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

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Abstract

We show that instant payment systems may unintendedly constrain bank liquidity transformation and exacerbate risk-taking. Guided by a theoretical model, we use administrative payment-level data from Brazil's Pix and a novel instrument to confirm 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 demand. This in turn leads to more risk-taking in lending under agency frictions. Our findings bear important implications on instant payment adoption and CBDC design.

Keywords: instant payments, banking, lending, 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 without the risk of crowding out bank funding.

While instant payments allow assets to remain on banks' balance sheets, we note that they affect bank liabilities 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, is affected by 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 a larger 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 induce bank equity holders to take on more credit risk when investing in illiquid assets like loans.

[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.

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 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.

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 use this cross-sectional variation in banks' exposure to Pix to estimate the effect on various outcome variables.

We note 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 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 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 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. 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. 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 riskiness of its lending, with riskier loans being more likely to default but earning higher realized returns absent default.

Depositors with unpredictable payment needs allocate their funds between demandable deposits, which can be used to make payments, and time deposits, which cannot be directly used for payments but provide higher returns. 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.

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

[2]Nevertheless, note that the increase in banks' liquid assets os 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.

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 and agency conflicts are worse. Increased payment processing under instant payments may also improve loan outcomes through better monitoring and screening, thereby reducing risk-taking. To this end, 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 banks take on riskier loans. 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 test the model predictions, we need to overcome the identification challenge that Pix usage may be correlated with bank characteristics that also affect the composition of bank balance sheets. To this end, we construct a novel instrument for Pix usage based on payment timeouts. The idea is that the availability of instant payments is only relevant if payments are successfully sent by the sending bank and then successfully received by the receiving bank without delay. If either bank fails to process the payment within 40 seconds, the payment attempt is unsuccessful and deemed as a "timeout". 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.

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.

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 and 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 Pix usage decreases the ratio of prime loans, while increasing the ratio of sub-prime loans. 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.

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, Parlour and Rajan, 2025). Most papers in this literature have focused on how modern payment technologies affect consumption, investment, credit access, and consumer default (e.g. Jack and Suri, 2014, Muralidharan, Niehaus, and Sukhtankar, 2016, Ghosh, Vallee, and Zeng, 2022, Berg, Fuster, and Puri, 2022, Dubey and Purnanandam, 2023, Alok, Ghosh, Kulkarni, and Puri, 2024, Higgins, 2024). A smaller set of papers has 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 our work are Parlour, Rajan and Walden (2022) and Garratt, Yu, and Zhu (2025). Parlour, Rajan and Walden (2022) study the unintended consequences of payment convenience for bank lending and show that settling interbank payments with liquid assets gives rise to a liquidity externality that constrains banks' lending capacity, an effect that is amplified when payment frictions are reduced. Garratt, Yu, and Zhu (2025) focus on

the interaction between payment innovations and interbank competition, highlighting how payment convenience affects deposit retention, reserve flows, and banks' lending incentives through interbank lending and reserve remuneration. Their analysis emphasizes the role of payment systems in shaping banks' liquidity management and lending behavior through interbank linkages. 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 do not merely provide faster and more convenient payments, but fundamentally remove banks' ability to delay and net outgoing payments with incoming ones. This loss of netting capacity directly constrains liquidity transformation and, through agency frictions between bank equity and debt, amplifies banks' incentives to take risk.

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' liquidity transformation (e.g. Diamond and Dybvig, 1983, Calomiris and Kahn, 1991, Goldstein and Pauzner, 2005, Chen, Goldstein, Huang, and Vashishtha, 2024). Volatility in bank funding constrains lending even in the absence of runs. Jermann and Xiang (2023) and Bolton, Li, Wang and Yang (2025) 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) find that banks with more volatile payment flows experience reduced loan growth. Another set of papers highlight the complementarity between liquid deposits and lending. Kashyap, Rajan and Stein (2002) argue that complementarity results when deposit withdrawals and commitment takedowns are not correlated, and Egan, Lewellen, and Sunderam (2022) further quantify the synergies between bank deposit-taking and lending. 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 liquidity 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, Acharya and Merrouche, 2013, 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 (Afonso, Duffie, Rigon and Shin, 2022, Goldstein, Yang, and Zeng, 2023, Correa, Du and Liao, 2025, Copeland, Duffie and Yang, 2025, d'Avernas et al., 2025) as well as the optimal level of aggregate reserves (Lopez-Salido and Vissing-Jorgensen, 2023). Relatedly, Acharya, Chauhan, Rajan, and Steffen (2023) and Acharya and Rajan (2024) 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 (2022) show that the liquidity needs of the banking sector are state-contingent. Our findings highlight instant payment systems, which reflect an innovation in bank liquidity supply, as a new contributing factor to the liquidity demand of the banking sector.

2 Institutional Setting and Data

2.1 Traditional Payment Systems

Before the implementation of Pix, Brazil's main payment system was Transferência Eletrônica Disponível (TED). TED already uses Real-Time Gross Settlement (RTGS), which means that each payment sent by one bank is individually received and settled by another bank in real-time. Nevertheless, banks are able to delay submitting a payment order received from a customer until the end of the business day, which resembles the Fedwire system in the US. Another payment system used in the US is the Automated Clearing House (ACH) network. Payment can be delayed by several business days under the ACH network unless a premium for expedited processing is paid. This is similar Documento de Ordem de Crédito (DOC) in Brazil, which is another predecessor of Pix on which payments can be delayed until the next business day.

Figure 1a provides an illustration of traditional payment systems in which banks have some capacity to delay initiating payments, which TED and DOC in Brazil and Fedwire and ACH in the US. Suppose Amy would like to pay Ben for a cup of coffee, she would send a payment request to her bank, bank A, to transfer funds from her deposit account to Ben's deposit account at bank B. Upon receiving this request, bank A can submit the payment order immediately or wait up to the end of the day under TED and Fedwire to submit the payment order. Once bank A submits the order, bank B

receives the funds in real time and makes them available for use by Ben. Thus, the payment delay comes from the discretion that bank A has over when to submit the payment order. In practice, banks indeed tend to delay payments towards later in the day, especially when liquidity is scarce Kroger and McAndrews (2016). In particular, banks can first wait for incoming payments before sending outgoing payments.

2.2 Instant Payment Systems

Instant payment systems are also RTGS bank-railed systems but payments are made instantaneously without banks' discretion over the timing. Figure 1b provides an illustration. In the same setting where Amy would like to pay Ben for a cup of coffee, she would send a payment request directly to the instant payment system. The instant payment system automatically and instantaneously transfers the funds from Amy's bank, bank A, to Ben's bank, bank B. In this process, neither bank A nor bank B have control of the timing of the transfer. In particular, they cannot delay outgoing payments in order to wait for incoming ones.

Pix in Brazil and FedNow in the US are instant payment systems. In fact, about 100 jurisdictions have introduced instant payments, and several others have announced plans to go live in the future.[3] Among other instant payment systems, Pix, which was first introduced in November 2020, stands out for its widespread adoption. Pix's success is in part attributed to its 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 the user experience, 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, which coordinated the adoption of Pix by the vast majority of banks right from the outset.[4] Finally, using Pix is free for individuals and of much lower cost for businesses than other means of payments. As a result, Pix saw an unparalleled adoption rate 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]

FedNow, a retail-focused instant payment system, was launched by the Federal Reserve in July

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

[4] The regulation refers to eligible accounts, i.e., savings, checking (demand deposits) and prepaid accounts, where prepaid accounts are only offered by payment institutions. PIX adoption by smaller participants is voluntary but widespread. See www.bcb.gov.br/content/estabilidadefinanceira/pix.

[5] See www.poder360.com.br/poder-economia/banco-central-muda-regras-para-instituicoes-que-participam-do-pix.

2023. FedNow resembles Pix in that users can send and receive payments 24/7 and without delay. Nevertheless, participation in FedNow is voluntary and adoption has been slow, especially among the largest banks. The decentralized approach to adopting fast payment services in the U.S., without substantial regulatory directives, contrasts with the strategies that fueled the rapid spread of Pix in Brazil. Nevertheless, the potential for FedNow to reach wider adoption remains large, given the prevalent use of bank deposits as a means of payment in the US.

