Digital Payments and Monetary Policy Transmission*

Pauline Liang† Matheus Sampaio‡ Sergey Sarkisyan§

May 10, 2024

Abstract

We examine the impact of digital payments on the transmission of monetary policy. Leveraging administrative data on Pix, a digital payment system introduced by the Central Bank of Brazil, we find that Pix adoption has diminished banks' market power, making them more responsive to changes in policy rates. Subsequently, we estimate a dynamic banking model in which digital payment amplifies deposit elasticity through the household sector. Our counterfactual results reveal that digital payments amplify the monetary policy transmission by reducing banks' market power – banks respond more to policy rate changes after Pix. We find that digital payments impact monetary transmission primarily through the deposit channel.

Keywords: Digital payments, monetary policy transmission, banking, Pix

JEL Codes: E42, G21, E52

*We are grateful to Juliane Begenau, Arvind Krishnamurthy, Amit Seru, Yufeng Wu, Yao Zeng, and seminar participants at Wharton School and Inter-Finance PhD Seminar for helpful suggestions. We thank Arjun Khanna for his outstanding research assistance.

†Department of Finance, Stanford GSB.
E-mail address: pliang20@stanford.edu
‡Department of Finance, Kellogg School of Management, Northwestern University.
E-mail address: matheus.sampaio@kellogg.northwestern.edu
§Department of Finance, Wharton School, University of Pennsylvania.
E-mail address: sesar@wharton.upenn.edu

1 Introduction

Monetary policy transmits to the real economy through banks' portfolio decisions. There are several proposed channels of how changes to the policy rate impact deposits and loans, but most of them rely on policy rate *pass-through*. For example, when central banks increase interest rates, they hope that banks will increase their deposit rates as well, thus attracting more deposits. In reality, banks are able to keep their deposit rates mostly unchanged without losing all of their depositors (Drechsler, Savov, and Schnabl (2017)). Digital payments facilitate transactions between deposit accounts, potentially changing the elasticity of the deposits to interest rates. This paper asks if digital payments improve the transmission of monetary policy. We argue that digital payments facilitate monetary policy by reducing banks' deposit market power.

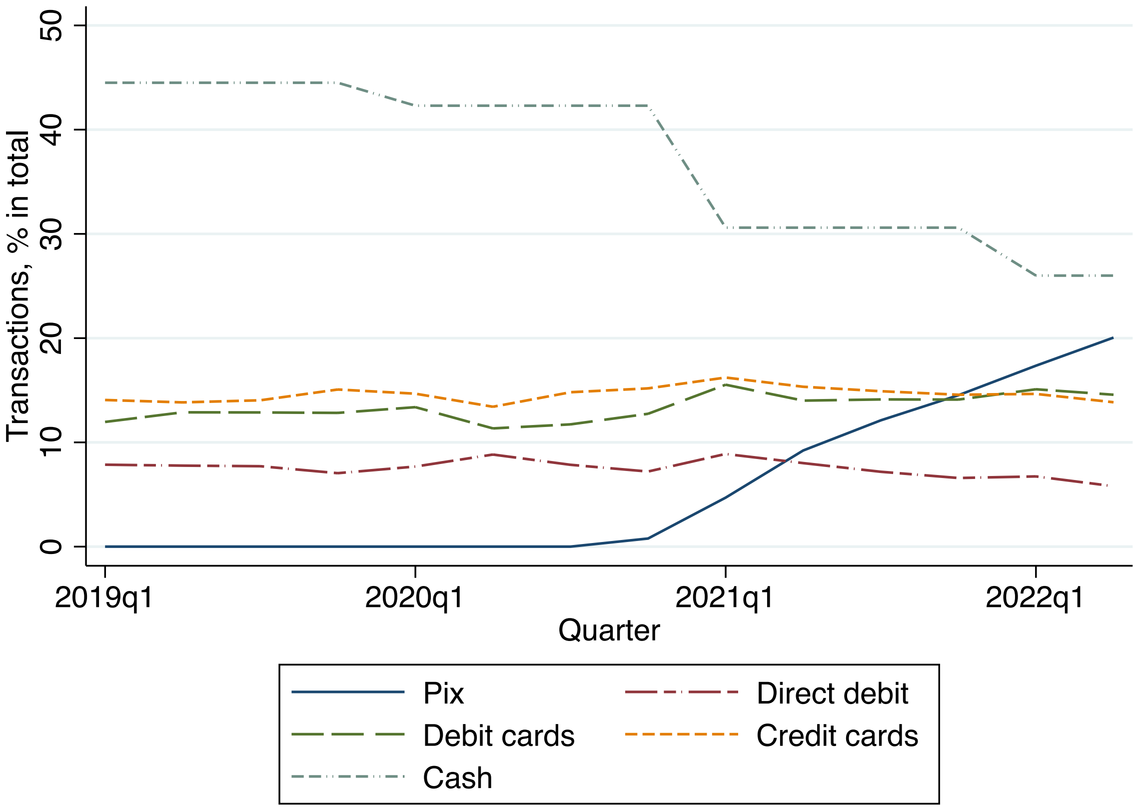
To address this question, we utilize administrative data on Pix, an instant payment system introduced by the Central Bank of Brazil (CBB) in November 2020. Pix not only enables instant transfers but also boasts widespread acceptance as a merchant payment method due to its lower fees compared to credit cards. Since its launch, Pix has emerged as a preferred payment method, surpassing other prominent options such as direct debits (*Boleto Bancário* and wire transfers), and even credit and debit cards (see Figure 1). As Figure 1 suggests, Pix mainly substitutes paper currency – cash transactions have steadily declined since Pix was introduced. By November 2022, Pix transactions reached almost R$ 3 trillion per quarter, equivalent to approximately $600 billion[1] with more than 65% of Brazilians actively using it.[2]

Although Pix replaces traditional payment systems that rely on bank deposits, it requires a bank account to be used. Central Bank of Brazil required large and medium-sized banks (banks with more than 500,000 depositors) to join Pix. Entry costs for smaller banks were fairly low because the total service costs of Pix are shared among participating banks. Hence, more than 90% of banks joined Pix within the first two

[1]Based on the January 2023 exchange rate

[2]For comparison, debit card transactions amounted to R$664 billion in 2019. See https://business.ebanx.com/en/brazil/payment-methods/debit-card.

Figure 1: Means of Payment in Brazil, % of Transactions



Note: The graph is from Sarkisyan (2022) using data from the Central Bank of Brazil. Data on cash transactions is from Statista. The graph plots the number of transactions as a percent of the total number of transactions for the main means of payment in Brazil – cash, Pix (instant payment system launched in November 2020), direct debit, debit cards, and credit cards.

months, creating an excellent context to study the impact of Pix on deposit market concentration.[3]

Instant payment systems can impact deposit market power in at least three ways. First, financial technology generally benefits large incumbents (in this case, banks with already high market power) (Hannan and McDowell (1990); Hauswald and Marquez (2003); Kwon, Ma, and Zimmermann (2021)), which can further limit monetary policy pass-through. Second, instant payment systems facilitate transfers between bank accounts, thus effectively making deposits more elastic by reducing switching costs. Third,

[3]Brazil is also one of the largest economies in the world and the largest in Latin America.

universally available instant payment systems like Pix can increase the competitiveness of smaller banks by allowing them to offer greater payment convenience to their clients (Sarkisyan (2022)) so that banks generally have to react more to the changes in policy rates.

If banks exercise their market power and keep deposit rates unchanged, the monetary policy transmission is limited due to at least two reasons. First, low deposit rates imply low loan rates and, as a result, a limited reduction in loans following interest rate hikes. Second, monetary authorities want banks to increase their rates to incentivize households to save instead of spending money. If banks do not respond to interest rate rises, the monetary policy goals are not fully achieved. In fact, historically, there has been a decline in deposit growth when interest rates increase (Drechsler, Savov, and Schnabl (2017)).

To understand if Pix changes monetary policy transmission, we combine municipality-level monthly data on Pix transactions sourced from the Central Bank of Brazil, branch-level bank balance sheet data, bank-level interest rates, and municipality-level demographic and economic data. Such data allows us to estimate how banks react to policy rate changes in different municipalities. Looking at bank-level deposit rates along with branch-level deposits accounts for banks' ability to utilize their local market power (Drechsler, Savov, and Schnabl (2021)) as well as includes branches that set their rates following the banks' headquarters (Begenau and Stafford (2022)).

We start by documenting that banks' market power declines more after the introduction of Pix in areas with more Pix usage. Specifically, we compute sensitivities of banks' deposits and deposit rates to the changes in policy rates in Brazil (*Selic rate*). Intuitively, banks with higher market power increase their deposit rates by *less* (positive deposit spread betas) and lose *more* deposits (negative deposit flow betas) after contractionary monetary policy rate changes. We find that after Pix, deposit betas change. Specifically, deposit spread betas decrease, and deposit flow betas decrease in areas with more Pix usage. In other words, banks respond more to policy rate changes after Pix is introduced, and hence, they lose fewer deposits.

To further argue that the drop in market power is due to the introduction of Pix, we estimate within-branch within-locality-time regressions. We address two challenges – branches of banks being fundamentally different and local unobservable demand. We find that in the areas with more Pix transactions, increases in policy rates lead to higher increases in deposit rates and lower deposit outflows, consistent with the reduced local market power and intensified monetary policy transmission.

To illustrate the channels that might drive an increase in monetary transmission after the introduction of digital payments, we propose a simple circular city model where households choose banks based on distances, interest rates, and convenience. We show that if it is easier to travel to banks and use their digital services, households are more likely to have multiple bank accounts. We also find that when banks with inferior technology join digital payments, the demand for their deposits also increases.

To understand how digital payments impact monetary policy transmission through various channels, we estimate a dynamic banking model with three frictions: imperfect competition, regulatory constraints, and financial frictions. The model features three types of agents – households, non-financial firms, and banks. Households choose the banks to invest their full endowment in return for the deposit rate and non-interest rate benefits offered by the bank. Firms choose the bank to borrow from if they decide to do it. Finally, banks issue deposits (retail and wholesale), originate loans, and buy reserve and government securities. The model mainly follows Wang, Whited, Wu, and Xiao (2022) and Whited, Wu, and Xiao (2022).

A digital payment system enters households' problem through the demand for deposits. Specifically, households value non-rate characteristics, such as the number of branches, differently with digital payments. Pix also makes switching between banks easier, effectively changing the deposit elasticity, and we allow households to have multiple bank accounts. We assume that all banks offer Pix to their clients, which is consistent with the data.

