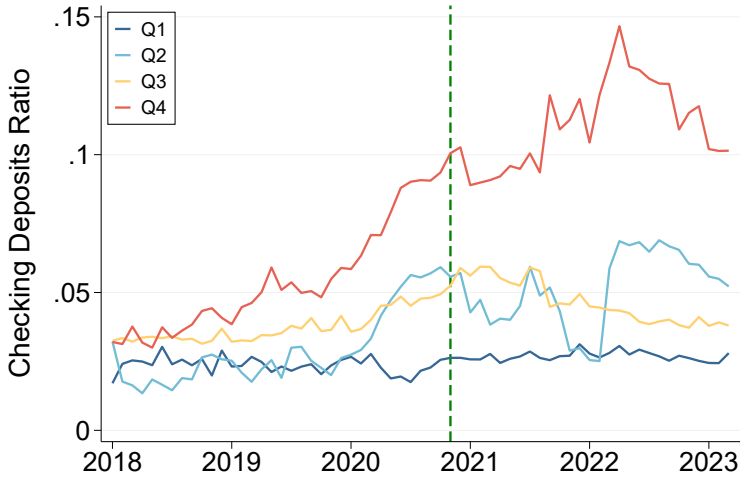
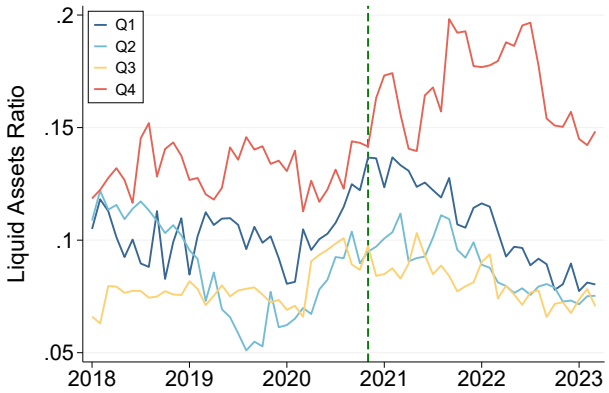


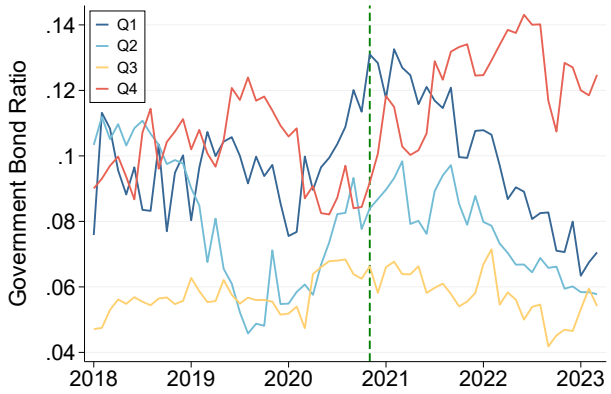
Figure 5: Liquid Assets Ratios by Pix Usage

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

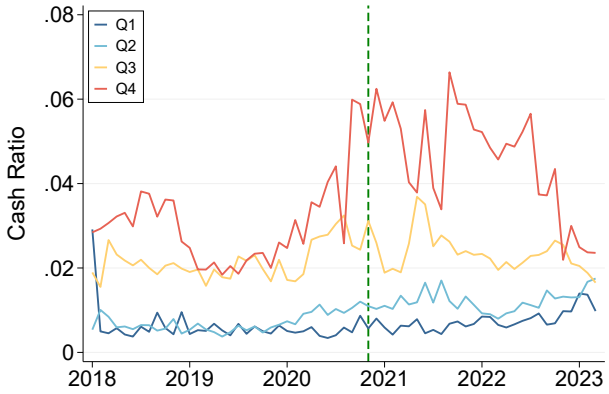
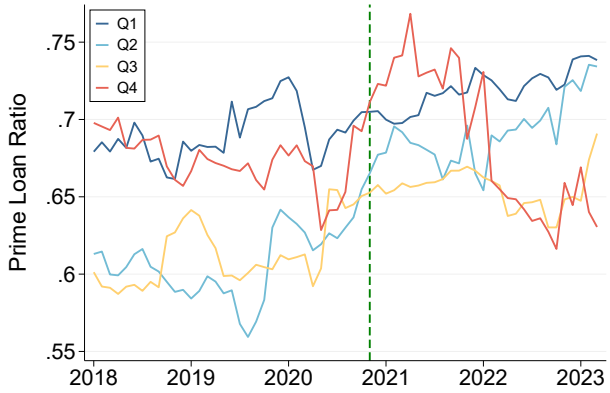


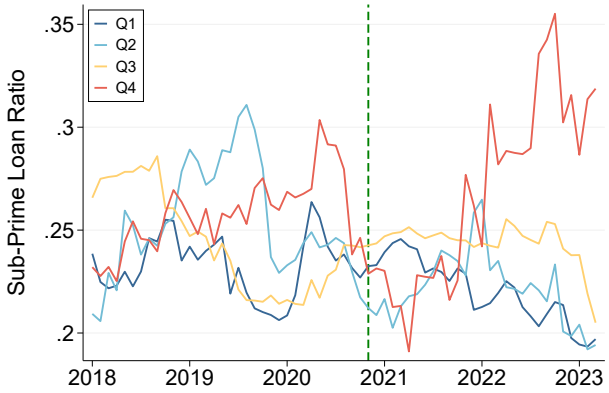
Figure 6: Prime, Subprime, and Default Loan Ratios by Pix Usage

