

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

Rodrigo Gonzalez

Yiming Ma

Yao Zeng

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## Abstract

We show that the introduction of instant payments may have the unintended consequences of constraining liquidity transformation and incentivizing risk-taking by banks. Using administrative banking data and transaction-level payment data from Brazil's Pix, one of the most widely adopted instant payment systems, we find that the use of instant payments led to an increase in banks' liquid asset holdings and a rise in their share of defaulting loans. We establish the causal relationship by constructing a novel instrument based on passive payment timeouts. These findings arise because the convenience of instant payments to consumers comes at the expense of banks' ability to delay and net payment flows. The inability to delay payments increases banks' demand for holding liquid assets over transforming illiquid ones, lowers their profitability per unit equity, and exacerbates their risk-taking incentives. Our findings bear important financial stability implications in light of the global surge in adopting instant payment systems, e.g., FedNow in the US.

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

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\*Gonzales is at the Central Bank of Brazil. Ma is at Columbia Business School. Zeng is at the Wharton School, University of Pennsylvania. The views expressed in this research does not represent views by the Central Bank of Brazil.

# 1 Introduction

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

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

In this paper, we provide the first evidence that instant payments may have the unintended consequences of constraining bank liquidity transformation and incentivizing bank risk-taking. Using administrative data on Brazil’s Pix, one of the most widely and successfully adopted instant payment systems, we document that the use of instant payments correlates with banks’ increased allocation towards liquid assets, such as government bonds, and a higher incidence of defaults on bank loans. We confirm that the observed relationship is causal by constructing a novel Bartik-style instrument based on passive payment timeouts. Our timeout instrument leverages the payment network structure to capture the variation in a bank’s unsuccessful payments that are due to the technological failure of their counterparty banks.

Economically, our findings arise because depositors’ benefit of immediate payment availability inadvertently imply a loss in banks’ autonomy in managing the timing of their payments. As our model shows, this reduced capacity to delay and net payments renders banks more exposed to the volatility of payment shocks, which induces them to hold a larger proportion of liquid asset buffers and a smaller fraction of illiquid assets. Banks are effectively becoming “narrower” and less profitable per unit funding. To make up for the lost profitability, banks are more incentivized

to take on credit risk due to a classic asset substitution problem, leading to potentially heightened financial stability risks despite a lower capacity for liquidity transformation.

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

Our empirical analysis mainly leverages two key administrative datasets from the Central Bank of Brazil. First, we use transaction-level Pix data to measure the extent of Pix usage for each bank. This data also records transactions that are unsuccessful and whether the timeout was due to the sending or receiving bank. We will use this information on failed timeouts to construct an instrument for Pix usage in our empirical analysis. Second, we use monthly balance sheet and income statement data for commercial banks and credit union from the regulatory version of ESTBAN,<sup>1</sup> the Brazilian counterpart of the Call Reports.

We uncover several novel stylized facts about the response of the Brazilian Banking system in response to the introduction of instant payments. We measure pix usage by the overlap between a bank's gross Pix sent and gross Pix received in a month divided by its total assets. Pix usage thus captures the turnover of Pix payments per unit bank size and reflects how actively Pix is used by a bank's customers.

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

We further find that banks with higher Pix usage cut down on their lending to other banks,

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<sup>1</sup>We use the version consolidated at the conglomerate version to correctly account for lending recorded by different subsidiaries within the same conglomerate. We also supplement our analysis with fees data on different products offered by banks.

while borrowing more in wholesale funding relative to other banks after the introduction of Pix. These observations are indeed consistent with rising deposit volatility because wholesale borrowing can supply liquidity on short notice, whereas lending out to other banks drains bank liquidity.

On the asset side, we find that banks with more Pix usage also increased their ratio of liquid assets by more, especially in the form of government bonds. One likely interpretation is that banks set aside these government bonds as precautionary liquidity buffers that can be deployed in the case of unanticipated payment demand shocks.

Finally, we find that banks with more Pix usage take on more credit risk in their portfolios. Our results on risk-taking are robust both in terms of the ratio of loan loss provisions as well as the ratio of loans in default where one or more payments are late by at least 90 days. Our model uncovers an intricate connection between Pix usage and risk-taking, where risk-taking is amplified to offset the loss in profitability from increased liquid asset holdings and wholesale funding following the introduction of instant payments.

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

On the liability side, deposits are a means of payment for depositors, subjecting the bank to random deposit flows, as in [Bolton, Li, Wang, and Yang \(2020\)](#) and [Jermann and Xiang \(2023\)](#). Specifically, depositors with unpredictable payment needs may choose to deposit their funds with the bank or invest in an outside option for a higher return without payment services. Most importantly, our model incorporates the introduction of instant payments, which requires the bank to settle payments without delays. Consequently, the bank provides greater payment convenience for its depositors at the expense of forgoing the ability to delay and net payment flows.

Our model makes three main predictions about the effects of fast payment systems on the bank's liquidity transformation and its risk-taking behaviors. First, as instant payment services improve the convenience of deposits through removing banks' ability to delay payments, they

also expose banks to more uncertainty in deposit flows.

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

Third, as the bank transforms less liquidity, the classic asset substitution problem arises from the agency conflict between debt and equity holders at the bank. The lower return on liquid asset holdings and the higher cost of wholesale funding cut into the bank's profits per equity share, which reduces equity holders' residual claims. Consequently, the bank takes on more credit risk in its lending than in a first-best scenario without agency conflicts.

To verify the model predictions on the impact of Pix usage on the banking system, we need to overcome the identification challenge that Pix usage may be correlated with observable and unobservable bank characteristics that also affect the composition of their balance sheets over time. To this end, we construct a novel instrument for Pix usage using transaction timeouts. The basic idea of our instrument is that the availability of Pix is only relevant if Pix payments are successfully sent by the sending bank and then successfully received by the receiving bank. If either the sending bank or the receiving bank fails to process the payment within a given time period, the payment attempt is unsuccessful and deemed as timeout by the Pix system. The convenient feature of Pix payments is lost in the case of a timeout and banks that experience more frequent timeouts should therefore have less Pix usage.

Although timeouts are for the most part driven by unexpected technical issues in banks' payment systems banks may still have some control over the speed and ability to resolve them. To this end, we construct our timeout instrument for a given bank  $i$  in month  $t$  only using variation in timeouts induced by other banks. This includes timeouts due to receiving banks if bank  $i$  is the sending bank in the transaction as well as timeouts due to sending banks if bank  $i$  is the receiving bank in the transaction. In both cases, the attractiveness of bank  $i$ 's Pix service is reduced, but bank  $i$  cannot actively fix the problem. Formally, we define the timeout instrument for bank  $i$  in month  $t$  as the weighted passive timeout probability due to its sending banks plus the weighted passive timeout probability due to its receiving banks, where the weights are the

fraction of transactions sent to and received by bank  $i$  from each counterparty bank, respectively. The identifying assumption is that these passively induced timeouts due to other banks do not affect bank  $i$ 's decisions over its balance sheet composition through channels other than bank  $i$ 's Pix usage.

After confirming that our timeout instrument is indeed negatively affecting Pix usage in the first stage, we use it to instrument for Pix usage to estimate the causal effect of Pix usage on banks' liability structure, asset composition, and risk-taking. Our sample period is from November, 2020 to January, 2023. We include controls for the value of each dependent variable before Pix in October, 2020, controls for other bank-level characteristics like capital ratio and expense ratio, and time fixed effects.

Our estimation results confirm the model predictions. First, we find that a one-standard deviation increase in Pix usage leads to a 1.5 to 1.9 standard deviation increase in the ratio of checking deposits, consistent with the increased convenience of payments making demandable deposits especially attractive. As our model shows, this increased convenience to depositors comes at the expense of banks losing their ability to delay payments, which exposes banks to unexpected funding shocks. Empirically, we find that Pix causes banks to increase their interbank borrowing and decrease their supply of liquidity to other banks, which are actions consistent with preserving more liquidity to prepare for volatile payment shocks.

Our empirical estimates also confirm that Pix usage increases the proportion of liquid asset buffers. A one-standard-deviation increase in Pix usage causes a 1.5 standard deviation increase in liquid assets as a proportion of bank assets. This increase in liquid assets primarily comes from government bond holdings rather than from cash holdings. This is likely because government bonds better reflects the ex-ante liquid asset holdings in the model, whereas the realized level of cash depends on both the ex-ante amount set aside and the amount used up at a given point in time.

Finally, we show that Pix usage exacerbates risk-taking in lending, as our model predicts. We find that a one-standard-deviation increase in Pix usage causes a 0.2 to 0.3 standard deviation increase in the ratio of loan loss allowances, which is an ex-ante forward-looking measure of risk-taking. We also find that a one-standard-deviation increase in Pix usage causes a 0.2 standard deviation increase in the ratio of defaulting loans, which captures the realization of risk-taking.

Our findings bear important implications regarding the funding costs of banks and the finan-

cial stability risks of the banking system as a whole. It is well known that banks' business model in liquidity transformation and lending depend critically on stable deposit funding (e.g., [Hanson, Shleifer, Stein, and Vishny 2015](#), [Drechsler, Savov and Schnabl 2017](#), [Egan, Lewellen, and Sunderam 2022](#)), while panic runs are largely viewed as the top threat to this business model (e.g., [Diamond and Dybvig 1983](#), [Egan, Hortacsu and Matvos 2017](#)). Complementing this perspective, our research offers a new framework, highlighting the role of deposits as a means of payment in tranquil times. As the demand for payment convenience becomes higher, banks face a more challenging liquidity management problem (e.g., [Parlour, Rajan and Walden 2020](#), [Li and Li 2021](#), [Afonso, Duffie, Rigon and Shin 2022](#), [Lopez-Salido and Vissing-Jorgensen 2023](#)). Our paper shows that the implications go a long way to affect banks' core business, resulting in potentially less liquidity transformation but higher financial stability risks.