2.3 Data

Our analysis draws on several regulatory datasets from the BCB. First, we use administrative transaction-level Pix data to measure Pix usage and to construct our timeout instrument. For each transaction, we observe the timestamp, amount, and both the sending and receiving banks. Importantly, failed transactions, i.e., 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 administrative monthly bank balance sheet and income statement data from Plano Contábil das Institicões do Sistema Financeiro Nacional (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 2a 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 when Pix was introduced. Figure 2b 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% to 88% throughout the sample period, confirming that

[6]The COSIF data also include a separate class of financial institutions labeled as "payment institutions," which may also offer Pix services to customers. We do not include payment institutions in our analysis, however, because they do not engage in lending.

Pix was widely adopted right from the outset.

3 Stylized Facts

We first show several stylized facts about the variation in Pix usage 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 model in Section 4.

3.1 Pix Usage and Intraday Payment Netting

Banks' exposure to the adoption of Pix 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 customers at adopting banks utilized Pix payments displays significant cross-sectional variation. 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 3. The figure reveals considerable heterogeneity in Pix usage levels across banks. 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.

Economically, Pix usage also proxies for the potential loss in a bank's capacity to net intraday 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, TED. 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 "intraday 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 have to settle payments instantaneously so they lose the ability to delay and net payments within the same day. Pix usage thus reflects the potential monthly loss of nettable payments per unit asset. Higher Pix usage then reflects higher vulnerability to payment shocks due to Pix. In Internet Appendix A.1, we more formally show that (3.1) captures the amount of nettable payments per unit asset absent Pix. We further show that (3.1) reflects the potential loss of nettable payments per unit asset due to Pix, even when banks can use incoming payments to pay for subsequent outgoing payments, that is, liquidity recycling.

We note that the loss of payment netting from Pix arises from its design as an instant bank settlement system operating on a real-time gross settlement (RTGS) infrastructure. If Pix were to allow banks to settle net balances with each other at the end of the day, Pix usage would not reduce banks' ability to net intraday payment flows. A related trade-off between net settlement and gross settlement has been studied extensively in the payment economics literature. In particular, Kahn and Roberds (1998, 2009) emphasize that while net settlement systems economize on liquidity through payment netting, they may also generate moral hazard incentives by allowing banks to accumulate large unsettled obligations during the settlement cycle. Our focus differs from this classic RTGS versus net settlement comparison. Importantly, not every RTGS system requires payments to be processed instantaneously. Systems such as Fedwire in the United States and TED in Brazil already rely on RTGS infrastructure for final interbank settlement, but banks generally retain operational flexibility over the intraday timing of customer payment processing. Under these systems, banks frequently delay or batch payment requests, which effectively uses incoming payments to offset outgoing payments to reduce the net amount to be settled (Afonso, Duffie, Rigon and Shin, 2022, Copeland, Duffie and Yang, 2025). Instant payment systems like Pix remove this operational margin by automatically and instantaneously processing and settling payment requests at all times. As a result, banks lose the ability to delay and net payment flows within the same business day. This distinction between RTGS settlement and instant payment execution is central to our empirical findings and underlies the interpretation of Pix usage as capturing the loss of banks' intraday netting capacity.

We find that the ability to net payments intraday 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 4a 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, 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 4b 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 Pix should vary with their 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 Asset Composition

We begin by examining banks' 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 may have initially set aside more cash in anticipation of Pix and subsequently drew 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.

3.3 Deposit Structure

We proceed to examine 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 6a 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 6b further confirms that the trend in Figure 6a 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.

3.4 Bank Risk-Taking

Finally, we explore how the riskiness of banks' lending to the real economy has evolved with the implementation of Pix. Figures 7a and 7b show the ratio of loans that are classified as prime and sub-prime over time, respectively. We define prime loans as those that banks assigned to 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] We see that 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 loans. In contrast, banks in the first two quartiles of Pix usage increased their ratio of prime loans and decreased 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 7c 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 because of the 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

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

[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.

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 in Section 3, and to guide the subsequent empirical analysis in Section 5 by illustrating the economic mechanisms through which instant payments influence bank business models. Internet Appendix A.3 contains the proofs.

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. There are two market-specific consumption goods, which are also indexed by j.

Each bank j is risk-neutral and funded through three types of liabilities: equity, demandable deposits, and time deposits. To focus on the composition of deposits, we consider the equity ratio, η, of the two banks as exogenous. Demandable deposits are available for use in payments at any date $1 \leq t \leq T-1$ and yield a normalized interest rate of 0 at T.[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 with 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.

[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.

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 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 on 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. This assumption aligns with the notion of bank maturity transformation, which implies that bank assets and liabilities typically have different durations. Similar assumptions have also been used 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. In

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

Appendix A.4, we show that 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 carried over from one date to the next, the loan investment can only be made at $t = 0$.

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 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

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

(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

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

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

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

Thus, (4.12) indicates that under a consumption shock, the traditional payment system may subject the household's payment from bank j to bank $-j$ to potential delays, 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 banks' 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)**.** *When ϕ is sufficiently large and η is sufficiently small, 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. 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)**.** *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 through the liquidity channel because it stems from Proposition 1 and the underlying liquidity demand mechanism.

To better understand the drivers of the risk-taking effect, it is helpful to examine the bank equity's problem of optimal risk-taking under a terminal portfolio of $(x, 1-x)$, in which the expected bank equity value can be written as

$$\Pi(x,p) = \int_{\theta^*(x,p)}^{1} \Big[x + (1-x)\, p\, R(p)\, \theta - D\Big]\, d\theta, \tag{4.13}$$

where debt obligations D are

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

and $\theta^*(x,p)$ denote the solvency cutoff, defined as the lowest realization of θ such that the bank breaks even. We can then solve for the bank's optimal risk-taking decision

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

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.4, 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, and 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 to 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 unit loan: $\Gamma_l = \frac{(1-x)pR(p)}{1-x} = pR(p)$ *;*

(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 depends 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*

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

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 the return on riskier loans is sufficiently high so that condition (4.15) holds, which increases Γ_o. One might therefore expect the net 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 sharp 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 conflict 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 outcomes to shed light on the net effect of instant payments on bank risk taking.

We augment our baseline model by letting the lending return $R(p)$ 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. When λ is higher, loan returns benefit more from payment-enhanced screening and monitoring.

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 increases the marginal benefit of risk-taking in boosting realized lending returns. For example, $R(p, \lambda Z) = R_2(\lambda Z)/p$ accommodates the possibility that the complementarity is particularly larger for riskier loans, 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

[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.

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 for risk-taking from 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 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. Hence, timeouts not only reduce the amount of successful Pix transactions for a given number of initiated transactions but also reduce the attractiveness and, hence, uptake, of Pix to make transactions in the first place.=

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 8 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.

We note again that the relevant of timeouts for Pix usage does not only arise because failed transactions directly reduce Pix usage. More importantly, prevalent timeouts makes Pix less attractive to customers and discourages adoption in the first place. Customers are aware of timeouts because

frequent timeouts at specific banks are spread by word of mouth, reported in the media, and appear in online discussion boards. Some of these reports refer to timeouts due to a bank's own technical issues.[14] Others blame banks for passive timeouts induced by others, which is consistent with the timeout message not specifying which bank was at fault.[15]

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 9 presents the coefficient estimates of γ along with their corresponding 95% and 99%

[14] See, for example, www.cnnbrasil.com.br/tecnologia/aplicativo-do-santander-apresenta-instabilidade-nesta-segunda-feira.

[15] See, for example, www.reclameaqui.com.br/banco-do-brasil/pix-https-tempo-excedido, www.reclameaqui.com.br/banco-do-brasil/a-mensagem-aparece-pix-rejeitado-mas-descontaram-da-minha-conta, www.reclameaqui.com.br/itau/pix-nao-gerou-comprovante-nao-teve-pagamento-confirmado-porem-debitou-da, and www.reclameaqui.com.br/banco-do-brasil/efetuado-pix-a-sky-a-mesma-alega-nao-ter-recebido-mesmo-tendo-sido-enviado.

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.[16] 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

[16]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.

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.