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

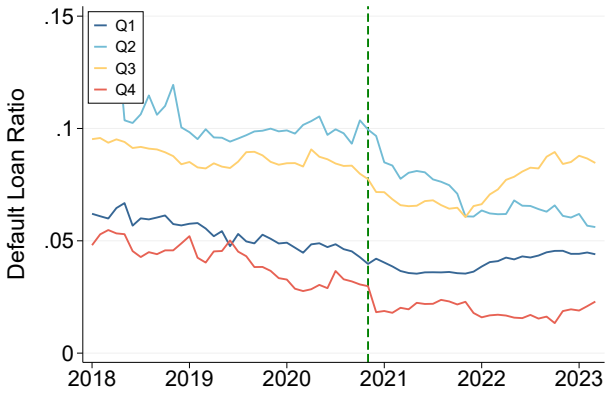


Figure 7: Variation in the Timeout Instrument and Pix Usage

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.

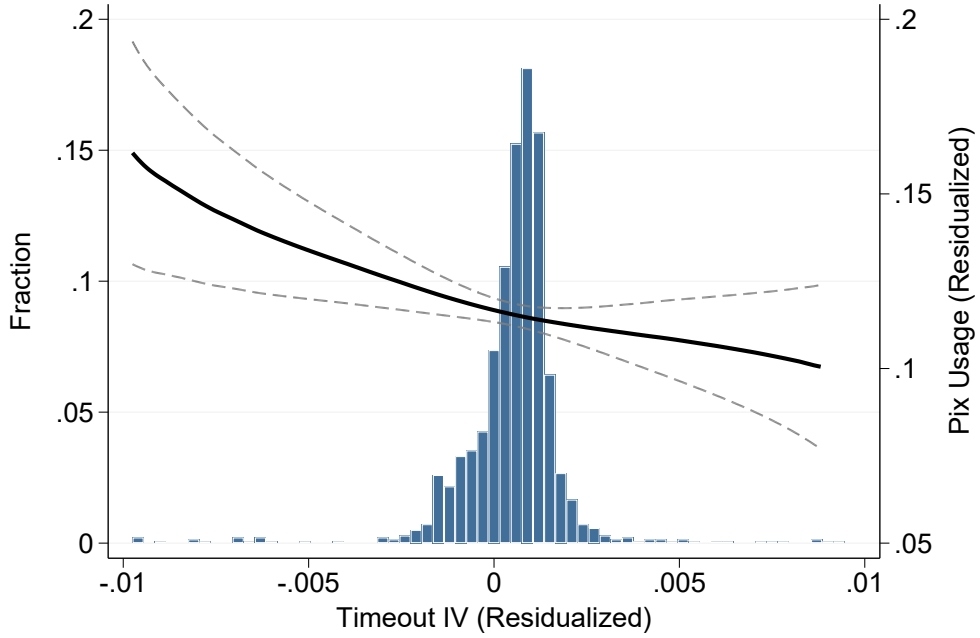


Figure 8: Relationship between the Timeout Instrument and Bank Covariates

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.