**Related Literature.** Our paper contributes to several branches of the literature on banking, money, and payments. First, our paper is closely related to the literature on bank liquidity transformation ([Diamond and Dybvig, 1983](#), [Allen and Gale, 2000](#), [Diamond and Rajan, 2005](#), [Goldstein and Pauzner, 2005](#)). Particularly focusing on the relationship between payments and lending, [Freixas, Parigi and Rochet \(2000\)](#), [Donaldson, Piacentino and Thakor \(2018\)](#), [Bolton, Li, Wang, and Yang \(2020\)](#), [Parlour, Rajan and Walden \(2020\)](#), and [Jermann and Xiang \(2023\)](#) theoretically show that payment risks lead to inefficient and unstable bank lending through banks' liquidity management.<sup>2</sup> The empirical literature has also studied interbank payments and explored its consequences on financial fragility (e.g., [McAndrews and Potter, 2002](#), [Bech and Garratt, 2003](#), [Afonso and Shin, 2011](#), [Copeland, Duffie and Yang, 2020](#), [Afonso, Duffie, Rigon and Shin, 2022](#)). Among them, [Li and Li \(2021\)](#) consider the setting of Fedwire, the predominant inter-bank payment system in the US, and show that an increase in payment risk is associated with a decline in loan growth, which is further amplified by funding stress and which is stronger for undercapitalized banks. Our key contribution to this literature is to link bank liquidity transformation to instant payments, one of the latest and most important innovations in shaping the role of bank deposits as a mean of payment.

Our paper also contributes to the literature of money and payments (see [Kahn and Roberds, 2009](#), for an early review). On the microeconomic side, this literature has extensively studied

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<sup>2</sup>Another related literature focuses on bank liquidity management due to uncertainty, asymmetric information, or counterparty risks (e.g., [Caballero and Krishnamurthy, 2008](#), [Allen, Carletti and Gale, 2009](#), [Acharya and Skeie, 2011](#), [Gale and Yorulmazer, 2013](#), [Heider, Hoerova and Holthausen, 2015](#)).

the fast development of new payment technologies in the last decade. Recent empirical literature shows that new payment technologies improve economic efficiencies in consumption, investment, and lending decisions (e.g. [Jack and Suri, 2014](#), [Muralidharan, Niehaus, and Sukhtankar, 2016](#), [Higgins, 2020](#), [Ghosh, Vallee, and Zeng, 2022](#)) without examining the financial stability implications. Recently, two notable studies consider two of the fastest-growing instant payment systems, India's UPI ([Dubey and Purnanandam, 2023](#)) and Brazil's Pix ([Sarkisyan, 2023](#)), showing that instant payment systems help even the playing field between large and small banks by universally increasing the payment convenience of deposits for all banks. We contribute to this literature by focusing on the impact of instant payment systems on the business model of banking: they may make banks "narrower" in terms of less liquidity transformation while riskier in terms of taking excessive risks in lending.

A burgeoning literature, partly motivated by the regional bank crisis of 2023 in the US, show that deposits at more digital banks are typically more flighty (e.g., [Benmelech, Yang, and Zator, 2023](#), [Erel, Liebersohn, Yannelis, and Earnest, 2023](#), [Jiang, Yu, and Zhang, 2023](#), [Koont, 2023](#), [Koont, Santos, and Zingales, 2023](#)). Our paper offers one precise economic foundation for these observed effects of bank digitalization at the bank level: deposits at more digital banks tend to serve as a more convenient means of payment. In this aspect, we particularly highlight the impact of payment flows on banks' funding risk.

Finally, the macroeconomic literature has increasingly and explicitly incorporated the payment role of money and payment risks, demonstrating their significant impact on macroeconomic outcomes and optimal policy design (e.g., [Lagos and Wright, 2005](#), [Lagos and Zhang, 2020](#), [Bianchi and Bigio, 2021](#), [Piazzesi, Rogers and Schneider, 2021](#), [Piazzesi and Schneider, 2021](#), [Bigio, 2022](#), [Bigio and Sannikov, 2023](#)). Focusing on the development of instant payments and linking it to risks in the banking sector, our paper offers a microeconomic perspective to shed light on broader macroeconomic implications of the potential of next-generation payment systems including fast payment systems, stablecoins, and central bank digital currencies (CBDCs), as discussed by [Brunnermeier, James and Landau \(2019\)](#) and [Duffie \(2019\)](#).



## 2 Institutional Setting and Data

### 2.1 Instant Payment Systems and Pix

Instant payment systems represent a global evolution in financial transactions, functioning as broadly accessible Real-Time Gross Settlement (RTGS) bank-railed systems that operate 24/7. This infrastructure enables instantaneous transactions between individuals across any day or time, provided their banks grant interoperable access to these systems. Unlike traditional payment technologies, instant payment systems facilitate instant transfers between parties at any time, provided their banks are interconnected through these platforms. They are pivotal in updating the mechanics of payments to align with the immediate transaction needs demanded by the digital economy. Various central banks also view instant payments as a building block for the modernization of the financial ecosystem. About 100 jurisdictions have introduced instant payments, and several others have announced plans to go live soon.<sup>3</sup>

The adoption and economic impact of these systems vary worldwide, with Pix standing out for its notable success. Pix, the instant payment system introduced by the Central Bank of Brazil, enables instant, around-the-clock payments between individuals, businesses, and government entities without the fees commonly associated with traditional banking services. Pix's success is largely attributed to its real-time banking infrastructure and user-friendly design, which includes an innovative alias resolution service. This feature allows users to make payments using simple identifiers, such as phone numbers, significantly simplifying and enhancing the user experience for daily financial activities. Moreover, the Central Bank of Brazil mandated that all banking customers must have access to Pix through applications that adhere to common standards, promoting universal access and integration within the Brazilian financial ecosystem. Within just two years of its launch, Pix saw an adoption rate unparalleled by any other payment system, with more than 150 million users in its first year alone. Currently, nine out of ten small businesses in Brazil utilize Pix, and the volume of transactions continues to grow.<sup>4</sup>

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<sup>3</sup>See <https://fastpayments.worldbank.org/resources#block-homenav>.

<sup>4</sup>See more details at: <https://blogs.worldbank.org/voices/fast-payments-offer-potential-faster-digital-financial-inclusion-and-faster-growth>.

### **2.1.1 Comparison to the US: Fedwire and FedNow**

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

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

## **2.2 Data**

Our analysis leverages several regulatory datasets from the Brazilian Central Bank. First, we use transaction-level Pix data to measure the extent of Pix usage and to construct our timeout instrument. For each transaction, we observe the time, amount, sending and receiving banks, and identifiers for whether the sender and receiver are individuals or firms. Importantly, failed transactions, called timeouts, are also recorded, including whether the timeout was due to the sending or receiving bank. We use the amount of successful Pix payments sent to capture banks' Pix usage, while we use the information on failed transactions to construct an instrument for Pix usage.

Second, we use monthly bank balance sheet and income statements from ESTBAN. We use the version that is consolidated at the conglomerate level because some banks record their loans and other assets to specific subsidiaries within the conglomerate. We limit our sample to commercial banks and credit unions because they engage in both deposit-taking and lending. We make use of the regulatory version of ESTBAN, which includes more granular breakdowns of

banks' assets, liabilities, default risk, income, and expenses.

Collectively, our data provide a comprehensive and in-depth picture of the development of the banking sector following the implementation of Pix. Our sample is from January, 2016 to January, 2023, although our main sample for observing the effect of Pix starts from the implementation in November, 2020 to January, 2023. Table 1 provides summary statistics for our sample of banks and their Pix usage.

### 3 Stylized Facts

We first show several novel stylized facts about the banking sector's response to Pix. To do so, we sort banks into quartiles of Pix usage and compare how the balance sheets of each quartile evolved after the introduction of Pix in November, 2020. Pix usage is defined as the overlap between a bank  $i$ 's gross Pix sent and gross Pix received in month  $t$  divided by that bank's total assets:

$$PixUsage_{it} = \frac{\min(PixSent_{it}, PixReceived_{it})}{TotalAssets_{it}}. \quad (3.1)$$

Intuitively, Pix usage captures the amount of turnover of Pix payments per unit bank size. The higher the Pix usage, the more actively a bank's customers send and receive instant payments and, potentially, the more that bank is exposed to payment shocks without the ability to delay relative to its asset size. In our measure of Pix usage, 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.<sup>5</sup>

We then sort banks into quartiles according to their Pix usage near the end of our sample in December, 2022 and plot the average monthly Pix usage for each quartile in Figure 1. First, we observe that average Pix usage in each quartile persistently follows the same order throughout the sample period as the one in December, 2022. In other words, banks that had higher Pix usage right after the introduction of Pix also had higher Pix usage about two years afterwards.<sup>6</sup> Second, we find that although Pix usage is generally trending up over time, there is substantial variation

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<sup>5</sup>In our empirical specifications, we include net Pix flows as a control variable and show that the effect of pix usage remains robust.

<sup>6</sup>In fact, we could have defined quartiles based on a different date in our sample and the results in this section would have looked very similar.

in the cross-section.

The remainder of this section shows how the liabilities, assets, and risk-taking of banks in each quartile evolves following the introduction of Pix. Of course, banks are not sorted into quartiles at random and banks in each quartile may have other observable and unobservable characteristics that affect the outcome variables we examine. That is why the following results are preliminary evidence that are not meant to be causal. In Section 5.3, we more formally estimate the effect of an instrumented version of Pix usage on the same outcome variables and find that most of the findings in this section remain.

### **3.1 Effects on Deposit Structure**

We first analyze how the structure of deposit funding has changed for banks. In practice, demandable deposits, including savings and checkings deposits, can be used to send Pix payments instantly without restrictions. Time deposits, however, cannot be withdrawn before maturity without incurring a penalty and are thus less compatible with making payments through Pix. In fact, funds withdrawn from time deposits would first enter a checkings account before being usable for making Pix transfers. Therefore, we would expect that checking deposits become more attractive to investors with more Pix usage.