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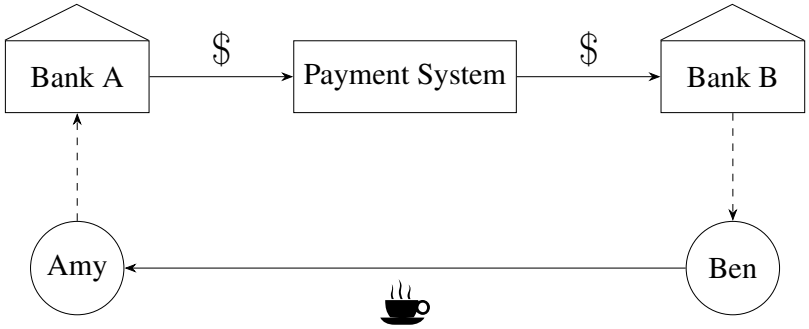
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Figures and Tables

Figure 1: Traditional versus Instant Payment System

This figure illustrates a payment sent from Amy to Ben for purchasing a cup of coffee in a traditional payment system (Panel (a)) and an instant payment sytem (Panel (b)). In the traditional payment system, Amy sends a request to her bank, bank A. Upon receicing the request, bank A decides the exact timing at which payments are sent to bank B, which is the bank of Ben. In the instant payment system, Amy directly sends a request to the instant payment system, which automatically and instantaneously transfers funds from bank A to B without delay.

(a) Traditional Payment System



(b) Instant Payment System

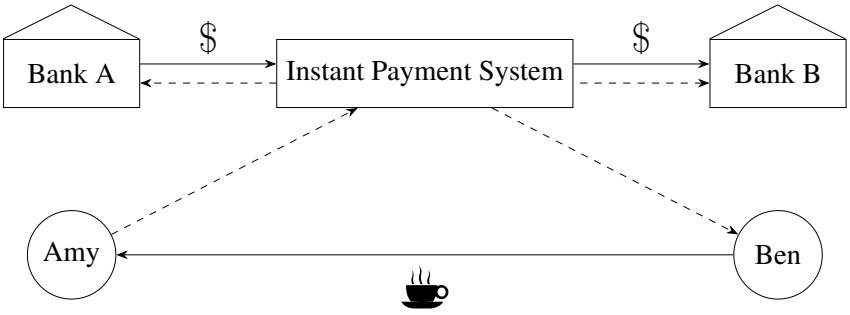
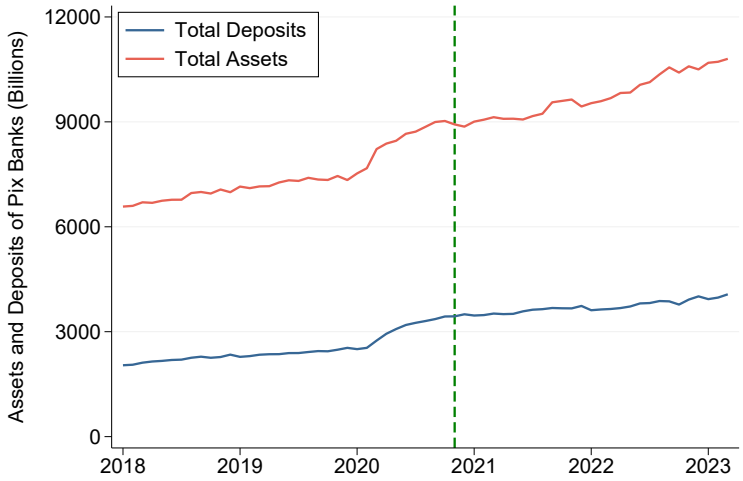


Figure 2: Assets and Deposits of Pix-Adopting Banks

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

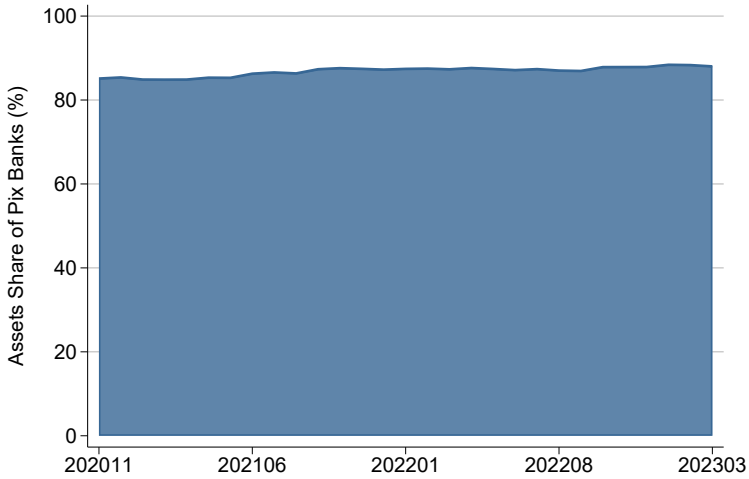


Figure 3: Pix Usage by Quantile

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

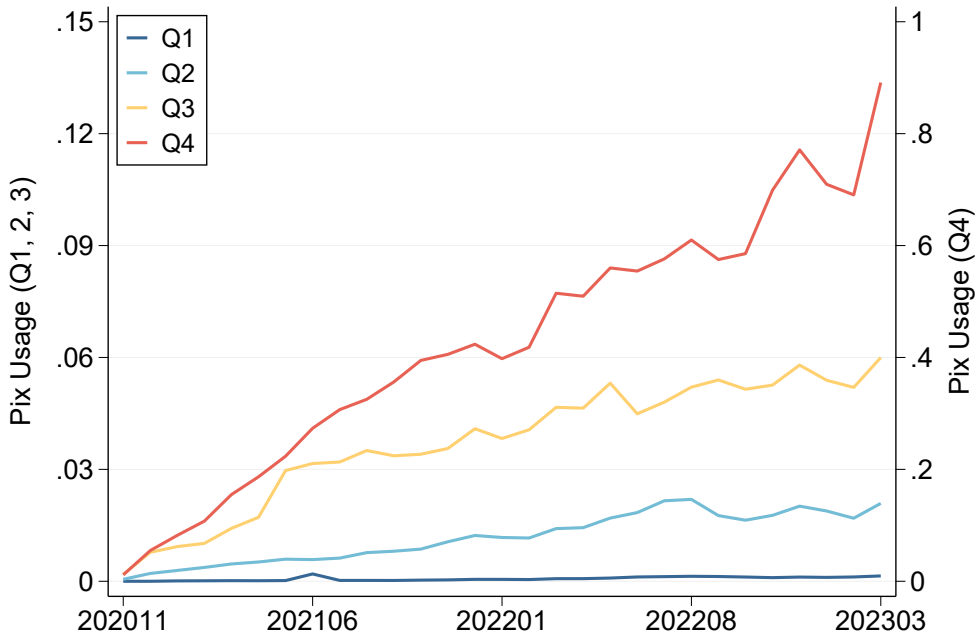
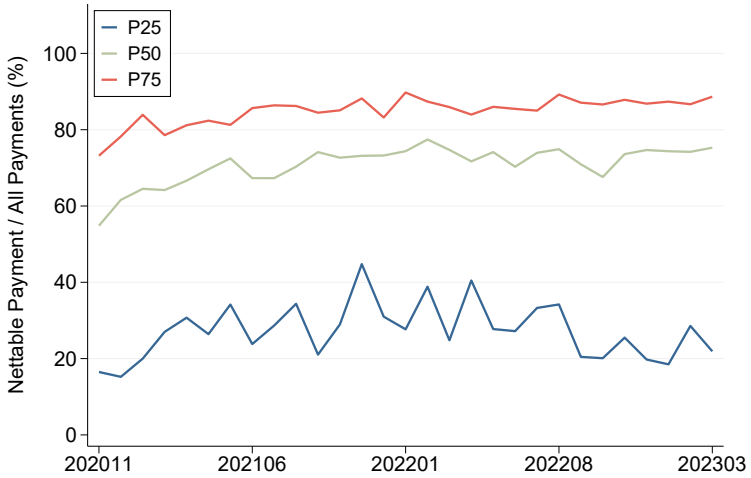


Figure 4: Nettable Payments Ratios

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 3.2. 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