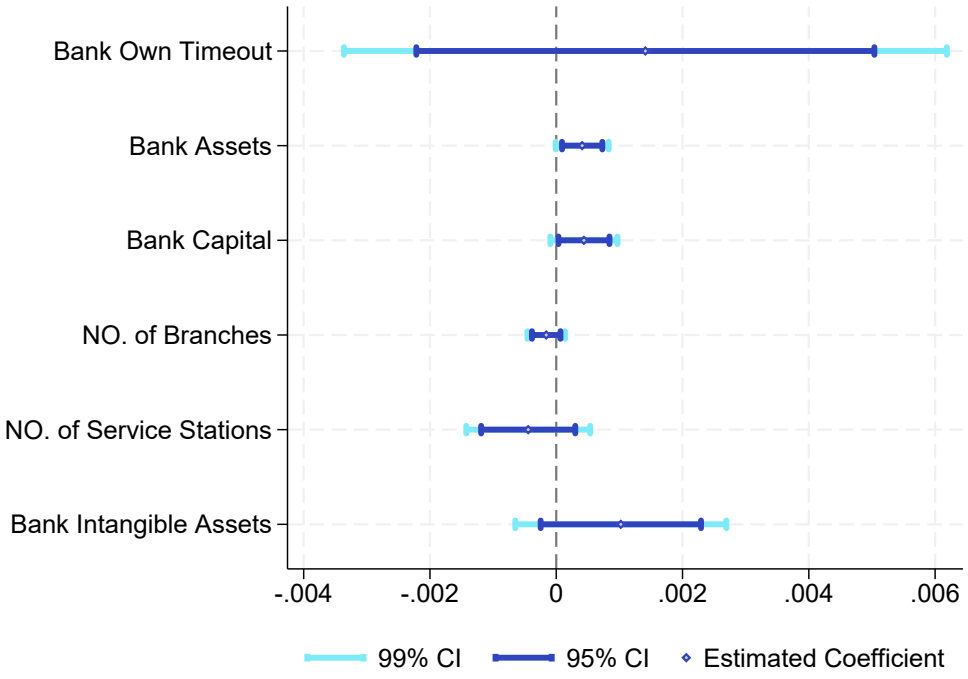


Table 1: Summary Statistics

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
Panel A: Pix Usage, Timeouts and Bank Characteristics						
Pix Usage (%)	9.20	19.96	0.22	1.96	6.30	1511
Timeout IV (%)	0.60	2.57	0.35	0.47	0.54	1481
Bank Assets (Billion)	183.48	481.34	1.24	7.04	48.84	1511
Bank Capital (Billion)	13.81	35.90	0.14	0.77	4.59	1511
No. of Branches	303.47	925.18	2.00	6.00	21.00	1499
Panel B: Assets Ratios						
Liquid Assets Ratio (%)	10.77	8.21	5.03	9.12	13.85	1511
Cash Ratio (%)	1.79	3.13	0.14	0.74	1.70	1511
Government Bond Ratio (%)	8.98	8.33	3.04	7.02	12.27	1511
Loan Ratio (%)	33.80	23.43	11.32	34.10	50.94	1511
Prime Loan Ratio (%)	69.70	23.44	56.37	74.54	88.55	1407
Sub-Prime Loan Ratio (%)	23.05	20.44	6.14	18.08	34.04	1407
Default Loan Ratio (%)	5.03	6.35	1.20	3.09	5.98	1407
Loan Loss Ratio (%)	5.95	7.19	1.71	4.32	6.78	1247
Panel C: Liabilities Ratios						
Demandable Deposits Ratio (%)	7.27	9.03	0.64	3.38	10.79	1511
Checking Deposits Ratio (%)	5.12	7.64	0.48	2.42	6.90	1511
Savings Deposits Ratio (%)	2.15	5.48	0.00	0.00	0.00	1511
Panel D: Income Ratios						
Loan Income / Loans (%)	2.53	16.02	1.03	1.48	2.19	1407
Loan Income / Assets (%)	0.65	0.62	0.10	0.50	0.94	1511
Total Income Ratio (%)	3.06	3.23	1.32	2.04	3.27	1511
Government Bond Income Ratio (%)	1.44	2.86	0.11	0.38	1.19	1511
Service Fee Income Ratio (%)	0.14	0.21	0.02	0.06	0.14	1511
Wholesale Fund Income Ratio (%)	0.01	0.03	0.00	0.00	0.01	1511

Table 2: Nettable Payments Ratios

This table shows summary statistics of nettable payment ratios from November 2020 to March 2023. In Panel (a) shows monthly averages for the ratio of nettable payments over all payments as defined in Equation (**??**), the ratio of daily nettable payments over total assets as defined in Equation (**??**), and the ratio of daily nettable payments over liquid assets as defined in Equation (3.3). Panel (b) shows the same ratios without averaging monthly.

	Mean	SD	P25	P50	P75	N
Nettable Payments / Gross Payments (%)	58.63	33.04	27.01	71.26	85.49	1511
Nettable Payments / Liquid Assets (Monthly) (%)	323.37	3532.52	2.77	24.99	106.62	1511
Nettable Payments / Liquid Assets (Daily) (%)	12.85	203.65	0.06	0.72	3.33	46697

Table 3: 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		-0.338
		(0.205)
Bank Capital		-0.092
		(0.170)
No. of Branches		0.167
		(0.237)
Bank FE	Yes	Yes
Time FE	Yes	Yes
Observations	1481	1469
Adjusted R^2	0.9	0.9
Kleibergen-Paap F	68.9	59.5
Montiel-Pflueger F	70.0	60.4

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 time-out 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	0.151***	0.153***	0.029***	0.030***	0.122***	0.124***	-0.279***	-0.283***
	(0.021)	(0.022)	(0.011)	(0.011)	(0.016)	(0.017)	(0.029)	(0.032)
Bank Assets		0.035		0.007		0.028		-0.143**
		(0.035)		(0.014)		(0.028)		(0.063)
Bank Capital		0.020		0.004		0.016		0.004
		(0.033)		(0.008)		(0.029)		(0.037)
No. of Branches		-0.012		-0.004		-0.008		0.031
		(0.042)		(0.011)		(0.034)		(0.052)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1481	1469	1481	1469	1481	1469	1481	1469

Table 5: 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***	0.123***	0.124***	0.004**	0.003*
	(0.016)	(0.017)	(0.015)	(0.016)	(0.002)	(0.001)
Bank Assets		-0.042		0.024		-0.066*
		(0.048)		(0.031)		(0.037)
Bank Capital		0.020		-0.001		0.021
		(0.042)		(0.033)		(0.022)
No. of Branches		-0.047		-0.023		-0.024
		(0.048)		(0.036)		(0.022)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1481	1469	1481	1469	1481	1469

Table 6: 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***	0.120**	0.123**
	(0.035)	(0.037)	(0.030)	(0.032)	(0.007)	(0.008)	(0.061)	(0.059)
Bank Assets		-0.017		0.011		0.004		0.052
		(0.051)		(0.043)		(0.016)		(0.045)
Bank Capital		0.003		-0.031		0.030*		0.030
		(0.038)		(0.028)		(0.016)		(0.027)
No. of Branches		0.064*		-0.054		0.001		-0.007
		(0.039)		(0.036)		(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	1381	1369	1381	1369	1381	1369	1226	1214