Figure 2a plots the average ratio of demandable deposits by quartile of Pix usage. Indeed, banks in the fourth quartile of Pix usage have a significant bump in their share of demandable deposits relative to banks in other quartiles. At the same time, Figure 2b shows banks in the fourth quartile also experience a relative decline in the ratio of time deposits. These findings are consistent with the introduction of Pix making demandable deposits more attractive because they can be used in instant payments without the restrictions of time deposits. From the perspective of the bank, however, a rise in the share of demandable deposits coupled with depositors' ability to send instant payments using demandable deposits may imply a rise in funding volatility.

### **3.2 Effects on Wholesale Lending and Borrowing**

One way banks can offset shocks to their deposit funding is through borrowing on the wholesale market. In this sense, banks whose deposit funding becomes more volatile may also increase their interbank borrowing by more. Echoing this idea, we see from Figure 4b that banks in the

fourth quartile of Pix usage also experienced a jump in wholesale funding relative to banks in the other quartiles.

At the same time, we observe from Figure 4a that banks consistently cut down on their lending to other banks following the introduction of Pix, with interbank lending by banks in the fourth quartile of Pix usage falling to the lowest level at the end of the sample. In contrast to interbank borrowing, interbank lending is a drain on liquidity so the drop in lending is consistent with banks' funding liquidity becoming more unpredictable. Similar to the US, interbank lending in Brazil is mostly in the form of short-term repos. But even with overnight repos, the lending bank effectively loses access to its funds until the next day, which can be very costly given that Pix allows for instant payments and thereby eliminates banks' ability to net incoming and outgoing payment shocks within the day.

### 3.3 Effects on Asset Composition

Another way banks can prepare for funding shocks is through altering their asset composition. In particular, banks that expect to face higher funding volatility can set aside liquid assets that can be converted into cash to meet payment demand upon short notice.

In Figure 3a, we see that the ratio of liquid assets as a proportion of total assets increases by more for banks with more Pix usage. Interestingly, the increase in liquid assets for these banks is primarily driven by an increased holding of government bonds, as evident from Figure 3b; while banks' holding of cash and cash equivalents does not show any persistent upward or downward trends following the implementation date of Pix, as seen from Figure 3c.

One likely interpretation is that government bonds are liquid assets that banks set aside in preparation for meeting future liquidity shocks so the higher proportion of government bonds is consistent with a higher level of precautionary liquid buffers. The level of cash at any given instant, on the other hand, depends on how many outgoing payments have been made, how many incoming payments have been received, as well as how much cash has been set aside. In other words, its level does not only indicate how much has been set aside but reflects the combination of various payment demands as well. In fact, taking a closer look at Figure 3c, we observe that the cash ratio of banks in the fourth quartile of Pix usage rises the most in anticipation of Pix and then experiences the largest volatility after the implementation. This observation is consistent with these banks setting aside more cash to prepare for the effect of Pix and then using the prepared

cash to meet their payment demands that have become more volatile after the introduction of Pix.

### 3.4 Effects on Bank Risk-Taking

Another important dimension of the banking system is the extent of risk-taking. In this regard, we find that Pix usage is associated with heightened risk-taking. Figure 5a shows the proportion of loan loss allowances banks set aside as a proportion of their loans. We observe that following the implementation of Pix, banks in the third and fourth quartiles of Pix usage experience an increase in loan loss provision ratios while those in the first and second quartile experience a drop.

While loan loss provisions are an ex-ante forward-looking way to gauge risk-taking, it may not fully correspond to the actual extent of risk-taking that realized ex post. That is why we further examine how the proportion of defaulting loans changes over time, where we measure loans in default following the official definition defined of loans with one or more payments late by 90 or more days. From Figure 5b, we observe that banks in the third and fourth quartiles of Pix usage also saw an increase in the ratio of defaulting loans over time, while loan defaults decreased for banks with less Pix usage over the same time period. There is some lag in the onset of this trend but it becomes increasingly pronounced over time, consistent with loan defaults taking time to realize. This result confirms that banks with more Pix usage also took on more risk in their loan portfolios.

The connection between Pix and risk-taking may appear less direct than the changes in asset and liability compositions that we discussed above. In the model, we will show that the increase in risk-taking materializes exactly because of the aforementioned changes in bank assets and liabilities. Specifically, we show that banks who have to rely on more expensive wholesale funding and set aside more low-yielding liquid assets to compensate for a more volatile deposit funding base are incentivized to make up for the lost profits through taking on more credit risk in their portfolios.

## 4 Model

In this section, we introduce a simple model along the lines of [Bolton, Li, Wang, and Yang \(2020\)](#), [Parlour, Rajan and Walden \(2020\)](#) and [Jermann and Xiang \(2023\)](#) to help reconcile the stylized facts and generate further empirical predictions, focusing on the effects of instant payments and

bank liquidity transformation and risk-taking. We intentionally keep the model stylized to reflect what we observe in the data.

Time is continuous. There is a competitive bank, whose deposits provide payment service, which we elaborate shortly below, and a competitive non-bank that serves as an outside option for storing wealth. Note that modeling the bank and non-bank as competitive doesn't imply they process zero market power in reality; what is crucial is that the bank provides payment service that the non-bank cannot provide, which just the difference between interest rates offered by the bank and non-bank. Specifically, we assume that each unit of deposit at the bank delivers an exogenous service flow at the rate of  $\kappa > 0$  to its depositor, capturing such payment convenience. To focus on liquidity transformation and lending, we also assume the interest rate  $r$  offered by the bank and non-bank to be  $r_b$  and  $r_n$ , with  $r_b < r_n$ , capturing non-banks such as money market funds typically offering higher expected returns compared to bank deposits.

The bank is financed by three types of liabilities: deposits, wholesale funding sources, and equity. For simplicity, we assume the equity ratio of the bank,  $\eta$ , and the wholesale funding rate,  $r_w$ , to be exogenous, with  $r_b < r_w$ . We also assume perfectly elastic supply of wholesale funding to the bank, capturing the relative scarcity of deposits. The bank decides for its capital structure at  $t = 0$ , where  $(d_0, w_0)$  capture the liability ratios of deposits and wholesale funding, respectively, with  $d_t + w_t = 1 - \eta$  for any  $t \geq 0$ .

At the same time, the bank makes its investment decision at  $t = 0$ , and it can choose a portfolio between a liquid, safe asset and an illiquid, risky asset, where the portfolio weights are  $(x, y)$  with  $x + y = 1$ . The liquid asset delivers a normalized return rate of 1, while the illiquid asset's return rate  $\gamma_t$  follows a Brownian motion  $\gamma_t = \sigma(d_t + dB_t)$ , where  $B_t$  is a standard Brownian motion. The illiquid asset is illiquid in the sense that only  $1 - \phi$ ,  $\phi > 0$ , fraction of it will be recovered if converted into the liquid asset. The bank can also choose  $\sigma > 0$  at  $t = 0$ , which determines the riskiness of the illiquid asset. Particularly, by construction, a riskier asset also delivers a higher return, capturing a notion of liquidity premium.

There is a continuum of households with utility  $u(\alpha_i \kappa, r)$ , which is increasing and concave in both arguments, where  $\alpha_i$  captures household  $i$ 's preference for the payment service and follows a distribution with support  $(0, \bar{\alpha})$ , where  $\bar{\alpha}$  is sufficiently large. Intuitively, this utility function parsimoniously captures households' required payment need, with a lower  $\alpha$  indicating a higher required payment demand. Specifically, each household  $i$ , if banking with a bank and becoming

a depositor, is subject to a consumption shock which requires her to withdraw her deposits and which takes place following an i.i.d. Poisson clock with a rate  $\lambda_i > 0$ , where  $\lambda_i$  decreases in  $\alpha_i$ . Each household is endowed with a normalized wealth at  $t = 0$  and makes an independent decision of whether banks with the bank or invests in the non-bank, where the non-bank delivers a convenience of  $\kappa = 0$ .

As a benchmark, we first present a lemma showing that a cutoff equilibrium exists in the sense that agents which sufficiently high payment need bank with the bank:

**Lemma 1.** *There exists a cutoff equilibrium in which households with  $\alpha > \alpha^*$  depositing their wealth with the bank. The bank optimally holds a positive share of liquid asset  $x^* > 0$  and a positive wholesale funding ratio  $w^* > 0$ , and takes optimal level of risk  $\sigma^* > 0$ .*

Lemma 1 has a simple interpretation of banks' business model of liquidity transformation. As long as a bank has access to deposit funding and deposits process service value to depositors, the bank optimally conduct liquidity transformation in the sense that it invests in relatively riskier, illiquid assets. At the same time, it also optimally holds liquid buffers and tap the wholesale funding market to compensate for the funding risks it bears due to the endogenous payment functions. Consistent with the ideas outlined in [Bolton, Li, Wang, and Yang \(2020\)](#), [Parlour, Rajan and Walden \(2020\)](#) and [Jermann and Xiang \(2023\)](#), such funding shocks stemming from deposits' payment function may ultimately limit the bank's capacity in conducting efficient liquidity transformation.

With this in mind, we now summarize the main theoretical results in the following proposition:

**Proposition 1.** *When deposits become more convenient in terms of its payment function, that is, when  $\kappa$  increases:*

- i). the bank attracts more depositors, that is,  $\alpha^*$  decreases;*
- ii). the bank increases its holdings in the liquid asset and its wholesale funding ratio, that is,  $x^*$  and  $w^*$  increase; and*
- iii). the bank increases its risk-taking, that is,  $\sigma^*$  increases.*

We elaborate on the three results that concern three principal impacts that fast payment systems have on a bank's liquidity transformation and its propensity for taking risks. Initially, the



enhancement of deposit utility by instant payment services, due to the removal of the banks' discretion to delay payments, directly leads to a significant increase in the unpredictability of deposit inflows and outflows. This unpredictability can complicate the bank's cash flow management and necessitate a more cautious approach to balancing assets and liabilities.