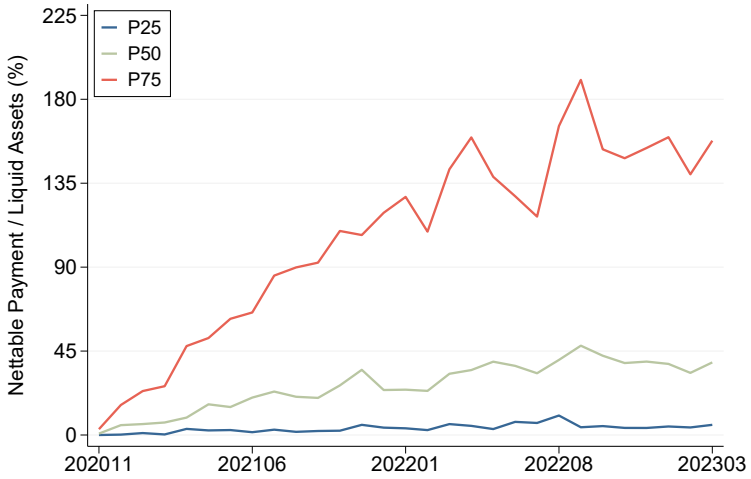
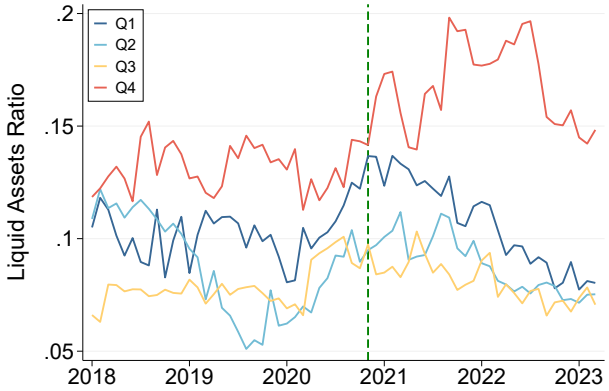


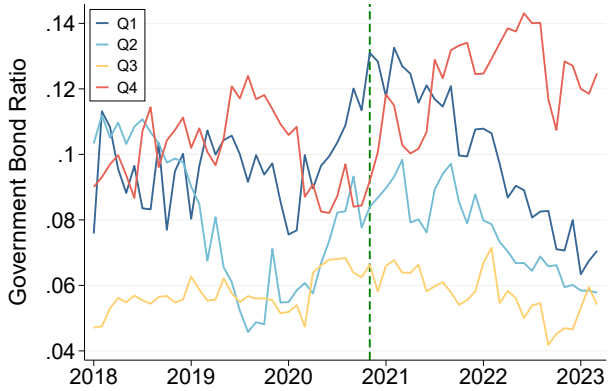
Figure 5: Liquid Assets Ratios by Pix Usage

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

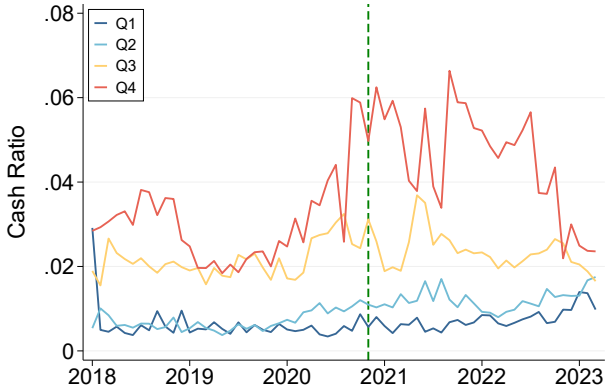
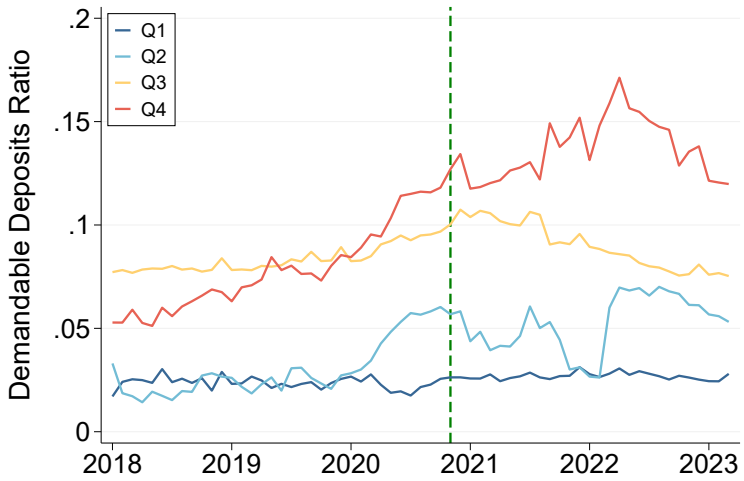


Figure 6: Deposits Ratios by Pix Usage

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

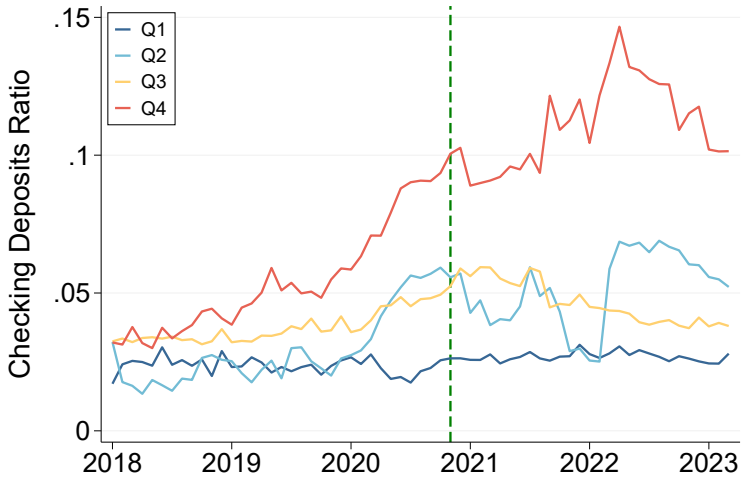
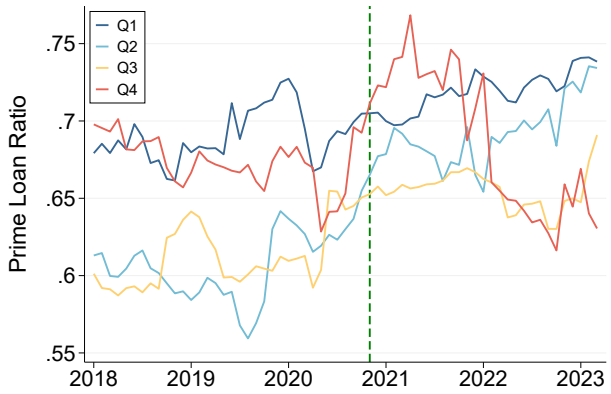


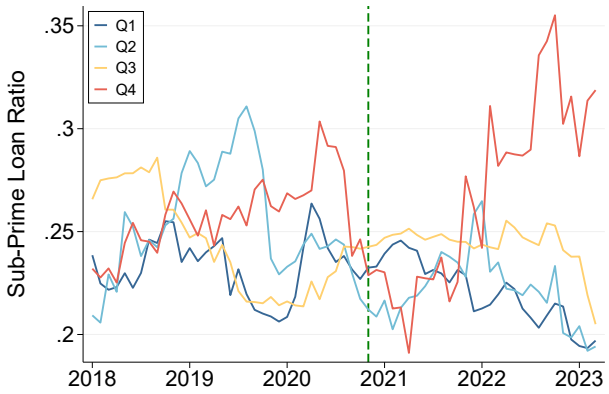
Figure 7: Prime, Subprime, and Default Loan Ratios by Pix Usage

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

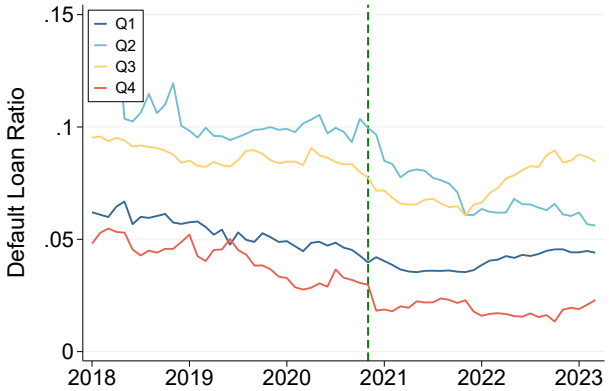


Figure 8: Variation in the Timeout Instrument and Pix Usage

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.