The model not only allows us to estimate the impact of Pix on monetary policy transmission in the general equilibrium framework, but it also allows us to gauge the importance of digital payments for different channels of monetary transmission. Our model considers three main channels. The first is a reserve channel, where interest rate decisions affect required reserves and hence, lending (Bernanke and Blinder (1988, 1992); Kashyap and Stein (2000)). The second one is a capital channel — interest rate movements tighten banks' capital and, therefore, affect their decisions (Bolton and Freixas (2000); Brunnermeier and Sannikov (2014); Elenev, Landvoigt, and Van Nieuwerburgh (2021)). Finally, we consider the deposit channel of monetary policy (Drechsler, Savov, and Schnabl (2017, 2021); Wang, Whited, Wu, and Xiao (2022)).

We use bank-level data from Brazil from 2014 to 2022 to estimate the model. We combine rich bank-level balance sheet data with interest rates. We also collect data on salaries and employment that are necessary for the identification. We start by estimating demands for deposits and loans separately using the methods from the industrial organization literature (Berry, Levinsohn, and Pakes (1995); Nevo (2001)). We find that deposit rates positively impact deposit demand, and the elasticity increases after Pix. The loan demand, on the other hand, declines if loan rates rise. To address the endogeneity of interest rates, we use supply shifters – instrumental variables that impact deposit and loan demand only through interest rates (Ho and Ishii (2011)). We then plug these estimates into our model and use simulated minimum distance (SMD) to obtain estimates of parameters that quantify financial frictions and operating costs.

The estimated model allows us to study important counterfactuals. First, we consider a scenario where Pix was never introduced. We show that the sensitivity of deposit rates to policy rate changes in that case would be lower, i.e., banks would have more market power. Pix also allows households to move deposits across banks and out of the banking sector more easily, especially if there are more profitable investment opportunities. Hence, we find that deposit volumes are lower due to the introduction of Pix. These findings suggest that digital payments facilitate monetary policy transmission by making deposit rates more sensitive to policy rates.

Finally, we evaluate the impact of each channel of monetary policy on the effect of digital payments on monetary transmission. We do it by sequentially eliminating each channel of monetary policy transmission and check how deposits respond to different channels with and without Pix. We find that the effect of Pix on monetary transmission is mostly driven by the deposit channel of monetary policy, i.e., through the reduction in banks' market power. The reason is that Pix mainly impacts depositors' decisions rather than firms' borrowing choices or banks' capital issuance and reserve purchase.

Our paper contributes to several strands of the literature. First, we add to the growing literature on monetary policy and digital finance. Recent papers document more monetary transmission in the economy with online and digital banks (Erel, Liebersohn, Yannelis, and Earnest (2023); Koont, Santos, and Zingales (2023); Cookson, Fox, Gil-Bazo, Imbet, and Schiller (2023)). Central bank digital currencies can also impact monetary policy by crowding out deposits and loans (Whited et al. (2022)). We contribute by showing that monetary policy transmission is facilitated by digital payments.

We also contribute to the growing literature on mobile payments and convenience. Mobile payments are growing and intervening in all spheres of the economy (Ferrari, Verboven, and Degryse (2010); Aker and Mbiti (2010); Jack and Suri (2014); Suri and Jack (2016); Muralidharan, Niehaus, and Sukhtankar (2016); Riley (2018); Duffie (2019); Ouyang (2021); Brunnermeier, James, and Landau (2019); Aker, Prina, and Welch (2020); Brunnermeier and Payne (2022); Brunnermeier, Limodio, and Spadavecchia (2023); Bian, Cong, and Ji (2023); Wang (2023); Mariani, Ornelas, and Ricca (2023)). While most of these papers rely on network formation in adopting platforms, Crouzet, Gupta, and Mezzanotti (2023) and Chodorow-Reich, Gopinath, Mishra, and Narayanan (2020) use demonetization in India to study the impact of technologies on welfare and consumption. Dubey and Purnanandam (2023) show that UPI in India spurs economic growth. Sarkisyan (2022) uses data on Pix to show that deposit markets become more competitive after the introduction of Pix. A large body of literature documents how FinTech lenders compete with traditional banks by providing convenience (including via payments) to clients underserved by banks (Buchak, Matvos, Piskorski, and Seru (2018); Erel and Liebersohn (2022); Ghosh, Vallee, and Zeng (2021); Chava, Ganduri, Paradkar, and Zhang (2021); Di Maggio and Yao (2021); Gopal and Schnabl (2022); Parlour, Rajan, and Zhu (2022); Babina, Buchak, and Gornall (2022); Beaumont, Tang, and Vansteenberghe (2022)).[4] We add to the literature by showing that cashless payments are an important facet of monetary policy transmission.

Finally, we add to the literature on bank market power. Commercial banks have significant deposit market power, which allows them not to respond strongly to monetary policy (Berger and Hannan (1989); Hannan and Berger (1991); Diebold and Sharpe (1990); Neumark and Sharpe (1992); Drechsler, Savov, and Schnabl (2017)). Some banks, at the same time, set deposit rates following the headquarters and are able to keep them unchanged (Begenau and Stafford (2022)). Deposit market power is one of the channels of monetary transmission but not the only proposed channel. Monetary policy transmits to lending and investments through various banking channels, including reserves, capital, and deposits (Bernanke and Blinder (1988, 1992); Kashyap and Stein (2000); Bolton and Freixas (2000); Brunnermeier and Sannikov (2014); Drechsler, Savov, and Schnabl (2017, 2021)). Wang, Whited, Wu, and Xiao (2022) estimate structural model and show that the deposit channel accounts for the largest part of the domestic monetary transmission. We contribute by showing that monetary transmission is facilitated by digital payments because they reduce banks' market power.

The rest of the paper is organized as follows. Section 2 provides details on institutional setting and data. Section 3 discusses the main empirical findings of the paper. Section

[4]For the literature review, see Berg, Fuster, and Puri (2022).

4 proposes a simple model to illustrate the main mechanisms of the paper. Section 5 proposes the dynamic banking model and discusses the identification and estimation. Section 6 presents results from baseline model and counterfactual analyses. Section 7 concludes.

2 Institutional details and data

Before describing the main empirical findings of the paper, we discuss the institutional setting and data.

2.1 Institutional setting

Digital payments have been developing worldwide to promote faster and more efficient payments. They effectively address several frictions existing in traditional banking payments. For example, cash has hoarding costs and opportunity costs (cash could be invested instead). Credit and debit cards have fees that merchants are often allowed to pass to customers. Direct debits and wire transfers are costly and usually take up to 3 business days to settle. Even cashless apps like Venmo and Zelle can be quite costly for banks, and they take days to settle.

FinTechs, banks, and governments work on creating digital payments to mitigate friction associated with payments. In this paper, we will focus on instant payment systems (henceforth, IPS), i.e., technologies for immediate payments. Moreover, we will discuss the technologies created by central banks. First, such IPS are ubiquitous, i.e., are offered by most banks and FinTechs. Second, the costs of using for all agents (households, merchants, and banks) are low. For example, entry costs to Swish (an instant payment platform operating in Sweden that six large banks created) are high, whereas the costs of using Pix are minuscule. That is why costs of entry are another friction that government-created IPS address – even in countries with advanced instant payment platforms, central banks work on creating a public analog (e.g., Rix in Sweden will be launched by Sveriges Riksbank, although Swish is successfully operating).

In this paper, we exploit a natural experiment from Brazil's Pix payment system. Pix is an instantaneous payment system created by the Central Bank of Brazil in November 2020. Pix is a Real-time gross settlement system (RTGS) that allows instant transactions at any time of the day with no limits on size. Transactions are validated by either a QR Code or a key that can be a social security number,[5] phone number, email, or random key. The key uniquely identifies a bank account for the transaction to take place.

Transactions to a person, the most common type, with 1.8 billion transactions moving 550 billion Reais in December 2022 alone, are usually performed with a key with the receiving party checking their online bank app to confirm the receipt of the money. Transactions to a business, with 0.7 billion transactions moving 500 billion Reais in December 2022 alone, are usually performed by generating a different QR Code or random key for each transaction that can be instantly validated by an adjacent software. That allows consumers to use Pix to pay online and in person without the need for someone to check if the payment went through.

Pix was introduced to address three of the main frictions in banking transfers and payments of Brazil. The first one of these frictions is the delay in transfers. In Brazil most transfers take up to three days to be verified. Boleto[6] transactions take up to 3 days, TED[7] can take up to a day, and credit and debit cards, even though businesses get the confirmation of payment instantaneously, can take up to 28 days to receive the money. In the US and many other countries, it is very common for a transaction to take up to 3 days to be completed, with transfers between the same bank usually taking less time. The delay in transactions already is a friction that maintains the market power of banks by making it harder to switch money from one account to the other optimally. Moreover, transfers between the same bank are quicker than between different banks, and this fact expands the market power of banks that are popular in certain areas.

[5]CPF and CNPJ are the equivalent to the SSN and EIN in the US.

[6]Payment slip used in Brazil for cashless payments. It is available to the clients of participating banks – around 15% of the banks in our sample.

[7]Wire transfer technology.

The second friction that Pix solves is the availability issue. Most bank transfers operate only during working hours on business days, and that is true for the two most common methods of bank transfers in Brazil besides Pix: Boleto and TED.

The third main friction is the pricing. Fees for transfers can be quite costly, thus discouraging trade and creating a barrier to having multiple bank accounts. For example, Brazil's underground economy, which comprises almost 20% of the GDP, used to be cash-only. Pix transactions are free for individuals and small firms. Even though there is a cost for Pix transactions for big firms, Duarte et al. (2022) shows that Pix fees are 0.22% for merchants as opposed to 2.2% for credit cards.

Due to those advantages, Pix became very popular in Brazil, with 133 million individuals and 12 million firms already using Pix by the end of 2022. Pix is one of the reasons for the growth in bank accounts in Brazil, with the average of bank accounts per capita moving from 3.5 in December 2020 to 5.2 in October 2022. In Brazil, due to Pix and mobile banking, it became convenient to have multiple accounts for multiple purposes.

Since Pix in Brazil was immediately adopted by most households, firms, and banks, and because we have access to rich banking data, Brazil is an excellent setting to study how digital payments impact monetary policy transmission.

2.2 Deposit market power and monetary policy

When central banks raise their policy rates, they expect banks to follow by increasing their deposit rates. Then, first, depositors will want to spend less, and they will open new deposit accounts, and second, loan rates will have to increase to maintain banks' profits. This will result in a reduction in lending and, hence, a contraction in investments. However, banks do not increase their deposit rates as much as the policy rates rise (Drechsler, Savov, and Schnabl (2017)) because banks have deposit market power – the ability to keep their deposit rates low without losing their depositors. In other words, banks are able to increase deposit spreads – the difference between policy rates and deposit rates.