In response to this amplified volatility in deposit funding, banks are inclined to take preemptive action by augmenting their reserves of liquid assets. This strategy is intended to mitigate the potential need for a distress sale of illiquid loans in the event of unanticipated payment demands. Moreover, to further cushion their positions, banks incrementally increase their use of wholesale funding. This reliance on external funding can be seen as a balancing act to counter any adverse effects on the bank's portfolio of long-term, illiquid loan investments. The overarching effect is a banking system that becomes inherently more cautious, with a greater emphasis on immediate liquidity over long-term investments, leading to a 'narrower' banking model characterized by a reduced scope of liquidity transformation activities.

Lastly, with a decrease in liquidity transformation, we observe the emergence of a classic dilemma known as the asset substitution problem. This issue stems from the agency conflict between the bank's debt holders and equity holders. The dynamics of a narrow bank holding more liquid and less profitable assets, combined with the heightened expenses associated with wholesale funding, results in a compression of the bank's equity margins. This reduction in profitability impacts the residual claims of equity holders, who are left with a smaller slice of the profit pie. In an effort to counterbalance these lower returns and the pressure of increased funding costs, the bank may be driven to adopt a more aggressive credit risk profile. It might start extending loans to borrowers with higher default risks or investing in high-yield, high-risk securities, moves that would not align with a first-best, conflict-free banking environment. This shift in the bank's risk-taking behavior has far-reaching implications, potentially affecting not only its own stability but also the broader financial system's health, especially in times of economic stress.

## **5 Empirical Analysis**

In this section, we formally estimate the relation between Pix usage and the funding structure, asset composition, and risk-taking of the banking sector. We first present our baseline results on the effect of Pix usage in the presence of control variables and fixed effects. Then, we further

use an instrument for Pix usage to estimate its causal effect on bank assets and liabilities by two-stage least squares. Using both approaches, we find that Pix usage increases banks’ (1) reliance on demandable deposits and wholesale funding, (2) liquid asset holdings, and (3) risk-taking. These findings are consistent with and corroborate our preliminary evidence in Section 3 and our model predictions in Section 4.

## 5.1 Baseline Specification

Our baseline analysis relates Pix usage for bank  $i$  in month  $t$  to various outcome variables of bank  $i$  in month  $t$ :

$$OutcomeVar_{it} = \beta PixUsage_{it} + Controls_{it} + PrePixOutcomeVar_i + \omega_t + \epsilon_{it}, \quad (5.2)$$

where  $PixUsage_{it}$ , captures the amount of Pix payment turnover per unit bank size and is defined as in equation (3.1). For each outcome variable, we control for its value before the introduction of Pix in October 2020 using  $PrePixOutcomeVar_i$ . Other control variables at the bank-month level include Time Deposit Spread, which is the time deposit rate minus the monetary policy rate, Service Fee Ratio, which is the proportion of banking service fees as a proportion of total income, Non-Deposit Expense Ratio, which is the proportion of non-deposit expense as a fraction of bank assets, and Capital Ratio, which is the proportion of bank equity as a fraction of bank assets. We also control for the net monthly inflow or outflow of Pix payments per unit bank size, Net Pix Uptake. We include these control variables in the hopes that they absorb time-varying heterogeneity in banks that may also affect the outcome variables. We further include time fixed effects to absorb aggregate shocks and a bank-type fixed effect to filter out shocks specific to commercial banks and credit unions. As mentioned, our sample is from November, 2020 to January, 2023.

## 5.2 Instrumental Variable Specification

Despite the use of control variables and fixed effects, readers may still worry that there are unobserved characteristics of banks that affect their Pix usage as well as the composition of their assets and liabilities over time. To this end, we further repeat our estimation using an instrumental variable approach to isolate plausibly exogenous variation in Pix usage.

The basic idea of our instrument is that the availability of Pix is only relevant if Pix payments are successfully sent by the sending bank and then successfully received by the receiving bank. If either the sending bank or the receiving bank fails to process the payment within a given time period, the payment attempt is unsuccessful and deemed as timeout by the Pix system. The sender will be notified and asked to re-attempt the payment at a later time. Even if successful on a later attempt, the instantaneous and convenient feature of Pix payments is lost to both the sender and receiver in the case of a timeout. Banks that experience more frequent timeouts should therefore be less able to adopt Pix efficiently.

We will use variation in timeouts to construct our instrument. What drives the variation in timeouts? Our conversations with the Pix operations team at the Bank of Brazil reveal that timeouts are for the most part driven by technical errors in the banks' payment system that cannot be easily anticipated. Nevertheless, we were told that the speed at which banks can resolve these technical errors varies. For example, some banks may have a 24-hour team to resolve any timeouts that occur, while smaller banks may not have the same resources to address timeouts, especially those occurring in non-business hours. Hence, one may still worry that a bank's own timeouts could be correlated with bank characteristics that affect both its Pix usage and balance sheet characteristics over time.

To this end, 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 in the transaction as well as timeouts by sending banks if bank  $i$  is the receiving bank in the transaction. In both cases, the attractiveness of bank  $i$ 's Pix service to its customers is reduced, which reduces the extent of its Pix usage in equilibrium. But at the same time, bank  $i$  cannot resolve the service timeouts in both cases because they stem from the counterparty bank. Also note that these counterparty banks are not actively chosen by bank  $i$  to transact with itself, but the banks where bank  $i$ 's customers receive payments from or send payments to. Formally, the timeout instrument for bank  $i$  in month  $t$ ,  $Timeout_{it}$ , is the sum of the passive timeout probabilities due to its sending banks and receiving banks:

$$Timeout_{it} = \sum_{j \in J, j \neq i} \frac{PixReceived_{ijt}}{PixReceived_{it}} SenderTimeout_{ij} + \sum_{j \in J, j \neq i} \frac{PixSent_{ijt}}{PixSent_{it}} ReceiverTimeout_{ij}, \quad (5.3)$$

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  $j$ s 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  $j$ s in month  $t$ , and  $ReceiverTimeout_{ij}$  is the proportion of payments sent by bank  $i$  to bank  $j$  that timed out due to the receiver, bank  $j$ . The identifying assumption is that these passively induced timeouts due to other banks do not affect bank  $i$ 's decisions over its balance sheet composition through channels other than bank  $i$ 's Pix usage.

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

$$PixUsage_{it} = Timeout_{it} + Controls_{it} + \omega_t + \epsilon_{it}, \quad (5.4)$$

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

From these first stage results, we obtain the predicted value of  $\widehat{PixUsage}_{it}$ . In the second stage, we use these predicted values to instrument for  $PixUsage_{it}$  in equation 5.2. The second-stage slopes on these predicted values estimate the causal effect of Pix usage on bank asset composition, liability structure, and risk-taking.

### 5.3 Estimation Results

Tables 3 and 4 present our estimation results for bank liability ratios. In the first four columns of both tables, we observe that the proportion of banks' savings deposits and checkings deposits both increase with larger Pix usage. This is consistent with the predictions of our model, where the increased convenience of using deposits as payments increases their attractiveness to investors, especially for demandable deposits like checkings and savings deposits that face the least restrictions to withdraw and use in payments. Our results are statistically significant at the 1% level for savings deposits in the OLS specification and for checking deposits in general. This is in part because in Brazil, all banks have checkings deposits, but only a fraction of banks have savings

deposits, which reduces the available variation in the ratio of savings deposits. The economic magnitudes are significant. According to Table 4, a one-standard-deviation increase in Pix usage causes an increase in the ratio of checking deposits by 1.5 to 1.9 standard deviations.

The last two columns of Tables 3 and 4 also show an increased reliance on repo funding for banks with more Pix usage. This result is again consistent with Pix eliminating banks' ability to delay payments and exposing banks to more volatile deposit funding, which triggers their use of repo funding to meet unexpected payment shocks.

Echoing the increased reliance on repo funding due to Pix usage, banks also become more reluctant to supply liquidity to other banks due to Pix usage. From Tables 7 and 8, we see that the proportion of interbank lending and repo lending both decrease with more Pix usage. In the OLS estimates, the coefficients are statistically significant before controlling for net Pix usage, which is likely because interbank lending is correlated with net incoming payments through Pix. The IV specification alleviates this concern and the corresponding coefficients are all statistically significant at 1%. Magnitude wise, a one-standard-deviation increase in Pix usage causes a 0.8 to 0.9 standard deviation decrease in interbank lending as a proportion of bank assets and a 1 standard deviation decrease in repo lending as a proportion of bank assets.

On the asset side, the results in Tables 5 and 6 confirm our model predictions regarding the effect of instant payments on banks' liquid asset holdings. In the first two columns of both tables, we see that the coefficient for Pix usage is positive and statistically significant at the 1% level. Based on the IV specification in Table 6, a one-standard-deviation increase in Pix usage causes a 1.5 standard deviation increase in liquid assets as a proportion of bank assets. This increase in liquid assets primarily comes from government bond holdings rather than from cash holdings, as evident from the last four columns in both tables. As alluded to in the stylized facts section, this is likely because government bonds are what banks set aside for future use, while cash is being readily deployed to meet payment shocks. Thus, the observed level of government bond holdings better reflects the ex-ante liquid asset holdings in the model, whereas the realized level of cash depends on both the ex-ante amount set aside as well as the amount used up at a given point in time. In fact, the coefficient for the effect of Pix usage on cash tends to be negative, indicating that banks with more Pix usage have used up more of their cash as a proportion of total assets than they have set aside ahead of time.

Finally, we shed light on the effect of Pix usage on bank risk-taking in Tables 9 and 10.

Across all specification, the coefficient is positive for the effect of Pix usage on the ratio of loan loss allowances, which is an ex-ante forward-looking measure of risk-taking. The coefficient is also positive for the effect of Pix usage on the ratio of defaulting loans, which captures the realization of risk-taking. These results confirm that instant payments cause banks to take on more credit risk, as our model predicts. The economic magnitude is sizable for both measures of credit risk. Based on the IV specification in Table 10, a one-standard-deviation increase in Pix usage causes a 0.2 to 0.3 standard deviation increase in the ratio of loan loss allowances and a 0.2 standard deviation increase in the ratio of defaulting loans. The former result is statistically significant at the 10% level, and the latter result is statistically significant at the 1% level.