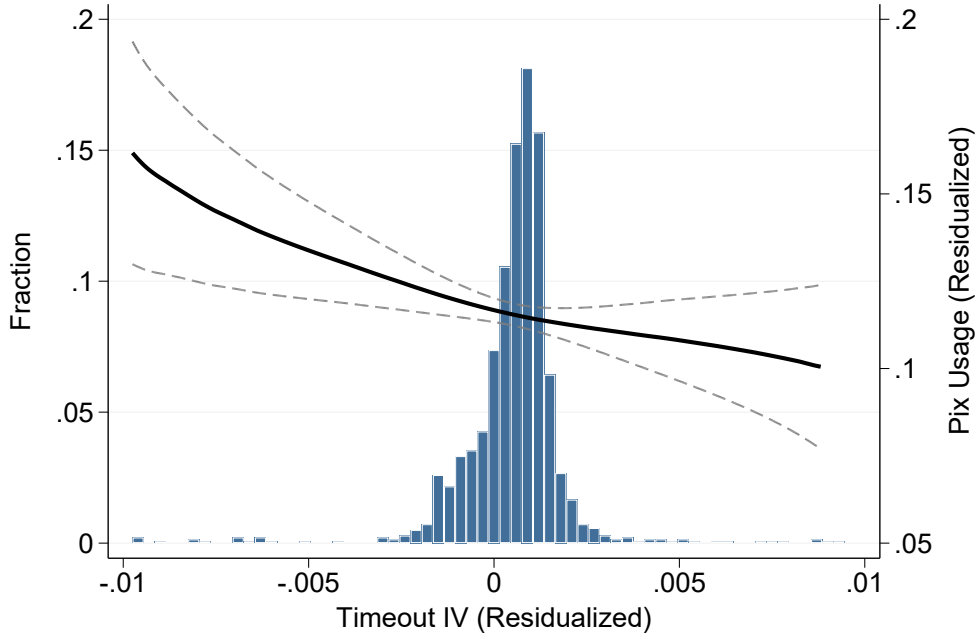


Figure 9: Relationship between the Timeout Instrument and Bank Covariates

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.

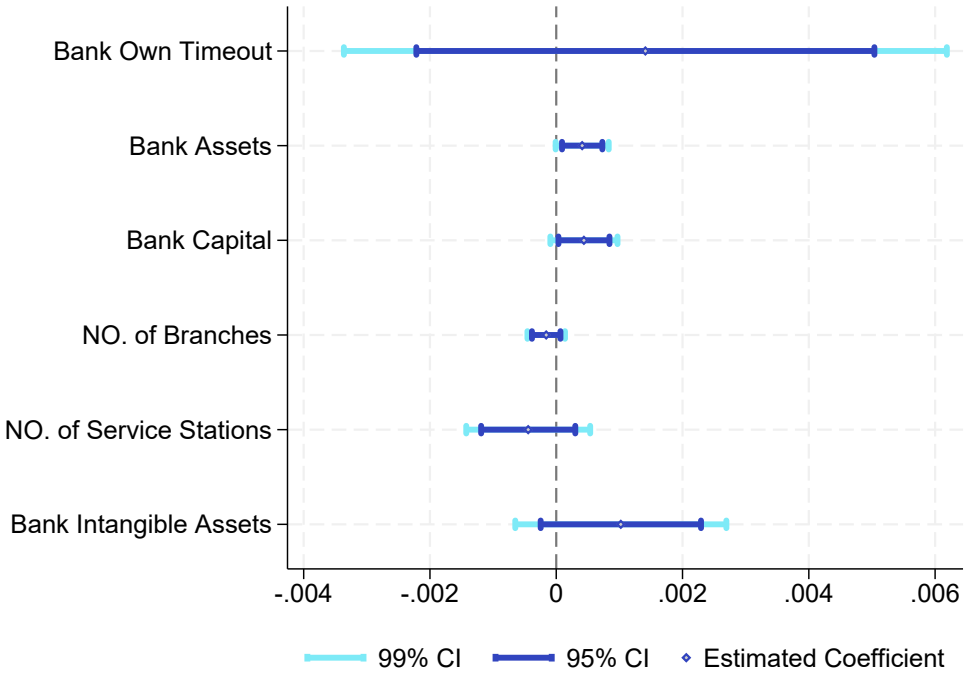


Table 1: Summary Statistics

This table shows summary statistics of our main variables. Asset ratios, liability ratios, and income ratio are expressed as a fraction of bank assets except for the following variables. Prime loan ratio, subprime loan ratio, default loan ratio, loan loss provision ratio, and loan income per unit loans are expressed as a fraction of total loans. All variables are expressed in percent except for bank assets and bank capital, which are expressed in billions, and the number of 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
Timeout Ratio by Trans Amount(%)	1.39	6.15	0.15	0.35	0.85	1511
Timeout Ratio by Trans Number(%)	1.55	4.52	0.25	0.52	1.18	1511
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. The ratio of nettable payments over gross payments is defined in Equation (3.2), while the ratio of nettable payments over liquid assets is defined in Equation (3.3).

	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 (%)	323.37	3532.52	2.77	24.99	106.62	1511

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: Effect of Bank Capital

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 loan income 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 derive the relationship between Pix usage defined in (3.1), nettable payments absent instant payments, and the potential loss of nettable payments due to instant payments.

Recall that Pix usage for bank i in month t is defined as

$$PixUsage_{it} = \frac{\sum_{d \in t} \min(Outflows_{id}, Inflows_{id})}{TotalAssets_{it}}. \tag{A.1}$$

Had the same payment flows occurred in the traditional payment system, which allows for netting of incoming and outgoing payment flows within the same business day, the amount of nettable payments for bank i on day d would have been

$$\min(Outflows_{id}, Inflows_{id}) \tag{A.2}$$

so that the amount of nettable payments for bank i in month t would have been

$$\sum_{d \in t} \min(Outflows_{id}, Inflows_{id}). \tag{A.3}$$

Thus, Pix usage is equal to the monthly amount of nettable payments without instant payments for bank i per unit asset size.

With instant payments, banks can no longer delay and net payments within the same business day. This is why the potential loss of nettable payments due to instant payments is also

$$\sum_{d \in t} \min(Outflows_{id}, Inflows_{id}) \tag{A.4}$$

and Pix usage can be interpreted as the potential loss of nettable payments due to Pix per unit asset size.

In practice, banks may be able to use incoming payments that arrive before outgoing payment requests within the same day to fund some of these outgoing payment requests even in the presence of instant payments. This practice is called liquidity recycling. As an extreme example, if all incoming payments of the day occurred before all outgoing payments for that day, the bank would be able to use all incoming payments to fund outgoing payments. In practice, it is unlikely that all incoming payments of the day occur before outgoing payments. Even if it were the case ex post, the bank is unlikely to predict the sequence of payment requests ex ante so it may have deployed some of the incoming funds for other purposes if it did not fully anticipate the subsequent outgoing payments requests. Therefore, although liquidity recycling may reduce the realized loss of nettable payments if incoming payments occur before outgoing payments during the day, the exact sequence of payments may not be expected by the bank and the magnitudes are limited if outgoing payments arrive before incoming ones. That is why we base our main analysis on Pix usage, which reflects the potential loss of nettable payments due to Pix that is independent of intraday payment sequencing and is likely more predictable by banks.