Table 7: The Effect of Pix Usage on Bank Risk-Taking: Agency Issues

This table shows how bank capital ratios influence the effect of instrumented Pix usage 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. The "High Cap Ratio" dummy is an indicator variable equal to 1 if a bank's core capital-to-risk-weighted assets ratio before Pix adoption in October 2020 is above the median in our sample. 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	-0.211***	-0.210***	0.180***	0.178***	0.026***	0.027***	0.122	0.124
	(0.029)	(0.031)	(0.023)	(0.024)	(0.008)	(0.009)	(0.084)	(0.085)
Pix × High Cap Ratio	0.250***	0.258***	-0.253***	-0.255***	0.034	0.028	-0.143	-0.153
	(0.094)	(0.098)	(0.092)	(0.093)	(0.082)	(0.077)	(0.112)	(0.117)
Bank Assets		0.049		-0.054		0.011		0.001
		(0.048)		(0.047)		(0.025)		(0.030)
Bank Capital		-0.011		-0.018		0.028		0.049
		(0.045)		(0.039)		(0.018)		(0.035)
No. of Branches		-0.005		0.015		-0.007		0.034
		(0.053)		(0.061)		(0.033)		(0.031)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1374	1364	1374	1364	1374	1364	1219	1209

Table 8: 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	2.709***	2.747***	-0.168***	-0.170***
	(0.421)	(0.448)	(0.035)	(0.037)
Bank Assets		0.632		-0.186**
		(0.796)		(0.081)
Bank Capital		0.461		0.100
		(0.653)		(0.068)
No. of Branches		-0.283		-0.047
		(0.966)		(0.088)
Bank FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	1380	1368	1481	1469

Table 9: The Effect of Pix Usage on Bank Income

This table shows the effect of instrumented Pix usage on bank income ratios based on the IV specification in (5.4). All ratios are denoted relative to total assets. 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	Total Income (%)		Gov bond Income (%)		Service Fee Inc (%)		Wholesale Fund Inc (%)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pix Usage	2.181**	2.200**	2.060**	2.103**	0.623***	0.630***	-0.017***	-0.019***
	(0.905)	(0.939)	(0.892)	(0.921)	(0.064)	(0.070)	(0.004)	(0.005)
Bank Assets		-2.446		-1.734		0.127		-0.013
		(2.562)		(2.116)		(0.141)		(0.018)
Bank Capital		1.383		1.872		0.057		-0.018**
		(1.166)		(1.296)		(0.108)		(0.009)
No. of Branches		-4.244		-2.638		-0.134		0.002
		(2.862)		(2.685)		(0.143)		(0.011)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1481	1469	1481	1469	1481	1469	1481	1469

Internet Appendix for

The Effect of Instant Payments on the Banking System

Ding Ding Rodrigo Gonzalez Yiming Ma Yao Zeng

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. Before the implementation of Pix, banks were able to perform end-of-day netting to reduce liquidity demands. To capture this idea, we define a bank's nettable payments during a given day d as the volume of inflows and outflows that could have been internally offset under end-of-day settlement:

$$\text{Nettable}_{id} = \underbrace{\sum_{\tau \in d} \text{Inflows}_{i\tau} + \sum_{\tau \in d} \text{Outflows}_{i\tau}}_{\substack{\text{Payment flows that must be} \\ \text{settled under Pix (i.e. real-time)}}} - \underbrace{\left| \sum_{\tau \in d} \text{Inflows}_{i\tau} - \sum_{\tau \in d} \text{Outflows}_{i\tau} \right|}_{\substack{\text{Payment flows that would be settled} \\ \text{without Pix (i.e. under intraday netting)}}}. \tag{A.1}$$

This expression captures the volume of payment flows that could have been internally netted. Importantly, it also reflects the *incremental* amount of payments to be settled after Pix, as banks lose the ability to net payments intraday.

Claim: The daily Pix Usage (in the numerator of Equation (1)) is exactly half of Nettable_{id}:

$$\text{Pix Usage}_{id} = \min \left\{ \sum_{\tau \in d} \text{Inflows}_{i\tau}, \sum_{\tau \in d} \text{Outflows}_{i\tau} \right\} = \frac{1}{2} \cdot \text{Nettable}_{id}. \tag{A.2}$$

Proof. Without loss of generality, suppose $\sum_{\tau \in d} \text{Inflows}_{i\tau} \geq \sum_{\tau \in d} \text{Outflows}_{i\tau}$. Then:

$$\begin{aligned} \text{Nettable}_{id} &= \sum_{\tau \in d} \text{Inflows}_{i\tau} + \sum_{\tau \in d} \text{Outflows}_{i\tau} - \left(\sum_{\tau \in d} \text{Inflows}_{i\tau} - \sum_{\tau \in d} \text{Outflows}_{i\tau} \right) \\ &= 2 \cdot \sum_{\tau \in d} \text{Outflows}_{i\tau} = 2 \cdot \min \left\{ \sum_{\tau \in d} \text{Inflows}_{i\tau}, \sum_{\tau \in d} \text{Outflows}_{i\tau} \right\}, \end{aligned}$$

concluding the proof. □

A.2 Omitted Proofs

Proof of Proposition 1: 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 $1 \leq t \leq T-1$, then at $t = T$ we have

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

and the expected profit is

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

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

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

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

$$\frac{dx^*}{dt} = -\frac{\partial F/\partial t}{\partial F/\partial x} = -\frac{(1-pR)\frac{\partial S(x,t)}{\partial t} + [x+(1-x)pR-(1+(1+\alpha)r)]\frac{\partial^2 S(x,t)}{\partial x \partial t}}{2(1-pR)\frac{\partial S(x,t)}{\partial x} + [x+(1-x)pR-(1+(1+\alpha)r)]\frac{\partial^2 S(x,t)}{\partial x^2}}\,. \tag{A.3}$$