Since banks keep their deposit rates low even after central banks hike rates, the monetary transmission is incomplete. Specifically, market rates (for example, money market funds) become more attractive to investors because they react more to policy rate changes. As a result, many depositors withdraw their deposits from the banks and invest them elsewhere. That is why deposits generally decline during contractionary monetary policy episodes. Note that raising spreads is an equilibrium decision of banks. Even though they end up losing deposits, profits from increased spreads outweigh losses from lost deposits.

Another consequence of increased deposit spreads is the slow reaction of loan rates – banks do not increase them much because their funding (deposits) does not become very expensive. Since loan rates do not increase as much as monetary authorities would want, loan contractions are limited. It is important to note that loans decline because deposits flow out – this is called the deposit channel of monetary policy. However, such contractions in loans are due to banks' endogenous decisions and not firms' decisions to cut their investments because loans are more expensive.

Deposit market power limits central banks' ability to conduct monetary policy because banks do not fully respond to policy rate changes. As a result, monetary policy is not completely passed to the real economy. If banks were to lose their market power, monetary transmission would potentially be more efficient. In this paper, we provide evidence for both – we show that banks' deposit market power declines when digital payments are developing and that monetary policy becomes more complete.

2.3 Data

We use the adoption of Pix in Brazil as a setting to study how instant payments impact investments and banks. We collect administrative data on monthly Pix transactions from the Central Bank of Brazil. The data include the municipality where the transaction is made, the total monthly value of transactions in Brazilian reals, and the number of users.

We can then calculate per capita and per-user transactions for all 5,570 municipalities. Pix data starts in November 2020 (the month of Pix launch).

We collect monthly balance sheet data for bank branches operating in Brazil from ESTBAN. The data covers 313 banks from August 1988 till November 2022. The data includes bank identifiers (cnpj) and balance sheet data – deposits by type, loans, financing, cash positions, reserves, interbank loans, etc.[8] Data also contain municipalities where branches operate, which allows us to calculate deposit market concentrations (Herfidahl-Hirschman index or HHI) for municipality m at time t as follows using private deposits for each bank i in a municipality:

$$HHI_{mt} = \sum_{i=1}^{N} \left(\frac{D_{it}}{D_{mt}} \right)^2 \tag{1}$$

$HHI_{mt} = 1$ for monopolies. A larger number implies more concentrated markets, whereas a smaller number implies competitive markets. We supplement the data with bank-level series of interest rates from the Central Bank of Brazil. Specifically, We collect quarterly data on interest expenses to use them as proxies for deposit rates and interest income to use them as proxied for loan rates.

3 Empirical results

We start by showing that digital payments lead to a reduction in banks' market power, i.e., their ability to keep deposit rates stable after changes to the policy rate without losing all of their customers. When central banks increase policy rates, commercial banks react by raising deposit rates but only by a fraction of the policy rate change. As a result, some depositors seek more profitable investment opportunities.

In our empirical analysis, we proceed in two steps. First, we provide cross-sectional evidence that deposit market power declines in areas with more Pix usage. We then

[8]We keep all branches in our sample, including those that do not actively set their deposit rates. This way, we address the points in Begenau and Stafford (2022).

acknowledge that bank branches, especially in distant localities, might respond differently to the introduction of Pix and changes in policy rates. To address the challenge, in the second step of the empirical analysis, we provide within-branch and within-locality-time evidence that banks respond more to policy rate changes in areas with higher Pix take-up. As a result, in such areas, banks' deposits fall less during contractionary monetary policy episodes.

3.1 Cross-sectional evidence

We follow Drechsler, Savov, and Schnabl (2017) and construct two measures of the deposit market power – deposit spread betas, i.e., the sensitivity of deposit spreads (policy rate minus deposit rate) to policy rates, and deposit flow betas, i.e., the sensitivity of deposit flows to policy rates. Specifically, for each branch of the bank we run the following sets of regressions:

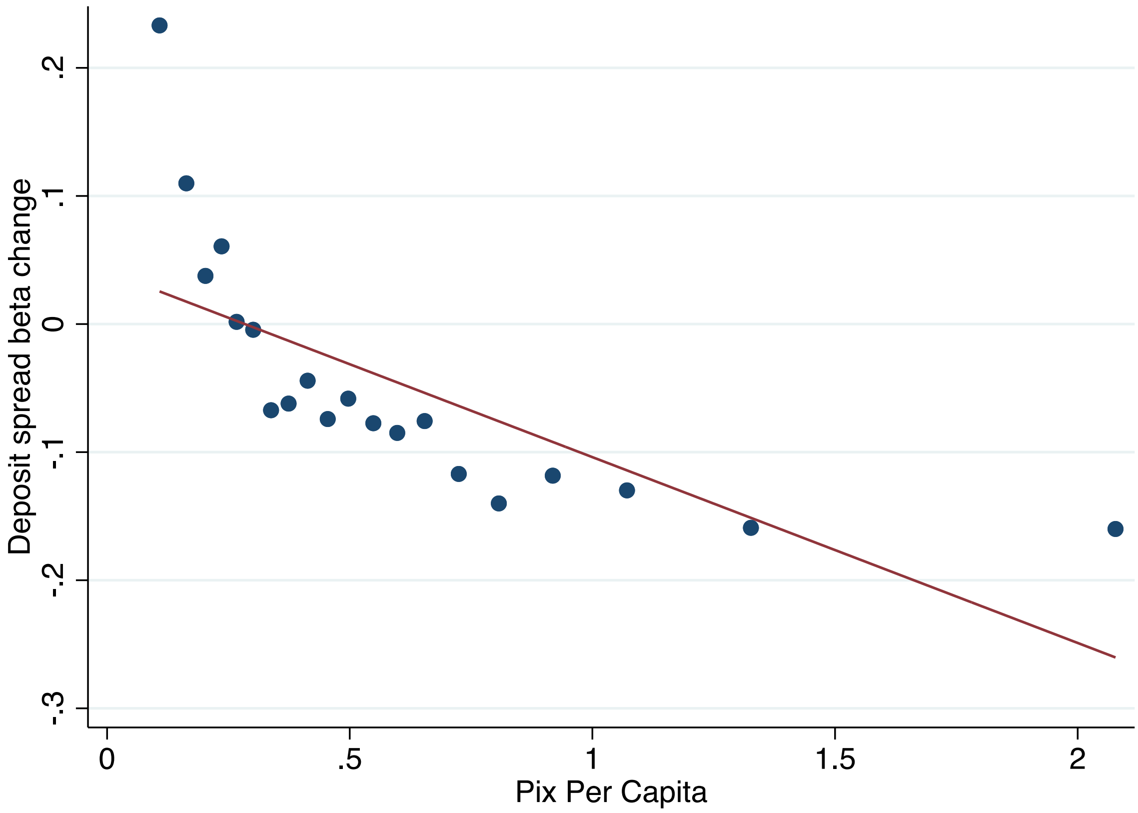
$$y_{it} = \beta_i MS_t + u_{it} \tag{2}$$

where y_{it} is either a change in deposit spreads of branch i, defined as the Selic rate less the deposit rate or the log change in deposit amounts (henceforth, deposit growth), MS_t is a change in the policy rate.

For each branch i, we can interpret β_i as the branch's i's elasticity of deposit spreads and deposit growth to monetary policy changes. We refer to β_i from the first set of regressions as *spread betas* (or deposit betas) and β_i from the second set of regressions as *flow betas*. High spread betas mean that banks respond less to policy rate changes, and hence, they have higher deposit market power. As a result, their flow betas are lower (more negative). We then evaluate the changes in deposit betas after Pix. Specifically, we evaluate the growth in deposit betas after Pix. We then check if the changes differ across municipalities in Brazil depending on Pix usage in the municipalities.

Figure 2 shows the changes in spread betas after the introduction of Pix, i.e., we check if banks' deposit rate sensitivities to policy rate changes are different after the instant payment system is introduced. Negative numbers on the graph mean that deposit spread

Figure 2: Changes in Spread Betas

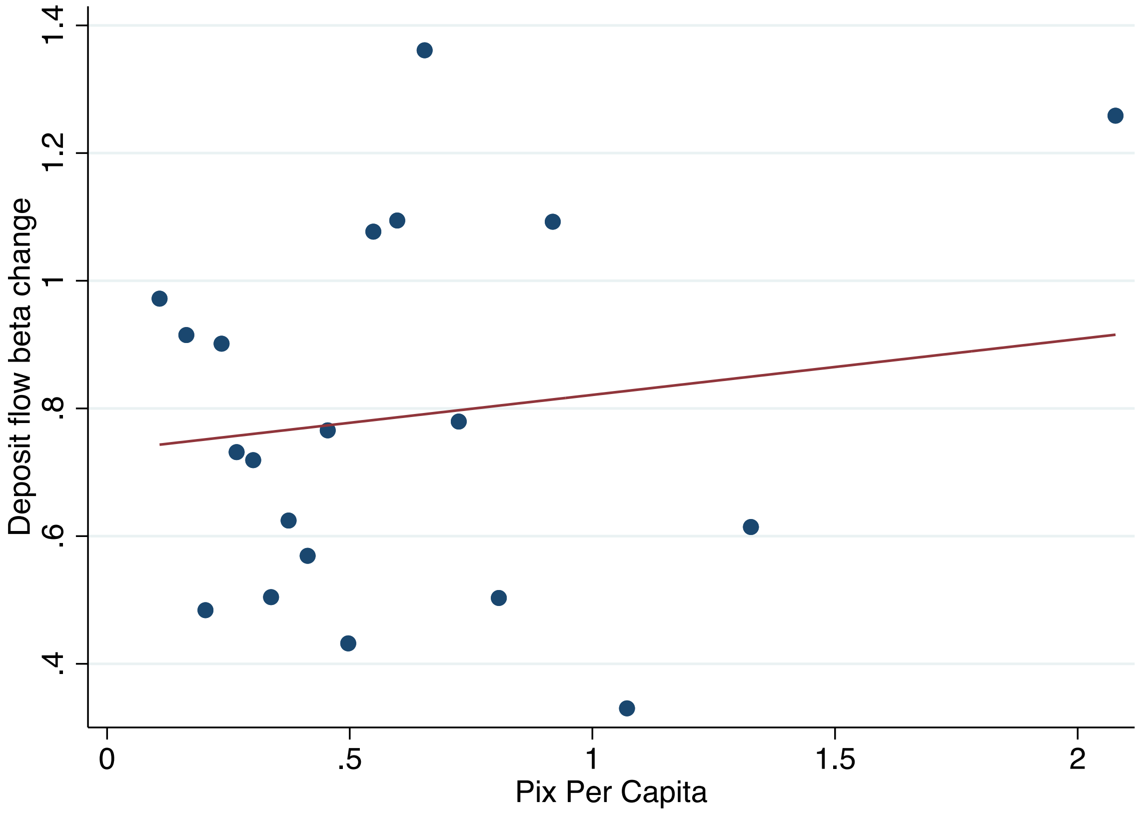


Note: The graph shows the changes in deposit spread betas in Brazil after the introduction of Pix.

betas are lower – banks change their deposit rates more in response to policy rate changes after Pix is introduced. Moreover, the deposit betas changes are lower in areas with more per capita Pix usage (municipalities with higher value of Pix transactions per person). In other words, banks' market power declines after Pix in the cross-section of bank branches.