[DIng Ding's original writeup below]

Under the traditional payment system, banks can delay and net payments within the same business day. To capture this idea, we define bank i's nettable payments during a given day d as the volume of inflows and outflows that could have been netted absent instant payments:

$$\text{Nettable}_{id} = \underbrace{\sum_{\tau \in d} \text{Inflows}_{i\tau} + \sum_{\tau \in d} \text{Outflows}_{i\tau}}_{\substack{\text{Payment flows that must be} \\ \text{settled under Pix (i.e. real-time)}}} - \underbrace{\left| \sum_{\tau \in d} \text{Inflows}_{i\tau} - \sum_{\tau \in d} \text{Outflows}_{i\tau} \right|}_{\substack{\text{Payment flows that would be settled} \\ \text{without Pix (i.e. under intraday netting)}}}. \tag{A.5}$$

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}:

$$\text{Pix Usage}_{id} = \min \left\{ \sum_{\tau \in d} \text{Inflows}_{i\tau}, \sum_{\tau \in d} \text{Outflows}_{i\tau} \right\} = \frac{1}{2} \cdot \text{Nettable}_{id}. \tag{A.6}$$

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 Pix Usage and Realized Nettable Payments under Liquidity Recycling

In this appendix, we further show that Pix usage defined in (3.1) also captures a notion of maximum incremental liquidity shortfall. This analysis captures the idea that that outflows are more costly for banks from a liquidity management perspective, and that liquidity recycling in that a bank can use incoming flows to meet outgoing flows during a day can mitigate such costs. From this standpoint, Pix Usage variable presents an upper bound of the true incremental liquidity pressure faced by a bank after Pix.

Incremental Liquidity Shortfall. When managing liquidity, banks typically focus more on outflows than inflows, as liquidity stress arises when outflow obligations must be met in real time. To capture this, we define a measure of incremental liquidity shortfall introduced by Pix's real-time nature, compared to a counterfactual with intraday netting before Pix.

Formally, and also consistent with our empirical construction, we define the incremental liquidity shortfall before and after Pix as:

$$\begin{aligned}\Delta\text{Liquidity Shortfall}_{id} = &\underbrace{\frac{\sum_{d \in t} \max_{\tau \in d} \left\{ \max \left(\sum_{\tau'=1}^{\tau} \text{Outflows}_{i\tau'} - \sum_{\tau'=1}^{\tau} \text{Inflows}_{i\tau'},\ 0 \right) \right\}}{\text{Total Assets}_{it}}}_{\substack{\text{Liquidity shortfall under Pix} \\ \text{(i.e. real-time, with intraday liquidity recycling)}}} \\ &\underbrace{- \max \left\{ \sum_{\tau \in d} \text{Outflows}_{i\tau} - \sum_{\tau \in d} \text{Inflows}_{i\tau},\ 0 \right\}}_{\substack{\text{Liquidity shortfall without Pix} \\ \text{(i.e. under intraday netting)}}}. \qquad \text{(A.7)}\end{aligned}$$

Claim and Proof: Pix Usage = Worst-Case Incremental Liquidity Shortfall. Assume a worst-case distribution of payments in which all inflows occur *after* all outflows. In this worst-case scenario, the cumulative net outflow position during the initial outflow period is strictly increasing and reaches

a maximum equal to the total outflows:

$$\max_{\tau \in d} \left\{ \sum_{\tau'=1}^{\tau} \text{Outflows}_{i\tau'} - \sum_{\tau'=1}^{\tau} \text{Inflows}_{i\tau'} \right\} = \sum_{\tau \in d} \text{Outflows}_{i\tau}. \tag{A.8}$$

Based on definition (A.7), the incremental liquidity shortfall is calculated as:

$$\begin{aligned} \Delta\text{Liquidity Shortfall}_{id} &= \sum_{\tau \in d} \text{Outflows}_{i\tau} - \max \left\{ \sum_{\tau \in d} \text{Outflows}_{i\tau} - \sum_{\tau \in d} \text{Inflows}_{i\tau},\ 0 \right\} \\ &= \min \left\{ \sum_{\tau \in d} \text{Inflows}_{i\tau}, \sum_{\tau \in d} \text{Outflows}_{i\tau} \right\} \\ &= \text{Pix Usage}_{id}. \end{aligned}$$

Pix Usage as An Upper Bound of Incremental Liquidity Shortfall. By the triangle inequality, we get:

$$0 \leq \Delta\text{Liquidity Shortfall}_{id} \leq \text{Pix Usage}_{id}, \tag{A.9}$$

Equation (A.9) shows that Pix usage as defined in (3.1) provides an upper bound on the incremental liquidity shortfall arising from the loss of netting ability after Pix (but when liquidity recycling is still possible). Under the worst-case distribution of payments, where all outflows precede all inflows during a day, this upper bound is tight.

Correlation between Pix Usage and Incremental Liquidity Shortfall. Define for $\text{Pix Usage}_{id} > 0$

$$\rho_{id} \equiv \frac{\Delta\text{Liquidity Shortfall}_{id}}{\text{Pix Usage}_{id}} \in [0,1], \qquad \text{and set } \rho_{id} = 0 \text{ if } \text{Pix Usage}_{id} = 0.$$

Then we can write

$$\Delta\text{Liquidity Shortfall}_{id} = \rho_{id}\, \text{Pix Usage}_{id}, \qquad \rho_{id} \in [0,1],$$

where $\rho_{id} = 1$ represents the worst-case timing of all outflows happening before inflows and ρ_{id} captures the (lack of) intraday liquidity recycling.

Consider the joint distribution of $\{(\text{Pix Usage}_{id}, \Delta\text{Liquidity Shortfall}_{id})\}$. Assume the intraday ordering of payments, which determines ρ_{id}, is mean-independent of Pix Usage_{id}:

$$\mathbb{E}[\rho_{id} \mid \text{Pix Usage}_{id}] = \mathbb{E}[\rho_{id}] \equiv \bar{\kappa} \in [0,1].$$

Then

$$\begin{aligned}
\mathrm{Cov}(\Delta\text{Liquidity Shortfall}_{id},\ \text{Pix Usage}_{id}) &= \mathrm{Cov}(\rho_{id}\,\text{Pix Usage}_{id},\ \text{Pix Usage}_{id}) \\
&= \mathbb{E}\big[\rho_{id}\,\text{Pix Usage}_{id}^2\big] - \mathbb{E}\big[\rho_{id}\,\text{Pix Usage}_{id}\big]\,\mathbb{E}\big[\text{Pix Usage}_{id}\big] \\
&= \bar{\kappa}\left(\mathbb{E}\big[\text{Pix Usage}_{id}^2\big] - \mathbb{E}\big[\text{Pix Usage}_{id}\big]^2\right) \\
&= \bar{\kappa}\ \mathrm{Var}\big(\text{Pix Usage}_{id}\big)\ \geq\ 0\,,
\end{aligned}$$

with strict inequality whenever $\mathrm{Var}(\text{Pix Usage}_{id}) > 0$ and $\bar{\kappa} > 0$. Therefore

$$\begin{aligned}
\mathrm{Corr}(\Delta\text{Liquidity Shortfall}_{id},\ \text{Pix Usage}_{id}) &= \frac{\mathrm{Cov}(\Delta\text{Liquidity Shortfall}_{id},\ \text{Pix Usage}_{id})}{\sqrt{\mathrm{Var}(\Delta\text{Liquidity Shortfall}_{id})}\,\sqrt{\mathrm{Var}(\text{Pix Usage}_{id})}} \\
&> 0 \quad \text{whenever } \mathrm{Var}(\text{Pix Usage}_{id}) > 0 \text{ and } \bar{\kappa} > 0.
\end{aligned}$$

Therefore, when the extent of intraday liquidity recycling captured by ρ_{id} is not systematically affected by Pix Usage$_{id}$, Pix usage as the maximum incremental liquidity shortfall is also positively correlated with actual incremental liquidity shortfall. Under the worst-case timing (no liquidity recycling), $\rho_{id} \equiv 1$ and the correlation is trivially 1. More generally, since ΔLiquidity Shortfall$_{id} = \rho_{id}$Pix Usage$_{id}$ with $\rho_{id} \in [0, 1]$, any nonnegative association between ρ_{id} and Pix Usage$_{id}$ (in particular, mean independence) yields a positive correlation between Pix usage and incremental liquidity shortfall.