## 6 Conclusion

We show that introduction of instant payments has important implications for the banks. Instant payments allow depositors to transfer funds without delay but 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, increase their reliance on wholesale funding, while becoming more reluctant to supply liquidity to other banks. To make up for the loss in profitability from allocating towards low-yielding liquid assets and changing their funding composition, banks take on more risk in their lending decisions and experience a rise in the ratio of defaulting loans. Taken together, our findings highlight that instant payments may lead to a more risky banking sector that is less engaged in liquidity transformation. Regulators should pay close attention to these potential side effects when introducing instant payment systems going forward.

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## A Figures and Tables

Figure 1: PIX Usage by Quartile

This figure shows the average pix usage for each pix usage quartile over time. Pix usage is the minimum of Pix received and Pix sent as a fraction of bank assets. Pix usage quartiles are defined by Pix usage as of December, 2022. The sample period is from November, 2020 to January, 2023.

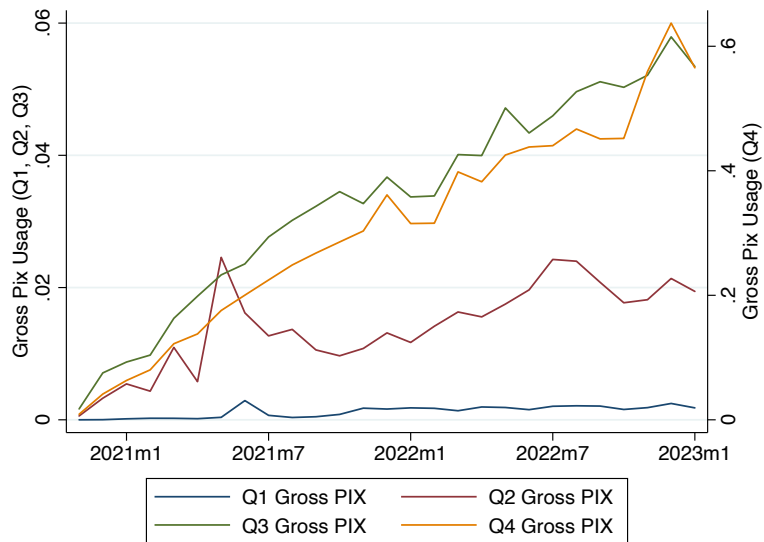




Figure 2: Liability Ratios by PIX Usage

Subfigure (a) shows the average proportion of demandable deposits as a fraction of bank assets for each PIX usage quartile over time. Demandable deposits are comprised of savings and checkings deposits. Subfigure (b) shows the average proportion of time deposits as a fraction of bank assets for each PIX usage quartile over time. Pix usage quartiles are defined by Pix usage as of December, 2022.

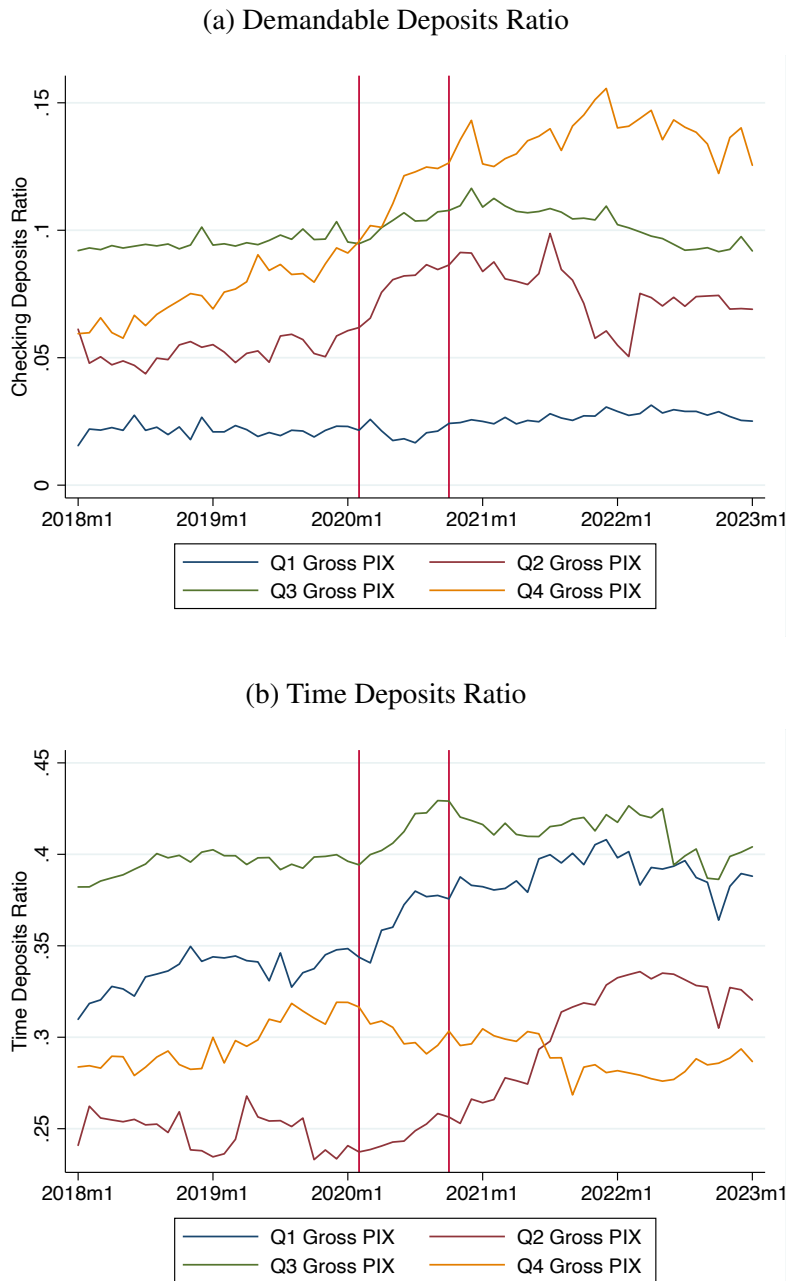


Figure 3: Liquid Asset Ratio by PIX Usage

Subfigure (a) shows the average proportion of liquid assets as a fraction of bank assets for each PIX usage quartile over time. Liquid assets are comprised of cash and government bonds. Subfigure (b) shows the average proportion of government bonds as a fraction of bank assets for each PIX usage quartile over time. Subfigure (c) shows the average proportion of cash as a fraction of bank assets for each PIX usage quartile over time. Pix usage quartiles are defined by Pix usage as of December, 2022.

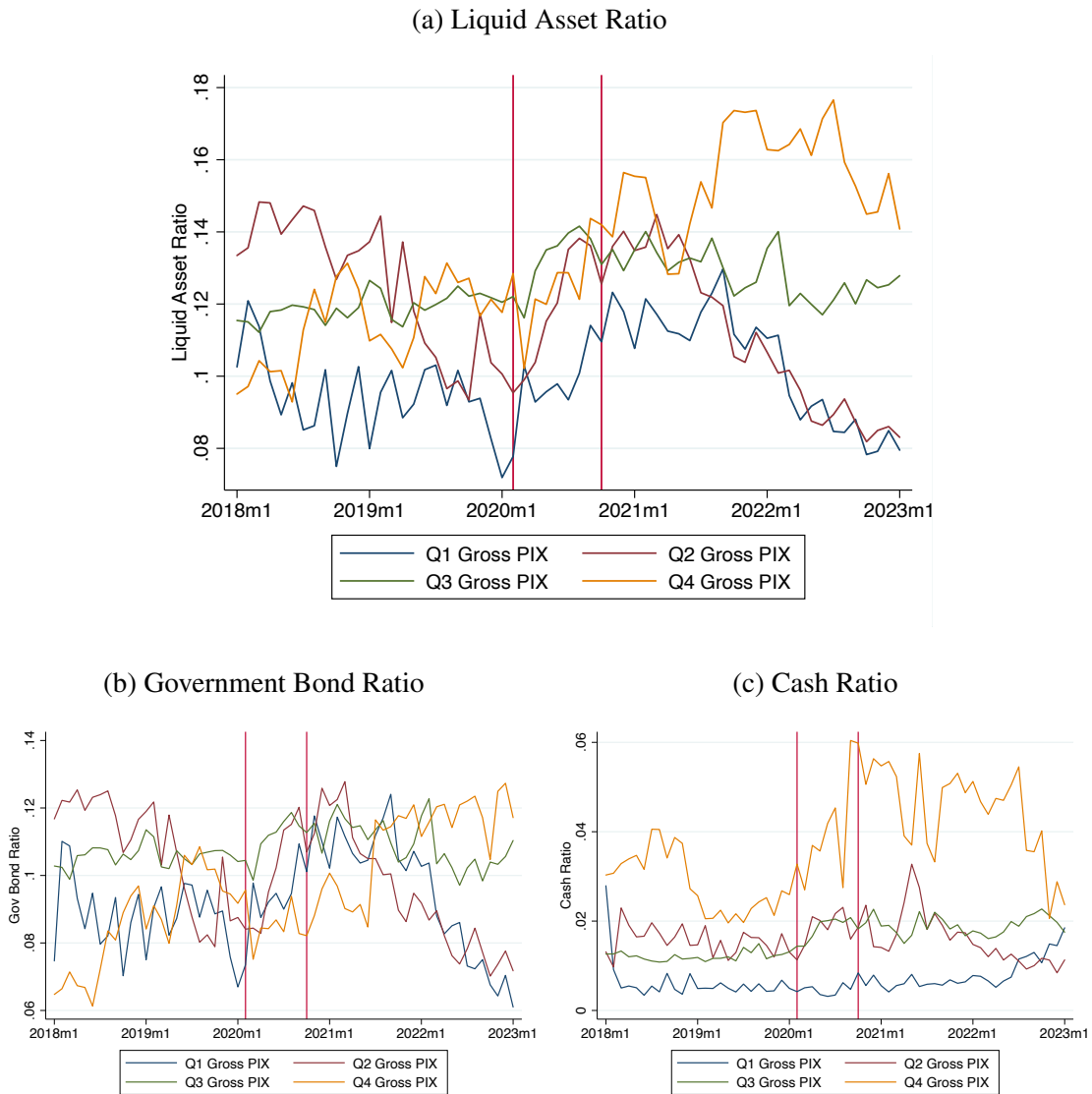


Figure 4: Interbank Lending and Borrowing by PIX Usage

Subfigure (a) shows the average proportion of interbank lending (asset side) as a fraction of bank assets for each PIX usage quartile over time. Liquid assets are comprised of cash and government bonds. Subfigure (b) shows the average proportion of interbank borrowing as a fraction of bank assets for each PIX usage quartile over time. Pix usage quartiles are defined by Pix usage as of December, 2022.