Figure 3 shows the changes to deposit flow betas as a function of the value of Pix transactions per capita in the area. Deposit flow betas increase, consistent with the reduced deposit market power. When banks react more to policy rate changes, their deposit rates are more competitive, and hence, fewer depositors withdraw their funds from the banks. Recall that monetary authorities generally want banks to get more deposits when policy rates increase, so the rise in deposit flow betas is an indication of a more efficient monetary policy.

Figure 3: Changes in Flow Betas



Note: The graph shows the changes in deposit flow betas in Brazil after the introduction of Pix.

The cross-section evidence shows that in areas with more Pix usage, banks started reacting more to policy rate decisions by changing their deposit rates. As a result, banks' deposits fall less following contractionary monetary policy actions. The cross-sectional analysis has a number of identification issues, which we address next.

3.2 Within-branch estimation

The cross-sectional evidence above has several identification challenges. First, different municipalities in Brazil may have various unobservable investment opportunities, which in turn can affect both banks' decisions and deposit demand after changes to policy rates. Second, branches of different banks can have their own branch-setting policies. For example, branches of larger banks can be more dependent on the head office than branches of smaller banks. We address both challenges in this section.

The first challenge is unobservable local investment opportunities that can differ across municipalities. For example, tech firms are more affected by policy rate hikes, so the areas with many tech firms can have a larger need for lending than other areas. The cross-sectional analysis does not account for such possibilities. We address the concern by including municipality-time fixed effects in our regressions following Drechsler, Savov, and Schnabl (2017). We then compare banks operating in the same municipality at the same time, and thus, we account for local demand.

The second challenge is differences across branches or banks. For example, some branches are actively setting their interest rates, while others are following their headquarters (Begenau and Stafford (2022)). We address the challenge by including branch fixed effects.[9] We then compare deposit spreads and deposit flows of the same branch across time, thus accounting for potential differences in branches that can bias our results.

We test if the reaction of deposit spreads and deposit flows to policy rate changes is different with Pix by estimating a within-branch within-locality-time panel regression. Specifically, we limit the sample to nine months before the launch of Pix and nine months after and run the following panel regression:

$$Y_{imt} = \beta MS_t \cdot PixPerCap_{mt} + \gamma X_{imt} + \alpha_{im} + \varepsilon_{imt} \tag{3}$$

where Y_{imt} is either deposit spreads or deposit flows, $PixPerCap_{mt}$ is the value of Pix transactions per person, α_{im} is branch fixed effects. The vector of controls includes deposit market concentration measure and all interaction terms.

Table 1 reports the results. Columns 1 and 2 show the results for deposit flows. Columns 3 and 4 correspond to deposit spreads. We find that deposit spreads are increasing less with policy rates in areas with more Pix usage. As a result, bank deposits

[9] Including bank fixed effects instead of branch fixed effects produces qualitatively similar results. Note that after including branch fixed effects, bank fixed effects are redundant.

Table 1: Impact of Pix on Deposit Flows and Deposit Spreads

$$Y_{imt} = \beta MS_t \cdot PixPerCap_{mt} + \gamma X_{imt} + \alpha_{im} + \varepsilon_{imt}$$

	Dependent variable:			
	Deposit flows		Deposit spreads	
	(1)	(2)	(3)	(4)
Pix Per Capita · MS	0.014***	0.013***	−0.496***	−0.507***
	(0.005)	(0.005)	(0.087)	(0.088)
Pix Per Capita	−0.008***	−0.010***	0.512***	0.451***
	(0.003)	(0.002)	(0.096)	(0.091)
MS	−0.025***	−0.024***	1.905***	1.964***
	(0.003)	(0.003)	(0.029)	(0.026)
Branch FE	Yes	No	Yes	No
Bank FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	162,337	162,366	172,986	173,013
R^2	0.064	0.019	0.659	0.654

Note: This table provides results of within-branch estimation of the effect of Pix on deposit flow and spread betas – equation (3). Columns 1 and 2 show the results for deposit flows. Columns 3 and 4 correspond to deposit spreads. Standard errors are clustered at the municipality level and displayed in parentheses. Bank and branch fixed effects are included. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

do not flow out as much. Specifically, in areas with a R$1000 (around $200 US dollars) higher per capita Pix value, a 1 p.p. increase in policy rates would outflow deposits by 1.4% less. The results suggest that banks' market power declines and monetary policy becomes more efficient.

Overall, the empirical results suggest that banks lose their market power when digital payments are introduced. We find that banks have to respond more to policy rate changes by changing their deposit rates. For example, in areas with more Pix transactions, banks increase their deposit rates more following contractionary monetary policy decisions. As a result, deposits do not flow out as much. The results are in line with the hypothesis that digital payments reduce banks' deposit franchise value by allowing depositors to transfer money more easily across banks and also by giving them access to digital payments even without an account at a large well-connected bank (or even at any traditional bank). For example, many Brazilians use Pix through FinTechs such as NU Bank or Matera. Small banks in Brazil also gained a significant deposit share relative to large banks after the launch of Pix (Sarkisyan (2022)), which is consistent with our findings.

The empirical results motivate us to understand how underlying channels interact. For example, how does the introduction of Pix change the demand of deposit from the household sector? Which channel of monetary policy transmission makes the pass-through more complete after the introduction of Pix? Also, would monetary policy be less efficient if Pix were not introduced or if Pix had lower take-up? We first illustrate the households' decision through a simple circular city model in the next section. Later in Section 5, we build and estimate a dynamic banking model to further investigate these questions.

4 Simple model

We start by providing a simple model to illustrate the main mechanisms highlighted in our paper. To set the stage for analyzing the households' decision on banking, we present a circular city model that is similar to Park and Pennacchi (2009). We then perform comparative statics on the impact of Pix introduction on deposit demand.

4.1 Settings

Consider a continuum D of households who live in a circular city of a unit length. Each household has one dollar to store as deposits indefinitely. There are n banks operating in the city, and they are located equidistantly, so the distance between any two banks is $\frac{1}{n}$.

Households receive deposit rate r_i from storing their money in bank i. Additionally, households receive a non-monetary benefit u_i because they value auxiliary services such as the payment network provided by the bank. Households have quadratic utility over the deposit rate and auxiliary services. To obtain these services, households need to travel to the bank and incur a travel cost of t_d per unit of distance.

Households can split their deposits into more than one bank account. We assume that the travel cost t_d is sufficiently large such that households only consider the two banks closest to them. So, if a household is located between bank i and $i-1$, they have three savings options – deposit with bank i, deposit with bank $i-1$, or split their deposit between the two banks. Consider a household located to the left of bank i. Their distance to bank i is x_-. The household's utilities from the three options are

$$v_-(\text{Bank } i) = (r_i + u_i)^2 - t_d x_-, \tag{4}$$

$$v_-(\text{Bank } i-1) = (r_{i-1} + u_{i-1})^2 - t_d(\frac{1}{n} - x_-), \tag{5}$$

$$v_-(\text{Mix}) = \alpha^2(r_i + u_i)^2 + (1-\alpha)^2(r_{i-1} + u_{i-1})^2 - t_d\frac{1}{n}, \tag{6}$$

where $\alpha \in (0,1)$ is the optimal deposit share allocated to bank i and it is

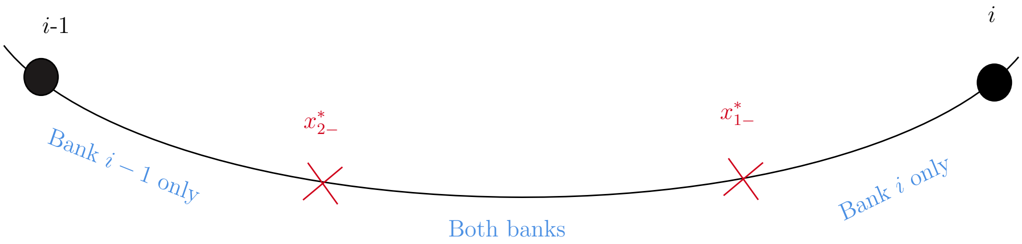
$$\alpha = \frac{(r_{i-1} + u_{i-1})^2}{(r_i + u_i)^2 + (r_{i-1} + u_{i-1})^2}. \tag{7}$$

4.2 Household's deposit decision

Intuitively, the household's deposit decision depends on their location in the city. Figure 4 illustrates the deposit equilibrium. Households located within x^*_{1-} from bank i find it optimal to deposit with bank i, whereas households located outside of x^*_{2-} from bank i find it optimal to deposit with bank $i-1$. In the middle region between x^*_{1-} and x^*_{2-}, households choose to deposit with both banks to maximize their utility.