A.3 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

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

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

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

and consequently, the expected profit is

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

Define the survival probability function as

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

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

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

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

$$\frac{dx^*}{dt} = -\frac{\partial F/\partial t}{\partial F/\partial x} = -\frac{(1-pR)\frac{\partial S(x,t)}{\partial t} + [x + (1-x)pR - (1+(1+\alpha)r)]\,\frac{\partial^2 S(x,t)}{\partial x \partial t}}{2(1-pR)\frac{\partial S(x,t)}{\partial x} + [x + (1-x)pR - (1+(1+\alpha)r)]\frac{\partial^2 S(x,t)}{\partial x^2}}\,. \tag{A.10}$$

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.10) 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

$$u'(\alpha^*_{\text{ins}}) - (1+r)\, u'\Big((1-\alpha^*_{\text{ins}})(1+r)\Big) = 0\,. \tag{A.11}$$

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

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

Define the aggregate discounted utility from the delayed consumption as

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

Then, the household's expected utility is

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

and the corresponding FOC is

$$\frac{(T-\kappa)\delta^{\kappa}u'(\delta^{\kappa}\alpha^*_{\text{tra}})}{2(T-2)} + \mathbf{1}_{\{\kappa\geq 3\}} \sum_{\tau=2}^{\kappa-1} \frac{\delta^{\tau}u'(\delta^{\tau}\alpha^*_{\text{tra}})}{2(T-2)} + \frac{\delta\, u'(\delta\alpha^*_{\text{tra}})}{2} - (1+r)\, u'\Big((1-\alpha^*_{\text{tra}})(1+r)\Big) = 0\,. \tag{A.12}$$

To compare (A.11) and (A.12), define

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

Since

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

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

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

which implies that

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

Thus, the left-hand side of (A.12) 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

$$u'(\alpha^*_{\text{tra}}) - (1+r)\, u'\Big((1-\alpha^*_{\text{tra}})(1+r)\Big) > 0\,. \tag{A.13}$$

Comparing (A.13) with (A.11), 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: Fix the terminal portfolio share $x \in (0,1)$. Let the bank's promised repayment at date T be

$$D \;=\; (1-\eta)\big[1+(1+\alpha)r\big].$$

The risky loan payoff satisfies

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

where $R'(p) < 0$ and $\theta \sim U[0,1]$.

Conditional on loan success, the bank is solvent if and only if

$$x + (1-x)R(p)\theta \;\geq\; D.$$

Define the solvency cutoff $\theta^*(x,p)$ by the break-even condition

$$x + (1-x)R(p)\theta^*(x,p) = D,$$

which yields

$$\theta^*(x,p) = \frac{D-x}{(1-x)R(p)}. \tag{A.14}$$

Thus, conditional on loan success, the bank defaults if $\theta < \theta^*(x,p)$ and remains solvent if $\theta \geq \theta^*(x,p)$.

Under limited liability, bank equity receives a strictly positive payoff only in states in which the loan succeeds and $\theta \geq \theta^*(x,p)$. The bank's expected equity value is therefore

$$\Pi(x,p) = p \int_{\theta^*(x,p)}^{1} \Big[x + (1-x)R(p)\theta - D \Big] \, d\theta,$$

where we use that θ is uniform on $[0,1]$.

Positive equity value requires $\theta^*(x,p) \leq 1$. Using (A.14), this feasibility condition can be written as

$$R(p) \geq \frac{D-x}{1-x}. \tag{A.15}$$

Because R is strictly decreasing in p, equity prefers a lower p whenever doing so raises $R(p)$ without violating feasibility. Hence, equity maximizes value by choosing p such that (A.15) holds with equality, which implies

$$R\big(p^*(x)\big) = \frac{D-x}{1-x}. \tag{A.16}$$

Since R is strictly decreasing, (A.16) pins down a unique optimal risk choice,

$$p^*(x) = R^{-1}\Big(\frac{D-x}{1-x}\Big). \tag{A.17}$$

Define $\Psi(x) = \frac{D-x}{1-x}$. Then

$$\Psi'(x) = \frac{D-1}{(1-x)^2}.$$

Under the maintained condition $D > 1$, we have $\Psi'(x) > 0$. Since R^{-1} is strictly decreasing, (A.17) implies that $p^*(x)$ is strictly decreasing in x.

Proposition 1 shows that the instant payment system induces a higher optimal liquid asset share,

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

Since $p^*(x)$ is decreasing in x, we obtain

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

Finally, note that $D = (1-\eta)\big[1 + (1+\alpha)r\big]$ is strictly decreasing in η. Since $\Psi(x)$ is increasing

in D and R^{-1} is decreasing, it follows from (A.17) that for any fixed x, $p^*(x)$ is increasing in η. Moreover, because $\Psi'(x)$ increases in D, the sensitivity of $p^*(x)$ to x is larger when η is lower. Therefore, the difference $p^*_{\text{tra}} - p^*_{\text{ins}}$ increases as the bank equity ratio η decreases.

This completes the proof. □

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

$$(1 - x^*)\, R(p^*) \;=\; (1 - \eta)\left[1 + (1 + \alpha)r\right] \;-\; x^*\,, \tag{A.18}$$

which equates the marginal loan return to the bank's required repayment. Denoting the right-hand side of (A.18) by $D \equiv (1-\eta)\,[1+(1+\alpha)r]$ for brevity, we can rewrite (A.18) 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.18) between x and p. Totally differentiating (A.18) 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.18) simplifies this expression to

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

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.4 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

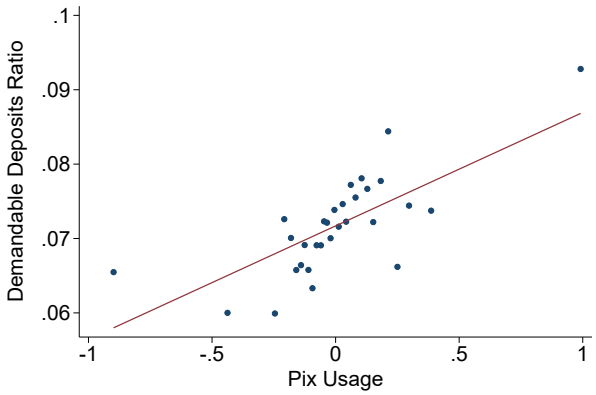
	Prime Loan Ratio		Sub-Prime Loan Ratio		Default Loan Ratio		Loan Loss Ratio	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pix Usage	-0.053**	-0.052**	0.055***	0.054***	-0.001	-0.000	0.007	0.007
	(0.024)	(0.024)	(0.014)	(0.014)	(0.005)	(0.005)	(0.006)	(0.007)
Bank Assets		0.035		-0.030		-0.004		-0.001
		(0.026)		(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

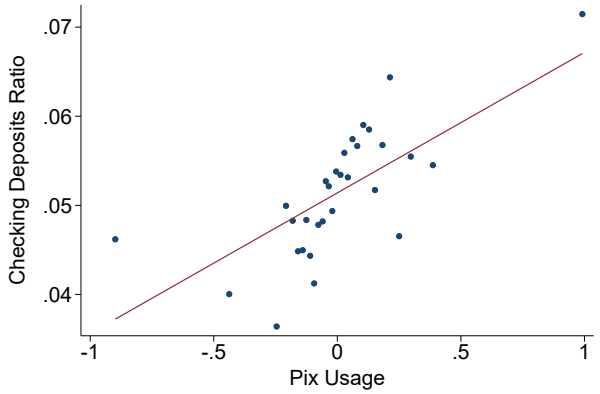
Figure 10: The Effect of Pix Usage on Deposit Ratios

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

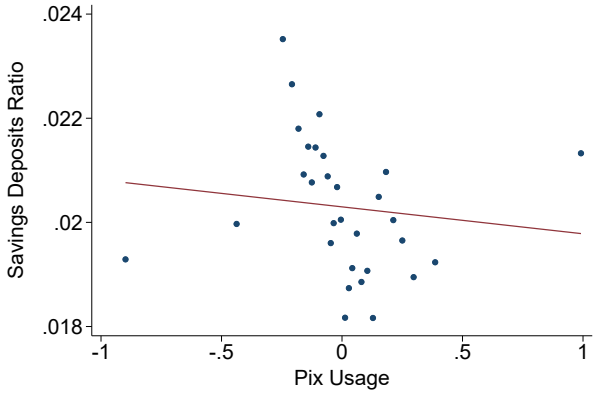
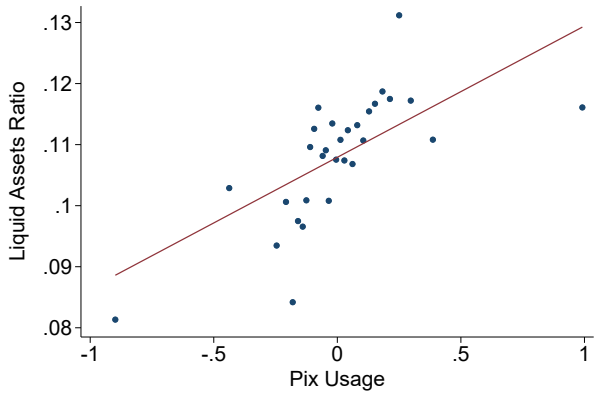