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.3) 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 2: We first consider the household's portfolio choice under the instant payment system. In this case, consumption is given by

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

Thus, the household's 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

$$u'(\alpha^*_{\text{ins}}) - (1+r)\, u'\Big((1-\alpha^*_{\text{ins}})(1+r)\Big) = 0\,. \tag{A.4}$$

Next, consider the household's 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 household's expected utility is

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

and the corresponding FOC is

$$\frac{(T-\kappa)\delta^{\kappa}u'(\delta^{\kappa}\alpha^*_{\text{tra}})}{2(T-2)} + \mathbf{1}_{\{\kappa\ge 3\}} \sum_{\tau=2}^{\kappa-1} \frac{\delta^{\tau}u'(\delta^{\tau}\alpha^*_{\text{tra}})}{2(T-2)} + \frac{\delta\, u'(\delta\alpha^*_{\text{tra}})}{2} - (1+r)\, u'\Big((1-\alpha^*_{\text{tra}})(1+r)\Big) = 0\,. \quad \text{(A.5)}$$

To compare (A.4) and (A.5), 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 $\tau \ge 1$ (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.5) 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

$$u'(\alpha^*_{\text{tra}}) - (1+r)\, u'\Big((1-\alpha^*_{\text{tra}})(1+r)\Big) > 0\,. \tag{A.6}$$

Comparing (A.6) with (A.4), 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

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

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

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

This completes the proof. □

Proof of Proposition 3: We first derive the bank's 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

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

where x is the fraction of the bank's 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:

$$\theta^*(x,p) \;=\; \frac{(1-\eta)\,\big[\,1+(1+\alpha)r\,\big] - x}{(1-x)\; p\, R(p)}\,. \tag{A.7}$$

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 bank's 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 bank's 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 bank's profit in state θ. Under uniform distribution, the expected profit simplifies to

$$\Pi(x,p) \;=\; \int_{\theta^*}^{1} \Big[\, x - (1-\eta)\big(1 + (1+\alpha) r\big) + (1-x) p R(p)\, \theta \Big] d\theta \,. \tag{A.8}$$

Evaluating the integral in (A.8) 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.7). 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

$$R(p^*) + p^*\, R'(p^*) \;=\; 0 \,. \tag{A.9}$$

Substituting θ^* from (A.7) into the optimality condition, one finds that $p^*(x)$ is characterized by

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

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.10) can be rearranged to express the optimal risk in closed form. Dividing both sides by $1-x$ gives

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

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,

$$p^*(x) \;=\; R^{-1}\!\left(\frac{(1-\eta)\,\big[\,1+(1+\alpha)r\,\big]-x}{1-x}\right), \tag{A.11}$$

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

From the solution (A.11), 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 1 established that under the instant payment system a bank will optimally choose a higher liquidity ratio than under the traditional payment system (formally, $x^*_{\text{ins}} > x^*_{\text{tra}}$). Applying the monotonic relation derived above, we conclude that the corresponding optimal risk choices satisfy

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

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 $p^*_{\text{ins}} < p^*_{\text{tra}}$.

We finally consider the comparative statics with respect to η. From the derivation in the proof of

Proposition 3, the optimal level of risk taking 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 1 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. □

Proof of Proposition 4: Fix an arbitrary $\alpha > 0$. By Proposition 3, the bank's optimal risk choice under instant payments is strictly higher than under the traditional payment 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 (iv), we need to compare $\Gamma^*_{a,\text{ins}}$ and $\Gamma^*_{a,\text{tra}}$ under the stated condition on $R(p)$. By Proposition 1, 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 payment 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. To determine the net effect on Γ_a, we

utilize the bank's break-even condition from the model. In particular, from the proof of Proposition 3 the optimal risk choice satisfies the implicit equation

$$(1 - x^*)\, R(p^*) \;=\; (1 - \eta)\left[1 + (1 + \alpha)r\right] \;-\; x^*\,, \tag{A.12}$$

which equates the marginal loan return to the bank's required repayment. Denoting the right-hand side of (A.12) by $D \equiv (1-\eta)\,[1+(1+\alpha)r]$ for brevity, we can rewrite (A.12) 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 payment systems. Now consider the difference in loan income per asset between the two systems:

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

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 payment 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: The stated condition in part iv) 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 bank's optimality condition) is accounted for.

To see this, we differentiate the expression $\Gamma_a = p\,D + (1 - p)x$ implicitly using the relationship (A.12) between x and p. Totally differentiating (A.12) 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.12) 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 stated in part (iv). Condition (iv) 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 the stated condition 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 (iv). □

A.3 Correlated Credit and Liquidity (Payment) Risks

In this appendix, we provide a stripped-down extension of the baseline model showing that our results of risk-taking in Proposition 3 remain qualitatively robust when the assumption is relaxed to allow for some, but not perfect, correlation between credit risk and liquidity shocks.