We derive the expression for the two thresholds x^*_{1-} and x^*_{2-} using the utilities from (4)-(6). At x^*_{1-}, households are indifferent between choosing bank i and mixed strategy. Similarly, at x^*_{2-}, households are indifferent between choosing bank $i-1$ and mixed

Figure 4: Households' deposit decision



strategy. The two thresholds are

$$x^*_{1-} = \frac{1-\alpha^2}{t_d}(r_i + u_i)^2 - \frac{(1-\alpha)^2}{t_d}(r_{i-1} + u_{i-1})^2 + \frac{1}{n}, \tag{8}$$

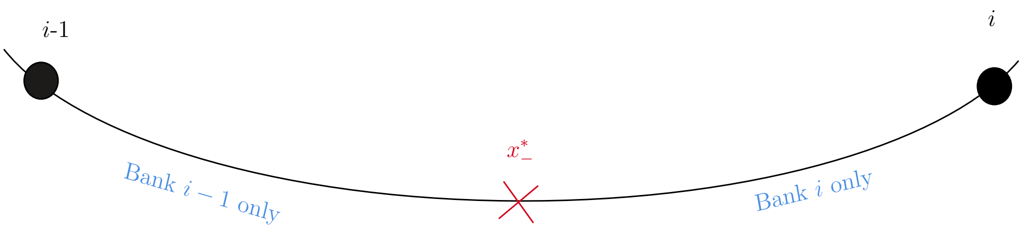
$$x^*_{2-} = \frac{\alpha^2}{t_d}(r_i + u_i)^2 + \frac{(1-\alpha)^2 - 1}{t_d}(r_{i-1} + u_{i-1})^2. \tag{9}$$

Of course, if the travel cost is large relatively to the additional benefits gained from having another bank account, the middle region will shrink until it reaches zero. Figure 5 shows the scenario where no households choose the mixed strategy. Households located within x^*_- from bank i find it optimal to deposit with bank i, whereas households located outside of x^*_- from bank i find it optimal to deposit with bank $i-1$. Households at x^*_- are indifferent between bank i and bank $i-1$. We solve for x^*_- which yields,

$$x^*_- = \frac{1}{2t_d}(r_i + u_i)^2 - \frac{1}{2t_d}(r_{i-1} + u_{i-1})^2 + \frac{1}{2n}. \tag{10}$$

It is worth noting that this threshold is the midpoint of x^*_{1-} and x^*_{2-}. Under what

Figure 5: No mixed strategy



condition will no households opt for the mixed strategy? This scenario occurs when households located at x^*_- prefer depositing with one bank rather than both banks. We have the following condition

$$\frac{1}{2n}t_d \geq (\alpha^2 - \frac{1}{2})(r_i + u_i)^2 + ((1-\alpha)^2 - \frac{1}{2})(r_{i-1} + u_{i-1})^2. \tag{11}$$

This condition implies that if the additional benefit gained from splitting deposits optimally cannot compensate for the travel cost, no households in the region will choose the mixed strategy.

The solutions to households located to the right of bank i are symmetric. Let x_+ be the household's distance from bank i. Similarly, we let x^*_{1+} be the threshold between choosing bank i and mixed strategy, x^*_{2+} the one between choosing bank $i+1$ and mixed strategy, and x^*_+ the one between choosing bank i and $i+1$. Their expressions are

$$x^*_{1+} = \frac{1-\alpha^2}{t_d}(r_i + u_i)^2 - \frac{(1-\alpha)^2}{t_d}(r_{i+1} + u_{i+1})^2 + \frac{1}{n}, \tag{12}$$

$$x^*_{2+} = \frac{\alpha^2}{t_d}(r_i + u_i)^2 + \frac{(1-\alpha)^2 - 1}{t_d}(r_{i+1} + u_{i+1})^2 \tag{13}$$

$$x^*_{+} = \frac{1}{2t_d}(r_i + u_i)^2 - \frac{1}{2t_d}(r_{i+1} + u_{i+1})^2 + \frac{1}{2n}. \tag{14}$$

4.3 Deposit demand

We can now derive the deposit demand of bank i. For illustration purposes, here we assume that deposit rates and non-monetary benefits are pre-determined. We allow banks to set deposit rate dynamically in our structural estimation in Section 5. We obtain bank i's deposit share by adding up the demand from both sides. Bank i receive all deposits from households choosing bank i only, and half of the deposits from households choosing mixed strategy.

$$\begin{aligned} DepShare_i &= x^*_{1-} + \frac{1}{2}(x^*_{2-} - x^*_{1-}) + x^*_{1+} + \frac{1}{2}(x^*_{2+} - x^*_{1+}) \\ &= \frac{1}{t_d}\underbrace{\left[(r_i + u_i)^2 - \frac{1}{2}[(r_{i-1} + u_{i-1})^2 + (r_{i+1} + u_{i+1})^2]\right]}_{\text{Competitiveness on deposit rate and services}} + \underbrace{\frac{1}{n}}_{\text{Concentration}} . \end{aligned} \tag{15}$$

Bank i's deposit demand depends on two terms. The first one is bank i's competitiveness on deposit rate and banking services, relative to its two neighboring banks. The second one is the number of banks, namely market concentration in the economy.

We can also derive the share of households who choose more than one bank. Assuming that the mixed strategy regions ($x^*_{2-} - x^*_{1-} \geq 0$ and $x^*_{2+} - x^*_{1+} \geq 0$) are present, the share of households who will choose bank i plus a neighboring bank is

$$\begin{aligned} MixDepositors_i &= (x^*_{2-} - x^*_{1-}) + (x^*_{2+} - x^*_{1+}) \\ &= \frac{1}{t_d} \underbrace{\left[(4\alpha^2 - 2)(r_i + u_i)^2 + [2(1-\alpha)^2 - 1][(r_{i-1} + u_{i-1})^2 + (r_{i+1} + u_{i+1})^2] \right]}_{\geq 0 \text{ by assumption}} - \frac{2}{n}. \end{aligned} \tag{16}$$

4.4 Comparative statics

The introduction of a fast payment system like Pix can affect multiple factors in the model. We consider three changes to the model fundamentals and analyze their impact on the deposit demand.

Reduction in transportation costs. If transportation costs, t_d, decline, the demand for deposits of bank i increases if bank i can provide a higher combined benefit of deposit rate and banking services. We see this by taking the derivative of (15) with respect to transportation costs:

$$\frac{\partial DepShare_i}{\partial t_d} = -\frac{1}{t_d^2} \left[(r_i + u_i)^2 - \frac{1}{2}[(r_{i-1} + u_{i-1})^2 + (r_{i+1} + u_{i+1})^2] \right] < 0 \text{ if } [\cdot] > 0$$

When transportation costs decline, households are more likely to have two bank accounts, especially when the non-monetary benefit terms are large. This can be inferred from the mixed strategy condition from (11), as well as the share of mixed strategy depositors from (16).

Equal payment utility, $u_i = u_{i-1}$. One potential impact of a fast payment system is its ability to offer universal payment services to depositors from all banks. In the model, this shows as an equal non-monetary benefit across all banks, $u_i = u_{i-1} = u_{i+1}$. From (15), we see that the uniform non-monetary benefit makes the competitiveness term smaller. If bank i has a higher non-monetary benefit initially $u_i > u_{i-1}$, the demand for deposits of bank i decreases after the introduction of payment technology. Conversely, if $u_i < u_{i-1}$ initially, the demand for deposits of bank i increases. When payment provision is equal between banks, there are more benefits to the bank that originally had inferior payment convenience. This bank will then attract depositors.

Decrease in concentration. Pix has the potential to lower the barrier for banks to enter a new market. With a digital payment system, banks can provide the same service without setting up a physical branch. In this case, the number of banks, n, increases. The change in concentration leads to two effects in the model. Firstly, choosing two banks is more likely, which is implied from the derivative of (16),

$$\frac{\partial MixDepositors_i}{\partial n} = \frac{2}{n^2} > 0.$$

Secondly, the demand for deposits of bank i generally decreases. We see this from the derivative of (15),

$$\frac{\partial DepShare_i}{\partial n} = -\frac{1}{n^2} < 0.$$

The results happen because an increase in the number of banks makes it less costly to travel to the nearby banks. Households are more likely to split their deposits into multiple banks, so demand for any individual banks decreases.

5 Dynamic model

To understand the mechanism behind the impact of digital payment on monetary policy transmission, we follow Wang, Whited, Wu, and Xiao (2022) and consider an infinite-horizon dynamic equilibrium model with three sectors: households, firms, and banks.

Households and firms solve static discrete-choice problems and make optimal savings and financing decisions. The existence of an instant payment system enters households' utility functions but does not affect firms' utility functions. Banks compete imperfectly. They act as intermediaries by taking short-term deposits from households and providing long-term loans to firms. Finally, the government sets monetary policy, which is exogenous in the model.

5.1 Households

At each point in time, the economy contains a continuum of households with total wealth W_t. Each point in time t is a separate market, and we model the banking sector at the national level. Given that households face a static problem, we drop subscript t for convenience. Each market consists of J banks, each of which offers a differentiated deposit product. Households allocate their endowments ($1 each) across three types of investments: cash, bond, and bank deposits. Hence, households' choice set is $\mathcal{A}^d = \{0, 1, \ldots, J, J+1\}$, where 0 denotes the cash option, $J+1$ denotes the bond option, and $1 \ldots J$ denote deposits in each bank.

The IO literature usually assumes that each household can put their dollar only in one bank. The assumption is justified by the fact that there is a continuum of households, and multiple bank investments can be interpreted as several households making independent decisions. While the "one-dollar-one-bank" assumption can be plausible in many settings, in ours, it is not – when payment systems are introduced, households might be more willing to have multiple bank accounts as illustrated in Section 4.4.

Solving the model that allows households to invest in multiple banks is challenging because the set of choices becomes continuous. To overcome the challenges, we make two simplifying assumptions. First, we assume that each household can put their endowment only in two banks (similarly to our theoretical framework) and only in equal shares. A different way to characterize it is if each household is endowed with two half-dollar coins, and they can put each of them in one bank. The second assumption is that if a household chooses to deposit in two banks, one of them must be a large public bank. Large public banks in Brazil are responsible for paying stimuli, social help, pensions, and often salaries.

Denote the total number of options that households have by $\mathcal{B}^d$. Each investment option is characterized by the interest rate r^d and a vector of non-rate characteristics x^d, and for banks. The interest rate on cash is zero, whereas the interest rate on bonds is the policy rate f (*Selic rate*). If a household deposits in two banks, the interest rate is calculated as a portfolio return, while non-rate characteristics are the best option. For example, if the first bank has branches in every state, while the second one has branches only in one state, having accounts at both banks allows a depositor to have branch access in all states.