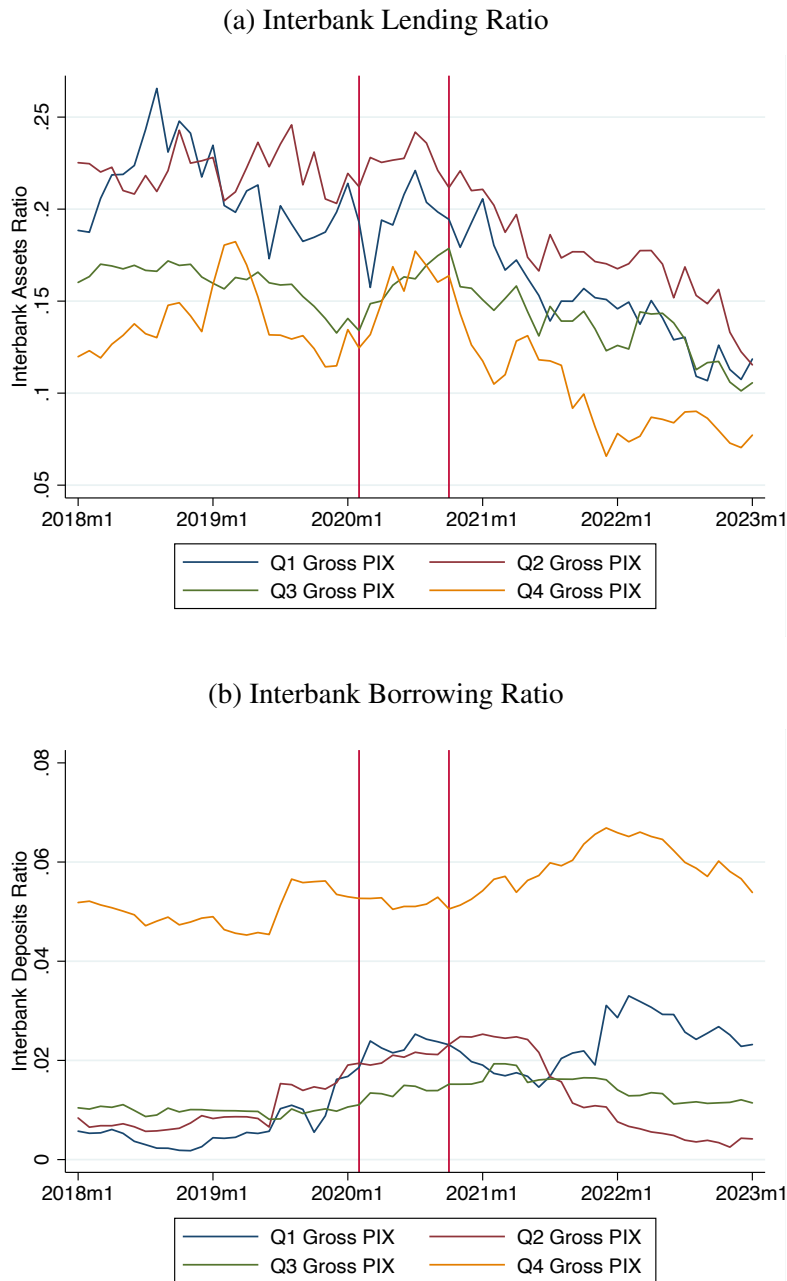


Figure 5: Loan Loss Provision and Loan Default Risk by PIX Usage

Subfigure (a) shows the average loan loss provision as a fraction of bank loans for each PIX usage quartile over time. Subfigure (b) shows the average proportion of loans in default as a fraction of bank loans for each PIX usage quartile over time. Loans are marked as in default when one or more payments is late by more than 90 days. Pix usage quartiles are defined by Pix usage as of December, 2022.

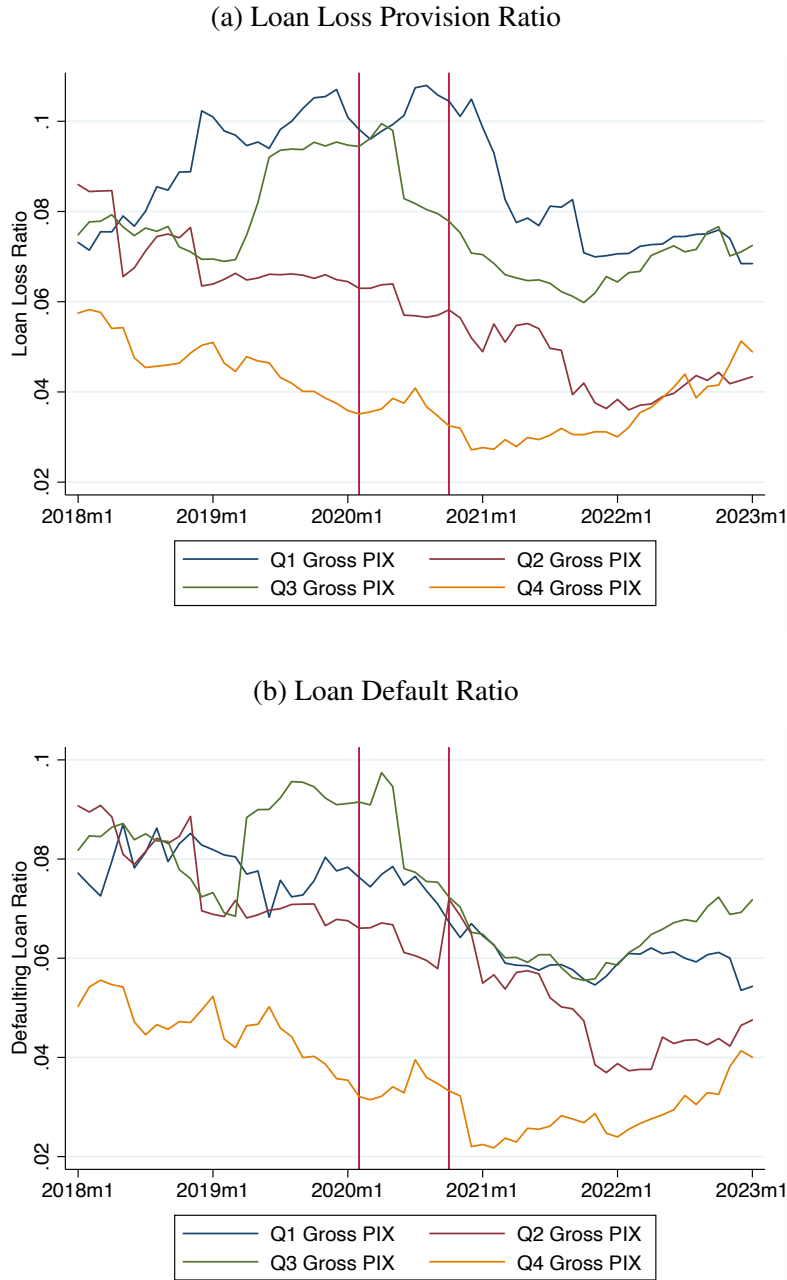


Table 1: Summary Statistics

Panels (a) and (b) show the summary statistics of our main variables and control variables, respectively. In panel (a), Pix usage is the minimum of Pix received and Pix sent as a fraction of bank assets. All asset and liability ratios are expressed as a fraction of bank assets. Loan Default Ratio is the proportion of defaulting loans over total loans and Loan Loss Ratio is the proportion of loan loss provisions over total loans. In Panel (b), Net Pix Uptake is the net amount of Pix received or sent as a fraction of bank assets, Time Deposit Spread is the time deposit rate minus the monetary policy rate, Service Fee Ratio is the proportion of banking service fees as a proportion of total income, Non-Deposit Expense Ratio is the proportion of non-deposit expenses as a fraction of bank assets, and Capital Ratio is the proportion of bank equity as a fraction of bank assets. All variables are expressed in percent.

(a) Main Variables

	mean	sd	p25	p50	p75
Gross Pix Usage	9.25	19.35	0.35	2.05	6.39
Checkings Deposit Ratio	5.54	7.43	0.37	2.83	7.71
Savings Deposit Ratio	2.30	5.46	0.00	0.00	0.00
Repo Ratio	6.87	10.08	0.00	1.43	11.23
Liquid Asset Ratio	13.14	11.54	5.29	9.94	16.45
Cash Ratio	3.03	7.68	0.16	0.77	1.88
Gov Bond Ratio	10.06	10.04	2.98	7.43	13.51
Interbank Asset Ratio	13.96	15.53	2.85	9.26	19.63
Repo Asset Ratio	11.73	14.97	0.74	6.84	15.54
Loan Default Ratio	5.09	6.05	1.23	3.56	6.11
Loan Loss Ratio	6.09	7.64	1.73	4.22	6.51

(b) Control Variables

	mean	sd	p25	p50	p75
Net Pix Uptake	-1.38	20.32	-1.10	0.10	1.21
Time Deposit Spread	-0.37	2.30	-1.46	-0.57	0.53
Service Fee Ratio	5.51	8.60	0.62	1.57	5.80
Non Deposit Expense Ratio	38.62	44.37	12.25	20.90	40.13
Capital Ratio	13.62	13.65	7.49	10.22	14.50

Table 2: The Effect of Timeouts on Pix Usage

This table shows the effect of the timeout instrument on Pix usage. Timeout IV is the timeout instrument defined in equation ?. For a given bank in a given month, this instrument captures the proportion of failed Pix transactions due to other banks. Time Deposit Spread is the time deposit rate minus the monetary policy rate. Service Fee Ratio is the proportion of banking service fees as a proportion of total income. Non-Deposit Expense Ratio is the proportion of non-deposit expenses as a fraction of bank asstes. Net Pix Uptake is the net amount of Pix received or sent as a fraction of bank assets. Capital ratio is the proportion of bank equity as a fraction of bank assets. The sample period is from November, 2020 to January, 2023.