Let the state be $s = (\theta, \{\pi_{j,t}\})$ where $\theta \in [0,1]$ is the aggregate credit shock in (4.1) and $\{\pi_{j,t}\}$ capture liquidity shock. For $k \in \{\text{ins}, \text{tra}\}$ let F_ρ denote a family of distribution of $(\theta, \{\pi_{j,t}\})$ indexed by a correlation parameter $\rho \in (-1,1)$, with F_0 imposing independence as in the baseline model and $F_\rho \Rightarrow F_0^k$ as $\rho \to 0$. Denote by $\ell_k \in \{0,1\}$ the probability event at which the bank defaults due to liquidity shocks before T. Then, for a portfolio $(x, 1-x)$ and risk choice p, the equity payoff in state s is

$$\Pi(x,p;s) = \big[x + (1-x)\,p\,R(p)\,\theta\,(1-\ell(1-\phi)) - D\big]_+,$$

and the bank's objective under system k is

$$\mathcal{V}_k(x, p; \rho) = \mathbb{E}_{F_\rho}\big[\Pi(x, p; s)\big] \,,$$

where x and p are all functions of k. For each k, note that $\mathcal{V}_k(\cdot, \cdot; \rho)$ is continuous in (x, p, ρ) and strictly concave in p. Also for each k and ρ, assume that the maximizers $(x_k^*(\rho), p_k^*(\rho)) \in \arg\max_{x,p} \mathcal{V}_k(x, p; \rho)$ are unique and interior. Therefore, Berge's Maximum Theorem guarantees continuity of the optimal policies in ρ:

$$x_k^*(\rho) \to x_k^*(0), \qquad p_k^*(\rho) \to p_k^*(0) \quad \text{as } \rho \to 0, \quad k \in \{\text{ins}, \text{tra}\}.$$

Define $\Delta p(\rho) := p_{\text{ins}}^*(\rho) - p_{\text{tra}}^*(\rho)$. Continuity implies $\Delta p(\rho) \to \Delta p(0)$ as $\rho \to 0$. Since $\Delta p(0) = p_{\text{ins}}^*(0) - p_{\text{tra}}^*(0) < 0$ by Proposition 3 under independence, there exists $\varepsilon > 0$ for which $\Delta p(\rho) < 0$ whenever $\rho \in (-\varepsilon, \varepsilon)$. Hence, for all sufficiently small correlation,

$$p_{\text{ins}}^*(\rho) < p_{\text{tra}}^*(\rho),$$

implying that Proposition 3 continues to hold.

B Empirical Appendix

B.1 Main OLS Regression Results

Table 10: 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		-0.080**		-0.013		-0.067*
		(0.039)		(0.015)		(0.038)
Bank Capital		0.010		-0.011		0.021
		(0.028)		(0.020)		(0.022)
No. of Branches		-0.031		-0.008		-0.023
		(0.031)		(0.017)		(0.022)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1511	1499	1511	1499	1511	1499
Adjusted R^2	0.876	0.873	0.841	0.841	0.977	0.978

Table 11: 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	0.022**	0.022**	-0.003	-0.004	0.025***	0.025***	-0.021**	-0.022**
	(0.010)	(0.010)	(0.004)	(0.004)	(0.009)	(0.009)	(0.009)	(0.010)
Bank Assets		-0.001		-0.005		0.004		-0.054*
		(0.026)		(0.008)		(0.026)		(0.029)
Bank Capital		0.010		0.001		0.010		0.028
		(0.022)		(0.005)		(0.022)		(0.027)
No. of Branches		0.015		0.003		0.012		-0.007
		(0.026)		(0.007)		(0.024)		(0.033)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1511	1499	1511	1499	1511	1499	1511	1499
Adjusted R^2	0.708	0.708	0.614	0.613	0.757	0.757	0.971	0.971

Table 12: 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

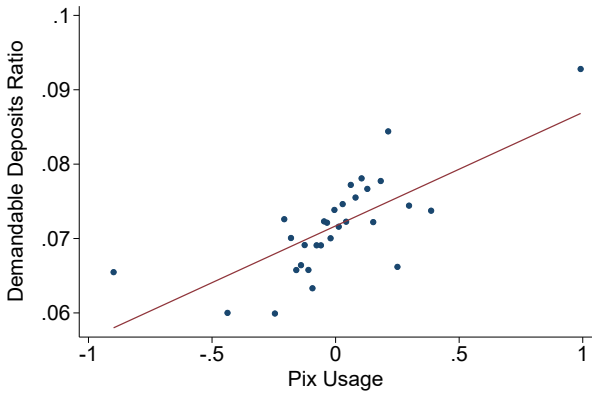
	Prime Loan Ratio		Sub-Prime Loan Ratio		Default Loan Ratio		Loan Loss Ratio	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pix Usage	-0.053**	-0.052**	0.055***	0.054***	-0.001	-0.000	0.007	0.007
	(0.024)	(0.024)	(0.014)	(0.014)	(0.005)	(0.005)	(0.006)	(0.007)
Bank Assets		0.035		-0.030		-0.004		-0.001
		(0.026)		(0.026)		(0.013)		(0.015)
Bank Capital		0.020		-0.045*		0.027*		0.025**
		(0.027)		(0.025)		(0.014)		(0.013)
No. of Branches		0.037		-0.033		0.005		0.009
		(0.037)		(0.044)		(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	1407	1395	1407	1395	1407	1395	1246	1234
Adjusted R^2	0.926	0.927	0.926	0.928	0.916	0.917	0.889	0.887