The households choose the best investment option to maximize utility

$$\max_{j \in \mathcal{B}^d} u_{i,j} = \alpha_i^d r_j^d + \gamma^d x_j^d + \beta^d p^d x_j^d + \mu_j^d + \epsilon_{i,j}^d, \tag{17}$$

where $u_{i,j}$ is the utility from household i choosing investment option j. The coefficient α_i^d is the sensitivity to the interest rate r_j^d. The coefficients γ^d are sensitivities to non-rate characteristics that include number of branches and time fixed effects. β^d is an additional sensitivity to non-rate characteristics after the introduction of Pix ($p^d = 1$). We let μ_j^d denote the product invariant demand shock, i.e., the bank fixed effect. The last term $\epsilon_{i,j}^d$ is the relationship shock specific to the household-bank combination. Household i's optimal choice of investment is then

$$\mathbb{I}_{i,j}^d = \begin{cases} 1, & \text{if } u_{i,j} \geq u_{i,k}, \quad j,k \in \mathcal{A}^d \\ 0, & \text{otherwise} \end{cases} \tag{18}$$

To compute the deposit share of each bank, we aggregate the optimal choice of each household in the economy. We assume the relationship-specific shock $\epsilon_{i,j}^d$ follows a type II extreme-value distribution. We can then derive the market share of each bank from a logit model:

$$
\begin{aligned}
s_j^d(r_j^d, p_j^d|f) &= \int \mathbb{I}_{i,j}^d dF(\epsilon) \\
&= \sum_i \mu_i^d \frac{\exp(\alpha_i^d r_j^d + \gamma^d x_j^d + \beta^d p^d x_j^d + \mu_j^d}{\exp(Bonds) + \exp(Cash) + \sum_{n=1}^J \exp(Banks)}
\end{aligned} \tag{19}
$$

$$
\begin{aligned}
Bonds &= \alpha_i^d f + \gamma^d x_{J+1}^d + \beta^d p^d x_J^d + \mu_{j+1}^d \\
Cash &= \gamma^d x_c^d + \beta^d p^d x_c^d + \mu_c^d \\
Banks &= \alpha_i^d r_n^d + \gamma^d x_n^d + \beta^d p^d x_n^d + \mu_n^d
\end{aligned}
$$

where μ_i^d is the fraction of total wealth W held by household i. The numerator is the utility of choosing bank j, whereas the denominator is the sum of the utilities of all investment options. From here, we derive the aggregate demand function for deposits:

$$
D_j(r_j^d|f, p_j^d) = s_j^d(r_j^d|f, p_j^d) \cdot W. \tag{20}
$$

5.2 Firms

The firm's sector is similar to the household sector. At each point in time, there is a continuum of firms, and the aggregate borrowing demand is K. Each bank offers differentiated lending businesses. Firms have three types of financing options. They can borrow from one of the J banks, finance through bonds, or choose not to borrow at all. Hence, firms' choice set is $\mathcal{A}^\ell = \{0, 1, ..., J, J+1\}$, where 0 denotes the outside option (not borrowing), and $J+1$ denotes the bond option.

Since both bank loans and bonds are long-term borrowing, a fraction η of the outstanding balance is due at each period of time. If the firm obtains a loan from bank j, the loan will have a fixed interest rate r_j^l. Similarly, if the firm decides to finance through long-term bonds, the interest rate will be the sum of a default cost δ and and the average policy rate $\bar{f}$ which is defined as

$$
\bar{f} = \eta f_t + \mathbb{E}_t \left[\sum_{n=1}^{\infty} \eta(1-\eta)^n f_{t+n} \right] \tag{21}
$$

Each financing option is characterized by the interest rate r^ℓ and a vector of non-rate characteristics x^l. The firms' maximization problem is

$$\max_{j \in \mathcal{A}^\ell} \pi_{i,j} = \alpha_i^\ell r_j^\ell + \gamma^\ell x_j^\ell + \xi_j^\ell + \epsilon_{i,j}^\ell \tag{22}$$

where $\pi_{i,j}$ is the utility from firm i choosing financing option j. The coefficient α_i^ℓ is the sensitivity to the interest rate r_j^ℓ, γ^ℓ are sensitivities to bank-level non-rate characteristics. We let ξ_j^ℓ denote the product invariant demand shock. The last term $\epsilon_{i,j}^\ell$ is the relationship shock specific to the household-bank combination. Firm i's optimal choice of financing is then

$$\mathbb{I}_{i,j}^\ell = \begin{cases} 1, & \text{if } \pi_{i,j} \geq \pi_{i,k}^h, \quad j,k \in \mathcal{A}^\ell \\ 0, & \text{otherwise} \end{cases} \tag{23}$$

We aggregate the optimal choice of each firm in the economy to compute the loan share of each bank. Again, we adopt the standard assumption that $\epsilon_{i,j}^\ell$ follows a type II extreme-value distribution. The loan share of each bank is

$$s_j^\ell(r_j^\ell|f) = \int \mathbb{I}_{i,j}^\ell dF(\epsilon) = \sum_i \mu_i^\ell \cdot \frac{\exp(\alpha_i^\ell r_j^\ell + \beta^\ell x_j^\ell + \xi_j^\ell)}{\underbrace{\exp(\alpha_i^\ell(\overline{f} + \overline{\delta}) + \beta^\ell x_{J+1}^\ell + \xi_{J+1}^\ell)}_{Bonds} + \underbrace{\exp(\beta^\ell x_n^\ell + \xi_n^\ell)}_{NotBorrowing} + \underbrace{\sum_{s=1}^{J} \exp(\alpha_i^\ell r_s^\ell + \beta^\ell x_s^\ell + \xi_s^\ell)}_{Banks}} \tag{24}$$

where μ_i^ℓ is the fraction of total loan demand K from firm i. The numerator is the utility of choosing bank j, whereas the denominator is the sum of the utilities of all financing options. The demand function for loans is

$$B_j(r_j^\ell|f) = s_j^\ell(r_j^\ell|f) \cdot K. \tag{25}$$

5.3 Banks

There are J banks in the market. Each bank simultaneously choose the deposit rate r_j^d and lending rate r_j^ℓ. The deposit and lending rates are set as spreads below or above the policy rate f_t, respectively. Since households can hold cash which has an interest rate of zero, deposit rate r_j^d has a zero lower bound:

$$r_j^d \geq 0. \tag{26}$$

Through the demand functions in (20) and (25), bank's decisions of rate setting determine the quantities of deposits and loans supplied to the economy. The quantity of loans supplied by bank j at time t is $B_{j,t}$ and the quantity of deposits supplied is $D_{j,t}$.

Assets: Let $L_{j,t}$ denote the outstanding loans in bank j at time t. Banks conduct maturity transformation in their lending businesses. In each period, a fraction η of the outstanding loans matures. Assume that firms pay the present value of the interest income $I_{j,t}$ at the end of the first period. It is computed as

$$I_{j,t} = \sum_{n=0}^{\infty} \frac{(1-\eta)^n B_{j,t} r_{j,t}^\ell}{(1+\gamma)^n} \tag{27}$$

where γ is the discount factor of the bank. Following this income structure, the evolution process of outstanding loans are

$$L_{j,t+1} = (1-\eta)(L_{j,t} + B_{j,t}). \tag{28}$$

Loans are risky. We assume a default rate of δ_t in each period. Hence, banks write off the delinquent loans from their balance sheet. The charge-off equals to $\delta_t \eta (L_t + B_t)$. Besides loans, banks also hold reserves R and government securities G on their balance sheet, with a return equal to the policy rate f_t.

Liabilities: On the liability side, banks can borrow from insured retail deposits $D_{j,t}$ or uninsured nonreservable funding $N_{j,t}$. Retail deposits follow the household demand function in (20). Uninsured nonreservable funding faces a quadratic cost:

$$\Phi^N(N_{j,t}) = \left(f_t + \frac{\phi^N}{2} \cdot \frac{N_{j,t}}{D_{j,t}}\right) N_{j,t} \tag{29}$$

The balance sheet constraint for the banking sector is then

$$L_{j,t} + B_{j,t} + R_{j,t} + G_{j,t} = D_{j,t} + N_{j,t} + \underbrace{E_{j,t}}_{Equity} \tag{30}$$

The evolution process for equity is

$$E_{j,t+1} = E_{j,t} + (1 - \tau)\Pi_{j,t} - C_{j,t+1} \tag{31}$$

where τ is the corporate tax rate, $C_{j,t+1}$ is the cash dividends distributed to the equity holders, and $\Pi_{j,t}$ is the bank's operating profits. We assume a deposit servicing cost ϕ^d, a loan servicing cost ϕ^ℓ, and a net fixed operating cost $\psi\bar{E}$. We can derive the operating profits as

$$\Pi_{j,t} = I_{j,t} - (L_{j,t} + B_{j,t})(\eta\delta_t + \phi^\ell) + G_{j,t}f_t - (r^d_{j,t} + \phi^d)D_{j,t} - \Phi^N(N_{j,t})N_{j,t} - \psi\bar{E}_j \tag{32}$$

Constraints: In our model, we impose several constraints to the banking sector. The first one is the dividend constraint. Cash dividends to equity holder can not be negative $C_{j,t} \geq 0$. The second one is capital constraint. Equity has to be no less than κ fraction of the total loans $E_{j,t} \geq \kappa(L_{j,t} + B_{j,t})$. The third one is reserve constraint. Banks need to keep at least θ fraction of deposit in central bank's reserve account $R_t \geq \theta D_t$.

5.4 Monetary Policy

Government set monetary policy on the selic rate. Following Wang et al. (2022), we model monetary policy as a process of the policy rate and allow it to correlate with loan charge-offs in the banking sector. The joint law of motion is

$$\begin{bmatrix} \ln \delta_{t+1} - \mathbb{E}(\ln \delta) \\ \ln f_{t+1} - \mathbb{E}(\ln f) \end{bmatrix} = \begin{bmatrix} \rho_\delta & \rho_{\delta f} \\ 0 & \rho_f \end{bmatrix} \cdot \begin{bmatrix} \ln \delta_t - \mathbb{E}(\ln \delta) \\ \ln f_t - \mathbb{E}(\ln f) \end{bmatrix} + \begin{bmatrix} \sigma_\delta & 0 \\ 0 & \sigma_f \end{bmatrix} \varepsilon_{t+1}. \quad (33)$$

The policy rate directly affects bank's cost on borrowing from uninsured nonreservable borrowing. Through expectations, the short-run policy rate affects the long-run policy rate, both of which have an impact on the outside options in the deposit and loan markets.

5.5 Estimation

We calibrate the parameters and estimate the model in four steps. The estimation uses national market as the market definition, with each quarter from 2014Q4 to 2021Q3 a separate market. We begin with a set of calibrated parameters from banking regulation in Brazil in step 1. Then, we estimate parameters related to monetary policy and loan maturity separately outside of the model. Next, we estimate the loan and deposit demand functions from the household and firm sectors, respectively. Finally, we use the simulated minimum distance (SMD) method to estimate the rest of the banking parameters. Table 2 presents the estimated parameters.