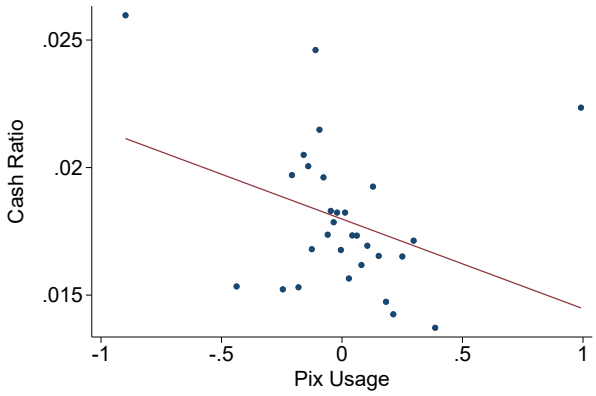
Figure 11: The Effect of Pix Usage on Asset Ratios

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.

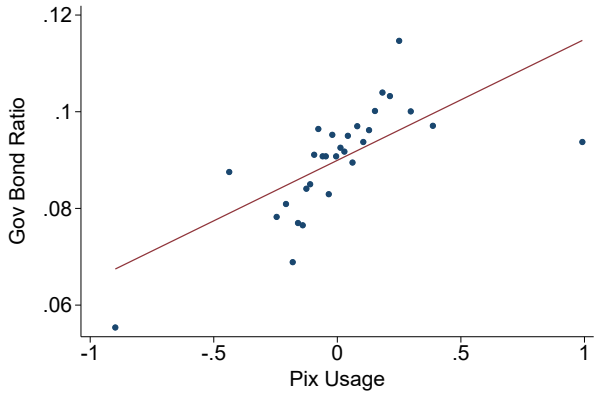
(a) Liquid Assets Ratio



(b) Cash Ratio



(c) Government Bond Ratio



(d) Loan Ratio

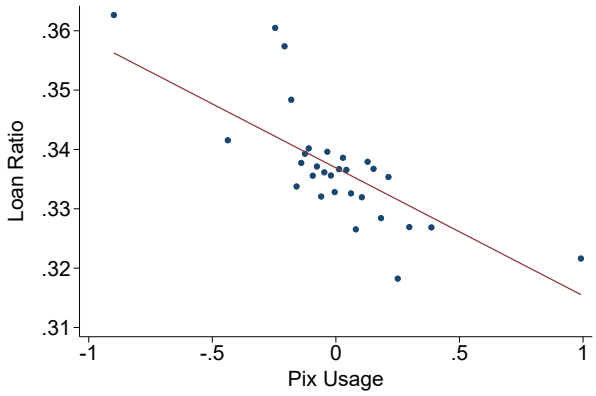
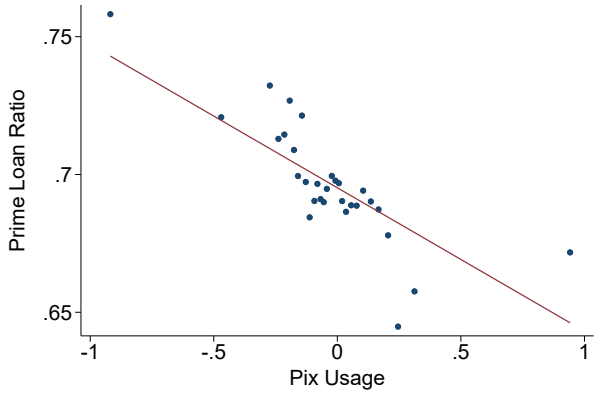


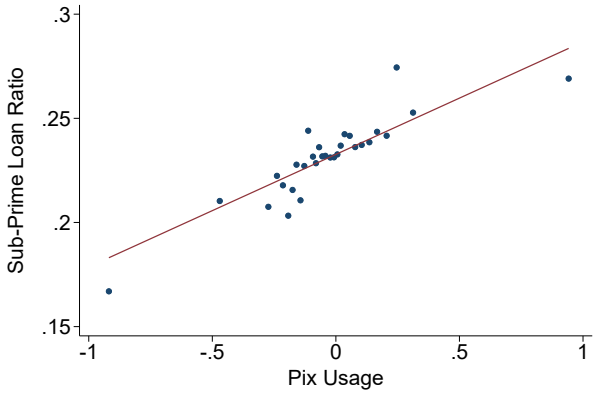
Figure 12: The Effect of Pix Usage on Bank Risk-Taking

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.

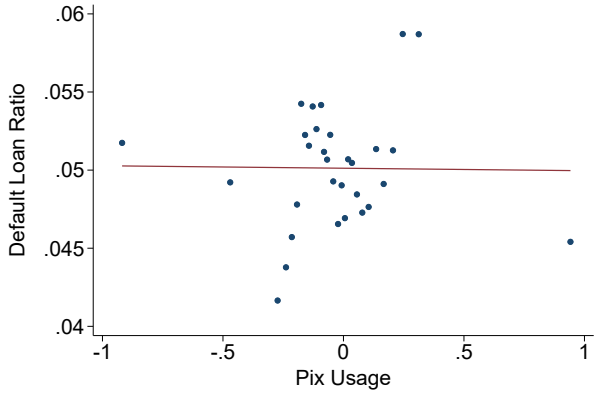
(a) Prime Loan Ratio



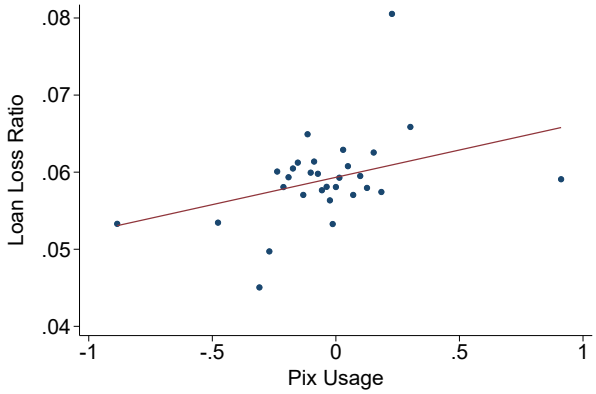
(b) Sub-Prime Loan Ratio



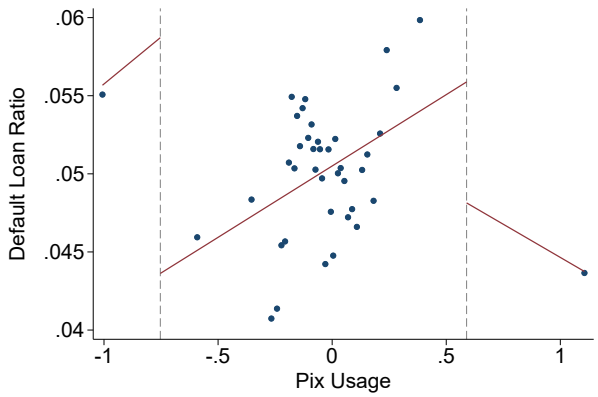
(c) Default Loan Ratio



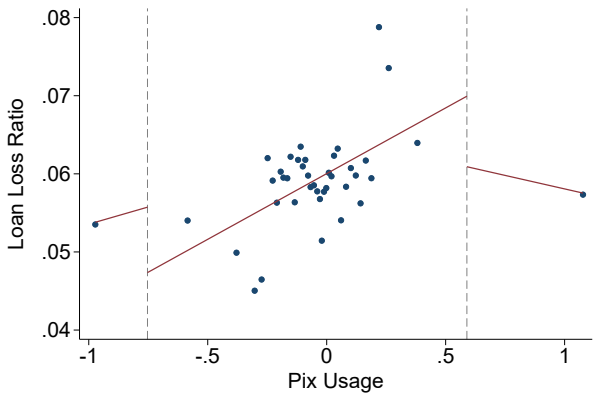
(d) Loan Loss Ratio



(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