B.2 Binscatter Plots of the Main OLS Results

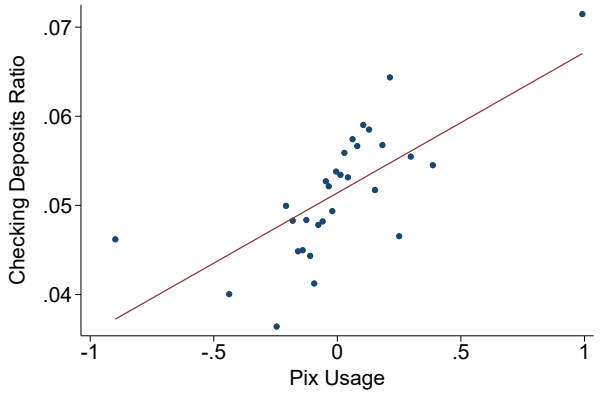
Figure 9: The Effect of Pix Usage on Deposit Ratios

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

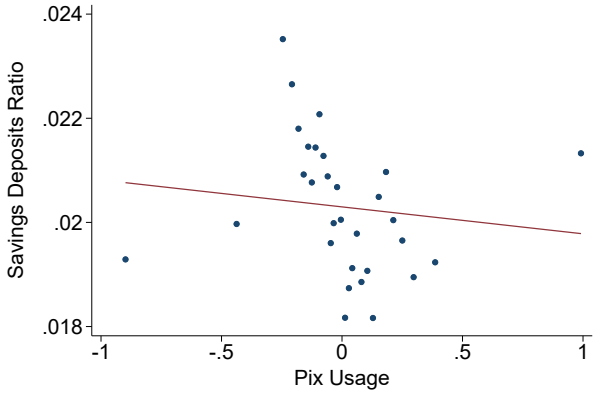
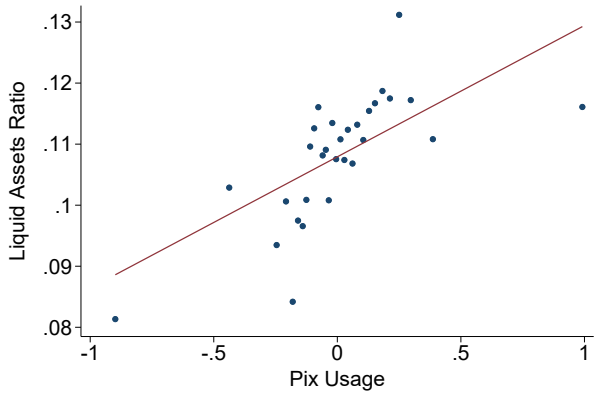


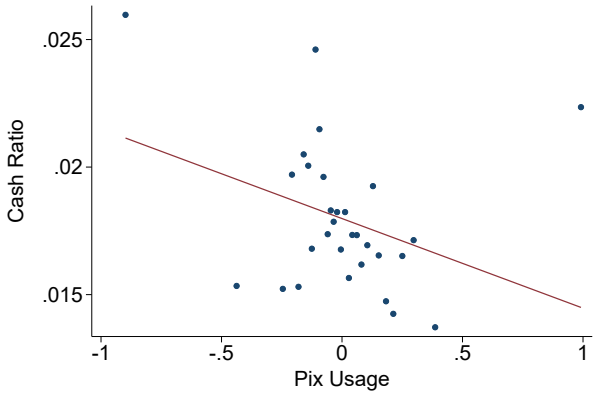
Figure 10: The Effect of Pix Usage on Asset Ratios

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.

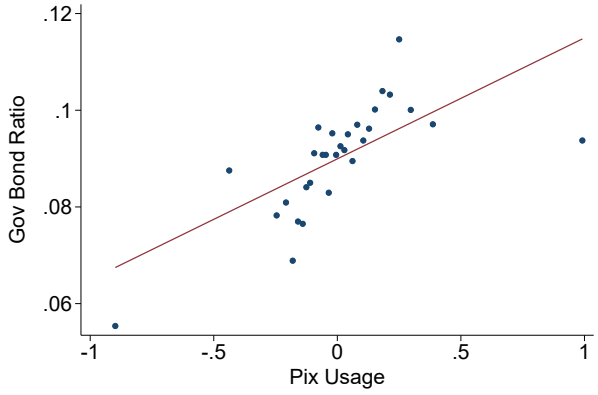
(a) Liquid Assets Ratio



(b) Cash Ratio



(c) Government Bond Ratio



(d) Loan Ratio

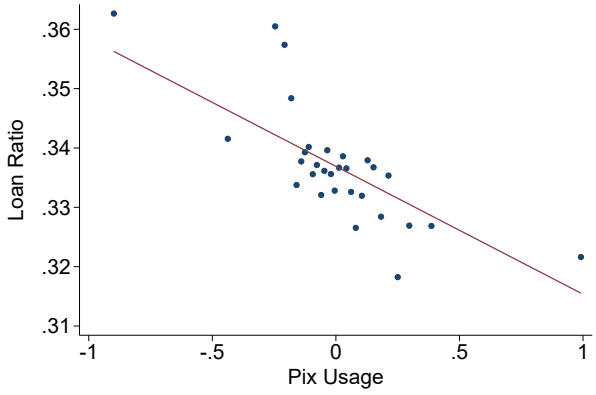
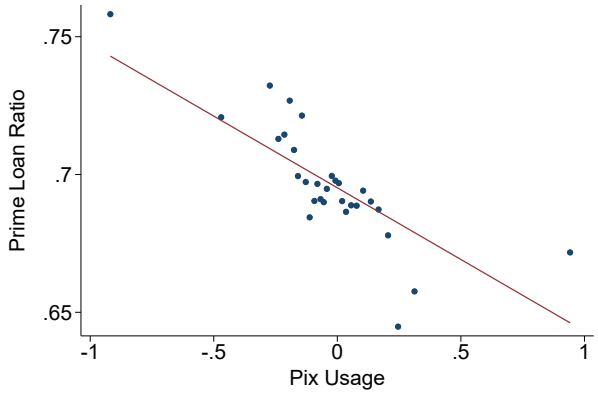