In Step 1, we set tax rate to be 34% which is consistent with the corporate tax rate in Brazil. Capital ratio is 6% according to Basel III accord. According to Banco Central do Brasil, the reserve requirement as of June 2023 is 21% for demand deposits, 20% for time deposits, and 20% for savings deposits. Since there's only one type of deposits in the model, we set reserve ratio to be 17%. This is the weighted average of the actual requirement ratios, where weights are the shares of a particular deposit type. Finally,

Table 2: Parameter Estimates

	Panel A: Calibrated parameters		
τ_c	Tax rate	0.34	
θ	Reserve ratio	0.17	
κ	Capital ratio	0.06	
J	Number of banks	5	
	Panel B: Parameters estimated separately		
μ	Avg loan maturity	3.26	
$\bar{f}$	Log selic rate mean	-2.655	
σ_f	Std of selic rate innovation	0.191	
ρ_f	Log selic rate persistence	0.97	
$\bar{\delta}$	Log loan chargeoffs mean	-3.425	
σ_δ	Std log loan chargeoffs innovation	0.517	
ρ_δ	Log loan chargeoffs persistence	0.77	
$\rho_{\delta f}$	Corr of selic innovation and log loan chargeoffs	0.32	
	Panel C: Parameters estimated from BLP		
α^d	Depositors' uniform sensitivity to deposit rates	0.006	
γ^d	Sensitivity to convenience	0.103	
β^d	Additional sensitivity to convenience from Pix	-0.034	
α^ℓ	Borrowers' sensitivity to loan rates	-0.123	
q_d^d	Convenience of holding deposits	0.8681	
q_c^d	Convenience of holding cash	-6.1498	
q_ℓ^ℓ	Convenience of borrowing through loans	0.886	
	Panel D: Parameters estimated from SMD		
γ	Discount rate	0.2739	[0.015]
W/K	Relative deposit market size	0.683	[0.305]
q_n^ℓ	Value of firms' outside option	2.0172	[1.131]
ϕ^N	Quadratic cost of nonreservable borrowing	0.1007	[0.004]
ϕ^d	Cost to service deposits	0.0117	[60.44]
ψ	Net fixed operating cost	0.0341	[145.8]

Note: This figure presents the list of parameters calibrated or estimated in the model. In Panel D, standard errors are reported in bracket for parameters estimated via SMD.

we set the number of banks to be five in the market.

Then in Step 2, we estimate a set of parameters related to loan maturity and monetary policy separately. The estimates are in Panel B of Table 2. Average loan maturity is 3.26 years and is computed from the bank-level data. The rest of the parameters are related to the law of motion of the monetary policy. These parameters include the means, standard deviations, and persistence of the selic rate and loan chargeoffs, as well as the correlation of selic rate innovation and loan chargeoffs. We estimate these parameters according to Equation 33.

Next in Step 3, we estimate the loan and deposit demand functions following method in Berry, Levinsohn, and Pakes (1995). Recall Equations (20) and (25), we can express the deposit and loan demands as logit functions and obtained the fitted values of the parameters from the right-hand sides,

$$D_j\left(r_j^d \mid f, p_j^d\right) = \frac{\exp\left(\hat{\alpha}^d r_j^d + \hat{\beta}^d p^d x_j^d + q_j^d\right)}{\exp\left(\hat{\alpha}^d f\right) + \exp\left(q_c^d\right) + \sum_{m=1}^{\hat{J}} \exp\left(\hat{\alpha}^d r_m^d + \hat{\beta}^d p^d x_m^d + q_m^d\right)} W, \tag{34}$$

$$B_j\left(r_j^\ell \mid f\right) = \frac{\exp\left(\hat{\alpha}^\ell r_j^\ell + q_j^\ell\right)}{\exp\left(\hat{\alpha}^\ell(\bar{f} + \bar{\delta})\right) + \exp\left(q_n^\ell\right) + \sum_{m=1}^{\hat{J}} \exp\left(\hat{\alpha}^\ell r_m^\ell + q_m^\ell\right)} K, \tag{35}$$

where q_c^d is the quality value, or convenience of holding cash. The variables q_j^d is the convenience of holding deposits from bank j, which is the quality value derived from unrelated to interest rate and Pix usage. The convenience of bank loans q_j^ℓ is defined analogously. In the estimation, we normalize the convenience of saving through government bonds, and borrowing in the bond market to be zero. We also assume homogeneous sensitivity of deposit and loan rates. Finally, the BLP method does not allow us to estimate convenience of firms' outside option q_n^ℓ since we do not observe the share of not borrowing in the data. Instead, we estimate it via SMD in the last step.

The key challenge for BLP method is endogeneity of the deposit and loan rates. That is, the interest rates are correlated with the unobserved demand shocks, which biases the estimates of elasticity. To overcome this challenge, we use fixed operation costs as supply curve shifters and instruments for the endogenous deposit and loan rates. The relevance condition states that banks' consider supply shifters when they make interest rate decisions. The exclusion restriction implies that unobserved deposit demand is not affected by supply shifters. For example, when households choose the bank to invest their deposits, they do not take into account how much it costs to rent a building for the bank branch.

Panel C of Table 2 presents the estimate from the BLP method. Depositors' uniform sensitivity to deposit rate α^d is 0.006. To interpret the magnitude, all else equal, deposit market share increases by 60 basis points for every 100bps increase in the deposit rate. The firms' sensitivity to bank loan rate is -0.123. On average, loan market share drops by 12.3 percentage points if banks raise their loan rate by 100 bps.

Finally, in Step 4, we assume banks take into account the demand functions (34) and (35) as estimated from BLP and choose the optimal deposit and loan rate to maximize future stream of cash dividends. We estimate the rest of the bank charateristics via a simulated minimum distance (SMD) method. Specifically, we use nine moments to directly estimate parameters and two free moments for model fits.

Following Wang, Whited, Wu, and Xiao (2022), we use dividend yield to identify banks' discount rate γ because a more impatient bank pays out more dividends to their shareholders. To identify the quadratic cost of uninsured nonreservable funding, we use the mean and standard deviation of the nonreservable to retail deposit ratio. A higher cost on nonreservable borrowing discourages banks from using wholesale funding as a substitute for retail deposits. Then, we use deposit spread to identify costs to service deposits. The intuition is that higher service cost incentives banks to charge a higher spread on their deposit products. Net fixed operating cost is pinned down by two moments: the average net noninterest expenses and the leverage ratio, defined as assets over equity. This first moment captures the operating costs outside of servicing loans and deposits, whereas the second moments follows the intuition that banks with higher fixed costs operate with a lower leverage ratio. Next, we jointly identify the relative size of deposit market W/K and the value of firms' outside option q_n^ℓ. To do that, we use two moments: the deposit to asset ratio and the sensitivity of deposits to selic rate. On one hand, a higher deposit-to-asset ratio indicates a larger deposit market. On the other hand, the sensitivity of deposit to the Selic rate naturally affects depositors' saving decisions. Moreover, since deposits are a major funding source for loans, these moments influence the value of firms' outside option. Finally, the estimation includes two free moments. We target the average market-to-book ratio to ensure that the model estimation captures the actual bank valuation. We also target the sensitivity of bank lending to selic rate to ensure the model reflect accurate monetary policy transmission. The sensitivity of bank lending to selic rate and the sensitivity of deposits to selic rate are estimated using a vector autoregression with aggregate data. Panel D of Table 2 presents the estimate from SMD method.

6 Results

6.1 Baseline results

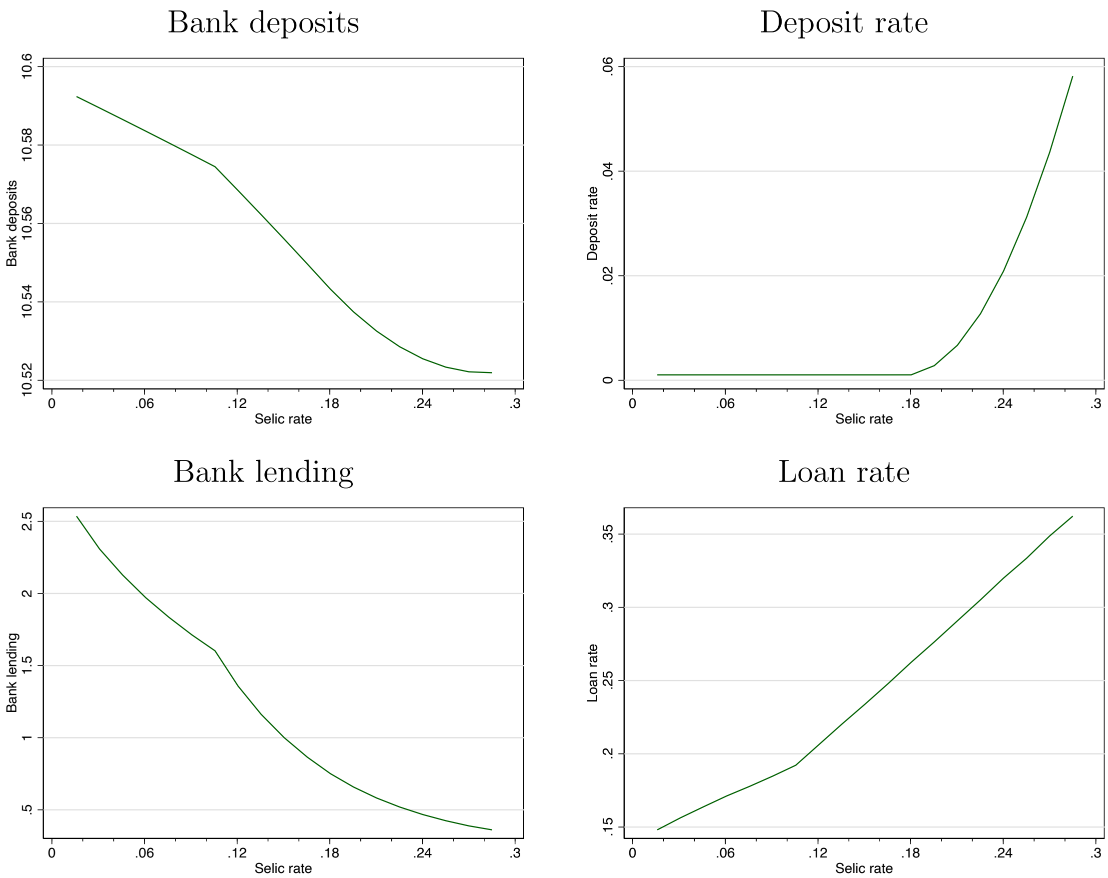
We present the policy functions of deposits and loans for an average bank from the baseline estimation in this section. The left panel of Figure 6 shows the evolution of bank deposits as the policy rate increases. We scale the deposit amount by steady-state bank lending. Deposits flow out of the banking system as policy rate hikes because deposits become increasingly less attractive relative to the outside option (bonds). Banks need to raise their deposit rate to attract more deposits. The right panel of Figure 6 shows the policy function of the deposit rate. The deposit rate is consistently below the policy rate, which reflects the deposit channel of monetary transmission from Drechsler, Savov, and Schnabl (2017)

The deposit channel also applies to loans and loan rates. Because banks increase deposit rates, their loan rates also go up. Loan rates tend to follow policy rates more closely than deposit rates. Bank lending declines because deposits are the main source of funding for banks.