	Gross Pix Usage		
	(1)	(2)	(3)
Timeout IV	-0.046*** (0.010)	-0.027*** (0.006)	-0.027*** (0.006)
Time Deposit Spread		0.081*** (0.018)	0.081*** (0.018)
Service Fee Ratio		0.135*** (0.016)	0.133*** (0.017)
Non Deposit Expense Ratio		-0.009** (0.004)	-0.010** (0.004)
Net Pix Uptake		-0.343*** (0.021)	-0.344*** (0.020)
Capital Ratio			-0.015 (0.010)
Time FE	Yes	Yes	Yes
Bank Type FE	Yes	Yes	Yes
Observations	1550	1439	1439
Adjusted R2	0.29	0.37	0.37

Table 3: The Effect of Pix Usage on Liabilities (OLS)

This table shows the effect of Pix usage on the ratio of savings deposits, checking deposits, and repo borrowing. Pix usage is the minimum of Pix received and Pix sent as a fraction of bank assets. Time Deposit Spread is the time deposit rate minus the monetary policy rate. Service Fee Ratio is the proportion of banking service fees as a proportion of total income. Non-Deposit Expense Ratio is the proportion of non-deposit expenses as a fraction of bank assets. Net Pix Uptake is the net amount of Pix received or sent as a fraction of bank assets. Capital ratio is the proportion of bank equity as a fraction of bank assets. We control for the level of each dependent variable in October, 2020 and the sample period is from November, 2020 to January, 2023.

	Savings Deposits		Checking Deposits		Repo Borrowing	
	(1)	(2)	(3)	(4)	(5)	(6)
Gross Pix Usage	0.021*** (0.004)	0.021*** (0.004)	0.154*** (0.042)	0.275*** (0.030)	0.017 (0.013)	0.059*** (0.018)
Time Deposit Spread	0.001 (0.006)	0.001 (0.006)	-0.026** (0.012)	-0.053*** (0.015)	-0.015 (0.016)	-0.027 (0.016)
Service Fee Ratio	-0.026*** (0.003)	-0.026*** (0.003)	0.019 (0.014)	0.056*** (0.016)	0.063*** (0.013)	0.073*** (0.013)
Non Deposit Expense Ratio	0.002 (0.002)	0.002 (0.002)	-0.017*** (0.005)	-0.022*** (0.005)	0.007 (0.011)	0.019 (0.013)
Net Pix Uptake	-0.004* (0.002)	-0.004* (0.002)		0.190*** (0.024)		0.066*** (0.017)
Capital Ratio	-0.020*** (0.001)	-0.020*** (0.001)		0.005 (0.008)		-0.040*** (0.005)
Savings Deposit Ratio (Pre)	0.968*** (0.015)	0.968*** (0.015)				
Checkings Deposit Ratio (Pre)			0.791*** (0.021)	0.744*** (0.023)		
Repo Ratio (Pre)					0.720*** (0.021)	0.717*** (0.021)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank Type FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1439	1439	1462	1439	1462	1439
Adjusted R2	0.97	0.97	0.81	0.82	0.70	0.73

Table 4: The Effect of Pix Usage on Liabilities (IV)

This table shows the effect of instrumented Pix usage on the ratio of savings deposits, checking deposits, and repo borrowing as a proportion of bank assets. Pix usage is the minimum of Pix received and Pix sent as a fraction of bank assets. We instrument for Pix usage with the timeout instrument, which captures the proportion of failed Pix transactions due to other banks. Time Deposit Spread is the time deposit rate minus the monetary policy rate. Service Fee Ratio is the proportion of banking service fees as a proportion of total income. Non-Deposit Expense Ratio is the proportion of non-deposit expenses as a fraction of bank assets. Net Pix Uptake is the net amount of Pix received or sent as a fraction of bank assets. Capital ratio is the proportion of bank equity as a fraction of bank assets. We control for the level of each dependent variable in October, 2020 and the sample period is from November, 2020 to January, 2023.

	Savings Deposits		Checking Deposits		Repo Borrowing	
	(1)	(2)	(3)	(4)	(5)	(6)
Gross Pix Usage	0.026 (0.030)	0.067 (0.040)	1.492*** (0.450)	1.865*** (0.539)	0.296 (0.302)	0.385 (0.343)
Time Deposit Spread	0.002 (0.007)	-0.005 (0.007)	-0.171*** (0.061)	-0.275*** (0.098)	-0.029 (0.029)	-0.050 (0.040)
Service Fee Ratio	-0.025*** (0.007)	-0.033*** (0.006)	-0.195** (0.082)	-0.021 (0.042)	0.003 (0.075)	0.029 (0.049)
Non Deposit Expense Ratio	0.005** (0.002)	0.001 (0.002)	-0.094*** (0.032)	-0.097*** (0.032)	0.016 (0.015)	0.021 (0.013)
Net Pix Uptake		0.012 (0.014)		0.780*** (0.210)		0.178 (0.118)
Capital Ratio		-0.021*** (0.002)		0.040** (0.018)		-0.033*** (0.008)
Savings Deposit Ratio (Pre)	0.972*** (0.015)	0.964*** (0.015)				
Checkings Deposit Ratio (Pre)			0.383** (0.140)	0.214 (0.186)		
Repo Ratio (Pre)					0.734*** (0.015)	0.724*** (0.017)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank Type FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1439	1439	1439	1439	1439	1439
Adjusted R2	0.97	0.97	0.24	0.21	0.69	0.69



Table 5: The Effect of Pix Usage on Liquid Assets (OLS)

This table shows the effect of Pix usage on the ratio of liquid assets, cash, and government bonds as a proportion of bank assets. Liquid assets are comprised of cash and government bonds. Pix usage is the minimum of Pix received and Pix sent as a fraction of bank assets. Time Deposit Spread is the time deposit rate minus the monetary policy rate. Service Fee Ratio is the proportion of banking service fees as a proportion of total income. Non-Deposit Expense Ratio is the proportion of non-deposit expenses as a fraction of bank assets. Net Pix Uptake is the net amount of Pix received or sent as a fraction of bank assets. Capital ratio is the proportion of bank equity as a fraction of bank assets. We control for the level of each dependent variable in October, 2020 and the sample period is from November, 2020 to January, 2023.

	Liquid Ratio		Cash Ratio		Gov Bond Ratio	
	(1)	(2)	(3)	(4)	(5)	(6)
Gross Pix Usage	0.100*** (0.029)	0.100*** (0.029)	-0.019 (0.017)	-0.019 (0.017)	0.150*** (0.025)	0.150*** (0.025)
Time Deposit Spread	0.017* (0.009)	0.018* (0.010)	0.029*** (0.010)	0.028*** (0.010)	0.011 (0.009)	0.011 (0.009)
Service Fee Ratio	0.046** (0.017)	0.047*** (0.017)	0.019** (0.008)	0.019** (0.008)	0.027 (0.018)	0.029 (0.018)
Non Deposit Expense Ratio	-0.111*** (0.011)	-0.110*** (0.011)	0.009 (0.007)	0.009 (0.007)	-0.126*** (0.012)	-0.125*** (0.012)
Net Pix Uptake	0.062*** (0.015)	0.063*** (0.015)	-0.038** (0.015)	-0.039** (0.015)	0.099*** (0.015)	0.100*** (0.015)
Capital Ratio		0.015** (0.007)		-0.003 (0.004)		0.023*** (0.007)
Liquid Asset Ratio (Pre)	0.626*** (0.036)	0.628*** (0.036)				
Cash Ratio (Pre)			0.560*** (0.055)	0.559*** (0.055)		
Cash Ratio (Pre)					0.700*** (0.032)	0.702*** (0.032)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank Type FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1439	1439	1439	1439	1439	1439
Adjusted R2	0.58	0.58	0.66	0.66	0.65	0.65

Table 6: Effect on Liquid Asset Holdings (IV)

This table shows the effect of instrumented Pix usage the ratio of liquid assets, cash, and government bonds as a proportion of bank assets. Liquid assets are comprised of cash and government bonds. Pix usage is the minimum of Pix received and Pix sent as a fraction of bank assets. We instrument for Pix usage with the timeout instrument, which captures the proportion of failed Pix transactions due to other banks. Time Deposit Spread is the time deposit rate minus the monetary policy rate. Service Fee Ratio is the proportion of banking service fees as a proportion of total income. Non-Deposit Expense Ratio is the proportion of non-deposit expenses as a fraction of bank assets. Net Pix Uptake is the net amount of Pix received or sent as a fraction of bank assets. Capital ratio is the proportion of bank equity as a fraction of bank assets. We control for the level of each dependent variable as of October, 2020 and the sample period is from November, 2020 to January, 2023.