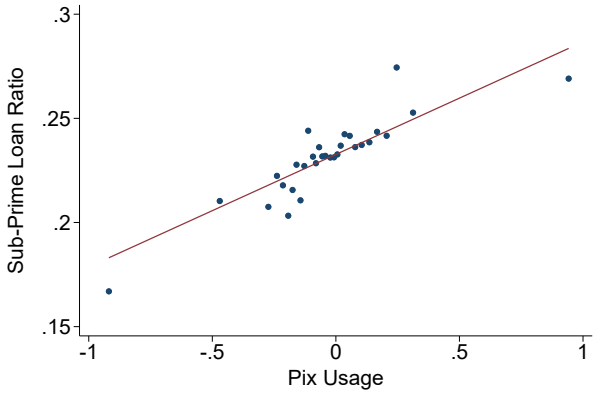
Figure 11: The Effect of Pix Usage on Bank Risk-Taking

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.

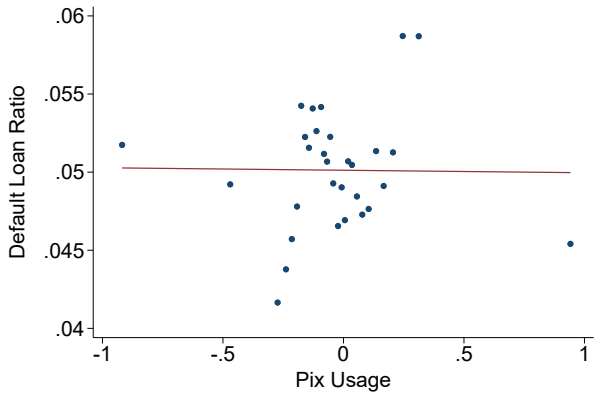
(a) Prime Loan Ratio



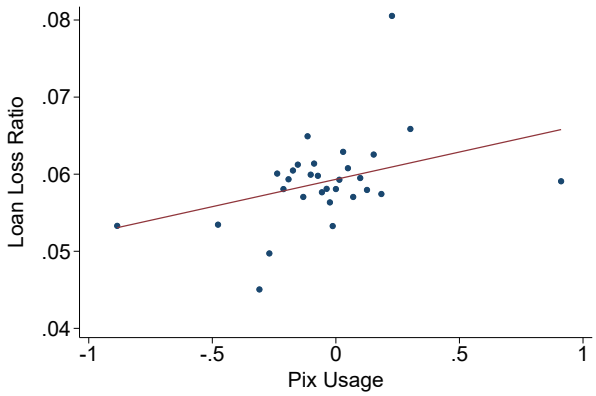
(b) Sub-Prime Loan Ratio



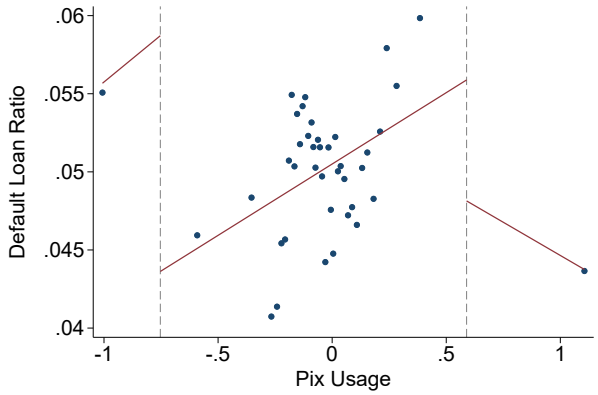
(c) Default Loan Ratio



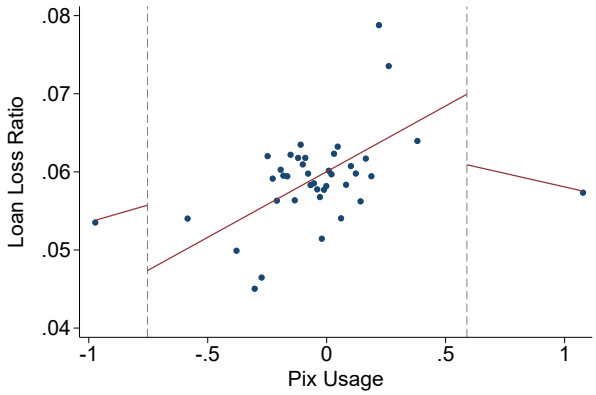
(d) Loan Loss Ratio



(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 "High Cap Ratio" dummy is an indicator variable equal to 1 if a bank's core capital-to-risk-weighted assets ratio before Pix adoption in October 2020 is above the median in our sample. 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	-1.151	-1.151*	-1.036	-1.029
	(0.690)	(0.684)	(0.784)	(0.772)
Bank Assets		-0.333		-0.311**
		(0.204)		(0.139)
Bank Capital		-0.100		0.043
		(0.172)		(0.151)
No. of Branches		0.164		0.267
		(0.238)		(0.209)
Bank FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	1474	1464	1474	1464
Adjusted R^2	0.899	0.900	0.933	0.934
Sanderson-Windmeijer F	233.573	201.106	228.111	198.308