	Liquid Ratio		Cash Ratio		Gov Bond Ratio	
	(1)	(2)	(3)	(4)	(5)	(6)
Gross Pix Usage	1.574*** (0.233)	1.520*** (0.231)	-0.346*** (0.124)	-0.346** (0.126)	1.355*** (0.215)	1.306*** (0.215)
Time Deposit Spread	-0.097*** (0.031)	-0.092*** (0.031)	0.059*** (0.015)	0.059*** (0.016)	-0.064** (0.028)	-0.059** (0.028)
Service Fee Ratio	-0.157*** (0.043)	-0.147*** (0.043)	0.068*** (0.024)	0.068*** (0.024)	-0.148*** (0.040)	-0.137*** (0.040)
Non Deposit Expense Ratio	-0.100*** (0.015)	-0.098*** (0.015)	0.006 (0.007)	0.006 (0.007)	-0.108*** (0.015)	-0.106*** (0.015)
Net Pix Uptake	0.568*** (0.078)	0.551*** (0.079)	-0.153*** (0.046)	-0.153*** (0.046)	0.501*** (0.081)	0.487*** (0.080)
Capital Ratio		0.035*** (0.012)		-0.000 (0.005)		0.049*** (0.011)
Liquid Asset Ratio (Pre)	0.635*** (0.062)	0.639*** (0.060)				
Cash Ratio (Pre)			0.633*** (0.048)	0.633*** (0.047)		
Cash Ratio (Pre)					0.803*** (0.036)	0.802*** (0.035)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank Type FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1439	1439	1439	1439	1439	1439
Adjusted R2	-1.17	-1.05	0.48	0.48	-0.20	-0.13

Table 7: The Effect of Pix on Interbank Assets (OLS)

This table shows the effect of Pix usage on the ratio of interbank assets and repo lending as a proportion of bank assets. Pix usage is the minimum of Pix received and Pix sent as a fraction of bank assets. Time Deposit Spread is the time deposit rate minus the monetary policy rate. Service Fee Ratio is the proportion of banking service fees as a proportion of total income. Non-Deposit Expense Ratio is the proportion of non-deposit expenses as a fraction of bank assets. Net Pix Uptake is the net amount of Pix received or sent as a fraction of bank assets. Capital ratio is the proportion of bank equity as a fraction of bank assets. We control for the level of each dependent variable in October, 2020 and the sample period is from November, 2020 to January, 2023.

	Interbank Asset Ratio			Repo Ratio		
	(1)	(2)	(3)	(4)	(5)	(6)
Gross Pix Usage	-0.038*	-0.039*	-0.024	-0.050**	-0.049**	-0.041
	(0.019)	(0.020)	(0.024)	(0.021)	(0.021)	(0.027)
Time Deposit Spread	-0.076***	-0.076***	-0.082***	-0.049***	-0.052***	-0.056***
	(0.013)	(0.013)	(0.013)	(0.012)	(0.012)	(0.013)
Service Fee Ratio	0.019	0.022	0.025*	0.056***	0.051***	0.054***
	(0.015)	(0.015)	(0.015)	(0.016)	(0.016)	(0.015)
Non Deposit Expense Ratio	0.003	0.004	0.010	0.018**	0.013	0.019**
	(0.008)	(0.008)	(0.007)	(0.009)	(0.009)	(0.008)
Net Pix Uptake			0.028			0.013
			(0.017)			(0.018)
Capital Ratio		0.032***	0.037***		-0.095***	-0.092***
		(0.011)	(0.011)		(0.015)	(0.015)
Interbank Asset Ratio (Pre)	0.600***	0.596***	0.600***			
	(0.029)	(0.029)	(0.030)			
Repo Asset Ratio (Pre)				0.580***	0.576***	0.576***
				(0.029)	(0.029)	(0.031)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank Type FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1462	1462	1439	1462	1462	1439
Adjusted R2	0.69	0.69	0.69	0.65	0.66	0.66

Table 8: The Effect of Pix Usage on Interbank Assets (IV)

This table shows the effect of instrumented Pix usage on the ratio of interbank assets and repo lending as a proportion of bank assets. Pix usage is the minimum of Pix received and Pix sent as a fraction of bank assets. We instrument for Pix usage with the timeout instrument, which captures the proportion of failed Pix transactions due to other banks. Time Deposit Spread is the time deposit rate minus the monetary policy rate. Service Fee Ratio is the proportion of banking service fees as a proportion of total income. Non-Deposit Expense Ratio is the proportion of non-deposit expenses as a fraction of bank asstes. Net Pix Uptake is the net amount of Pix received or sent as a fraction of bank assets. Capital ratio is the proportion of bank equity as a fraction of bank assets. We control for the level of each dependent variable as of October, 2020 and the sample period is from November, 2020 to January, 2023.

	Interbank Asset Ratio			Repo Ratio		
	(1)	(2)	(3)	(4)	(5)	(6)
Gross Pix Usage	-0.819*** (0.183)	-0.851*** (0.193)	-0.851*** (0.193)	-1.037*** (0.235)	-0.968*** (0.239)	-0.966*** (0.241)
Time Deposit Spread	-0.051*** (0.013)	-0.035** (0.016)	-0.035** (0.016)	-0.009 (0.018)	-0.015 (0.018)	0.003 (0.023)
Service Fee Ratio	0.222*** (0.061)	0.168*** (0.045)	0.168*** (0.045)	0.320*** (0.078)	0.298*** (0.078)	0.217*** (0.056)
Non Deposit Expense Ratio	0.005 (0.007)	-0.003 (0.006)	-0.003 (0.006)	0.019** (0.008)	0.015* (0.008)	0.001 (0.006)
Net Pix Uptake		-0.264*** (0.071)	-0.264*** (0.071)			-0.314*** (0.089)
Capital Ratio		0.043*** (0.012)	0.043*** (0.012)		-0.075*** (0.019)	-0.112*** (0.019)
Interbank Asset Ratio (Pre)	0.525*** (0.043)	0.493*** (0.049)	0.493*** (0.049)			
Repo Asset Ratio (Pre)				0.479*** (0.048)	0.482*** (0.048)	0.454*** (0.055)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank Type FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1439	1439	1439	1439	1439	1439
Adjusted R2	0.05	0.11	0.11	-0.40	-0.26	-0.09

Table 9: Effect on Loan Loss Provision and Loan Defaults (OLS)

This table shows the effect of Pix usage on the ratio of loan loss provisions and defaulting loans as a proportion of bank loans. Loans are marked as in default when one or more payments is late by more than 90 days. Pix usage is the minimum of Pix received and Pix sent as a fraction of bank assets. Time Deposit Spread is the time deposit rate minus the monetary policy rate. Service Fee Ratio is the proportion of banking service fees as a proportion of total income. Non-Deposit Expense Ratio is the proportion of non-deposit expenses as a fraction of bank asstes. Net Pix Uptake is the net amount of Pix received or sent as a fraction of bank assets. Capital ratio is the proportion of bank equity as a fraction of bank assets. We control for the level of each dependent variable in October, 2020 and the sample period is from November, 2020 to January, 2023.

	Loan Loss Ratio		Default Loan Ratio	
	(1)	(2)	(3)	(4)
Gross Pix Usage	0.046*** (0.014)	0.044*** (0.014)	0.028 (0.016)	0.034** (0.013)
Time Deposit Spread	0.022*** (0.006)	0.024*** (0.006)	0.024** (0.009)	0.022*** (0.007)
Service Fee Ratio	-0.006 (0.005)	-0.003 (0.005)	-0.016*** (0.004)	-0.017*** (0.003)
Non Deposit Expense Ratio	-0.071*** (0.009)	-0.064*** (0.008)	0.005 (0.007)	0.002 (0.008)
Net Pix Uptake	0.055*** (0.007)	0.058*** (0.007)	0.038*** (0.006)	0.038*** (0.006)
Capital Ratio		0.056** (0.022)		-0.046 (0.039)
Loan Loss Ratio (Pre)	0.699*** (0.030)	0.680*** (0.035)		
Loan Default Ratio (Pre)			0.875*** (0.013)	0.902*** (0.018)
Time FE	Yes	Yes	Yes	Yes
Bank Type FE	Yes	Yes	Yes	Yes
Observations	1412	1412	1319	1319
Adjusted R2	0.71	0.71	0.82	0.82

Table 10: Effect on Loan Loss Provision and Loan Defaults (IV)

This table shows the effect of Pix usage on the ratio of loan loss provisions and defaulting loans as a proportion of bank loans. Loans are marked as in default when one or more payments is late by more than 90 days. Pix usage is the minimum of Pix received and Pix sent as a fraction of bank assets. We instrument for Pix usage with the timeout instrument, which captures the proportion of failed Pix transactions due to other banks. Time Deposit Spread is the time deposit rate minus the monetary policy rate. Service Fee Ratio is the proportion of banking service fees as a proportion of total income. Non-Deposit Expense Ratio is the proportion of non-deposit expenses as a fraction of bank assets. Net Pix Uptake is the net amount of Pix received or sent as a fraction of bank assets. Capital ratio is the proportion of bank equity as a fraction of bank assets. We control for the level of each dependent variable as of October, 2020 and the sample period is from November, 2020 to January, 2023.

	Loan Loss Ratio		Default Loan Ratio	
	(1)	(2)	(3)	(4)
Gross Pix Usage	0.260** (0.123)	0.227* (0.131)	0.191*** (0.065)	0.231*** (0.059)
Time Deposit Spread	-0.002 (0.013)	0.003 (0.014)	0.006 (0.013)	-0.002 (0.011)
Service Fee Ratio	-0.058* (0.031)	-0.048 (0.033)	-0.058*** (0.014)	-0.068*** (0.013)
Non Deposit Expense Ratio	-0.070*** (0.010)	-0.064*** (0.009)	0.008 (0.007)	0.003 (0.007)
Net Pix Uptake	0.164** (0.067)	0.151** (0.070)	0.120*** (0.026)	0.134*** (0.024)
Capital Ratio		0.048* (0.024)		-0.084** (0.035)
Loan Loss Ratio (Pre)	0.716*** (0.031)	0.698*** (0.038)		
Loan Default Ratio (Pre)			0.899*** (0.016)	0.952*** (0.014)
Time FE	Yes	Yes	Yes	Yes
Bank Type FE	Yes	Yes	Yes	Yes
Observations	1412	1412	1319	1319
Adjusted R2	0.69	0.70	0.81	0.80