6.2 Counterfactual: no Pix

With the baseline model in mind, we now examine the effect of the introduction of Pix on the monetary transmission. Our theoretical model suggests that absent Pix banks should have higher market power, and hence, their deposit rates should be lower. Similarly, less

Figure 6: Policy functions



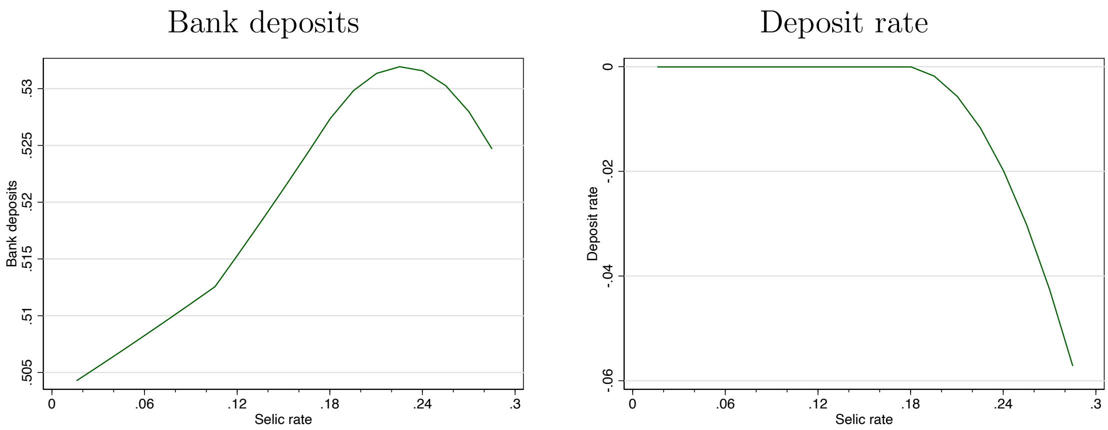
Note: This figure shows policy functions of bank deposits, deposit rates, loans, and loan rates from the baseline model. Bank deposit and loan amounts are scaled by steady-state bank loan amount.

efficient payment methods should result in lower deposit outflows.

To analyze the counterfactual, we set β_d in (17) to 0. The absence of Pix changes the demand for deposits, so we plug the new demand into the bank problem and allow banks to reoptimize. We then compare deposit amounts and deposit rates in the baseline model with their counterfactual counterparts.

Figure 7 plots the results. The right figure shows the difference between deposit rates absent Pix and deposit rates when Pix is introduced. Banks generally pay lower deposit rates absent Pix because without digital payments, banks have higher market power, and hence, they can charge higher deposit spreads. The left figure shows the difference between bank deposits absent Pix and bank deposits with Pix. Bank deposits are larger without Pix because it is less common to move out when interest rates are high if Pix is

Figure 7: Deposits and deposit rates without Pix



Note: This figure shows the counterfactual results without the launch of Pix. The lines correspond to the differences in deposits and deposit rates without and with Pix. Bank deposit amounts are scaled by steady-state bank loan amounts from the baseline model.

not introduced. This is an indication that Pix is used by Brazilian households to move their deposits across banks and out of the banking sector.

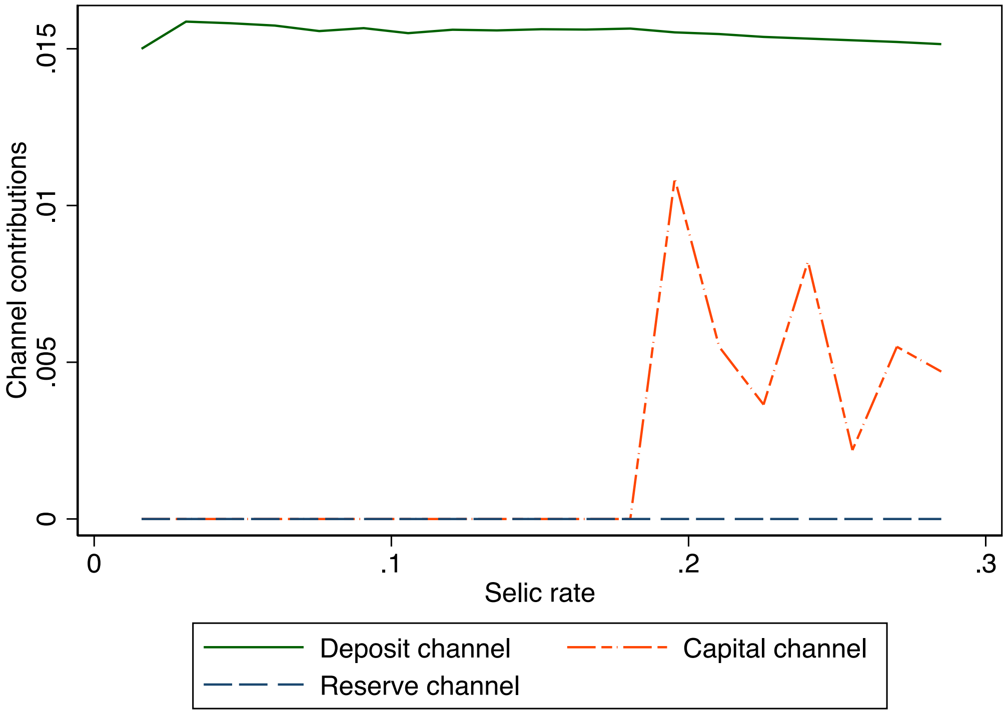
6.3 Counterfactual: different channels of monetary policy

Now, we investigate the quantitative forces that shape the relationship between digital payment and monetary policy. Specifically, we sequentially eliminate a channel in the model and check how deposits react to changes in policy rates. We perform the analysis in two scenarios, one with Pix usage and another one without Pix usage. We then check how much Pix contributes to each channel of monetary policy transmission.

Figure 8 shows the results. The solid green line plots the contribution of Pix to the deposit channel. Specifically, we consider the counterfactual where banks do not hold market power over bank deposits. We then compare the cases with and without Pix. Larger numbers mean that Pix impacts the deposit channel's contribution to bank deposits. Similarly, the orange line plots the contribution of Pix to the capital channel. To get that counterfactual, we eliminate capital requirements from the model. Finally, the blue line corresponds to the reserve channel, where we eliminate the reserve requirements.

The results show that Pix impacts monetary policy transmission primarily through

Figure 8: Different Channels of Monetary Policy



Note: This figure shows the counterfactual results when eliminating different channels of monetary policy. The green line shows how much Pix contributes to the deposit channel of monetary policy. The orange line shows how much Pix contributes to the capital channel. Finally, the blue line shows how much Pix contributes to the reserve channel.

the deposit channel, i.e., through the reduction in banks' market power. The capital channel has a smaller but yet significant impact. Pix does not impact the reserve channel primarily because the reserve requirements in Brazil are not binding.

7 Conclusion

This paper investigates the impact of digital payment systems on the transmission of monetary policy. In Brazil, Pix boasts a user base of more than 65% of the population, all of whom maintain deposit accounts with banks. Leveraging branch-level data and Pix transaction data, we empirically establish that Pix adoption mitigates banks' market power. Specifically, in regions with a higher volume of Pix transactions, hikes in policy rates result in more substantial rises in deposit rates and reduce deposit outflows.

Our dynamic banking model provides a theoretical framework to elucidate the mechanisms through which Pix enhances monetary transmission. We demonstrate that digital payments facilitate monetary policy transmission by making deposit rates more sensitive to policy rates – banks lose part of their deposit market power. Lastly, we find that the principal driver of this effect lies in the deposit channel of monetary policy.

References

Aker, J. C. and I. M. Mbiti (2010). Mobile Phones and Economic Development in Africa. *Journal of Economic Perspectives 24*(3), 207–232.

Aker, J. C., S. Prina, and C. J. Welch (2020). Migration, Money Transfers, and Mobile Money: Evidence from Niger. *AEA Papers and Proceedings 110*, 589–593.

Babina, T., G. Buchak, and W. Gornall (2022). Customer Data Access and Fintech Entry: Early Evidence from Open Banking. *SSRN Electronic Journal*.

Beaumont, P., H. Tang, and E. Vansteenberghe (2022). The Role of FinTech in Small Business Lending. *SSRN Electronic Journal*.

Begenau, J. and E. Stafford (2022). Uniform Rate Setting and the Deposit Channel. *SSRN Electronic Journal*.

Berg, T., A. Fuster, and M. Puri (2022). FinTech Lending. *Annual Review of Financial Economics 14*(1), 187–207.

Berger, A. N. and T. H. Hannan (1989). The Price-Concentration Relationship in Banking. *The Review of Economics and Statistics 71*(2), 291.

Bernanke, B. and A. Blinder (1988). Credit, Money, and Aggregate Demand. *American Economic Review 78*(2), 435–439.

Bernanke, B. and A. Blinder (1992). The Federal Funds Rate and the Channels of Monetary Transmission. *American Economic Review 82*(4), 901–921.

Berry, S., J. Levinsohn, and A. Pakes (1995). Automobile Prices in Market Equilibrium. *Econometrica 63*(4), 841.

Bian, W., L. Cong, and Y. Ji (2023). The Rise of E-Wallets and Buy-Now-Pay-Later: Payment Competition, Credit Expansion, and Consumer Behavior. *SSRN Electronic Journal*.

Bolton, P. and X. Freixas (2000). Equity, Bonds, and Bank Debt: Capital Structure and Financial Market Equilibrium under Asymmetric Information. *Journal of Political Economy 108*(2), 324–351.

Brunnermeier, M., H. James, and J.-P. Landau (2019). The Digitalization of Money. Technical report, National Bureau of Economic Research, Cambridge, MA.

Brunnermeier, M., N. Limodio, and L. Spadavecchia (2023). Mobile Money, Interoperability and Financial Inclusion. *Working Paper*.

Brunnermeier, M. and J. Payne (2022). Platforms, Tokens, and Interoperability. *Working Paper*.

Brunnermeier, M. K. and Y. Sannikov (2014). A Macroeconomic Model with a Financial Sector. *American Economic Review 104*(2), 379–421.

Buchak, G., G. Matvos, T. Piskorski, and A. Seru (2018). Fintech, Regulatory Arbitrage, and the Rise of Shadow Banks. *Journal of Financial Economics 130*(3), 453–483.

Chava, S., R. Ganduri, N. Paradkar, and Y. Zhang (2021). Impact of marketplace lending on consumers' future borrowing capacities and borrowing outcomes. *Journal of Financial Economics 142*(3), 1186–1208.

Chodorow-Reich, G., G. Gopinath, P. Mishra, and A. Narayanan (2020). Cash and the Economy: Evidence from India's Demonetization. *The Quarterly Journal of Economics 135*(1), 57–103.

Cookson, J. A., C. Fox, J. Gil-Bazo, J. F. Imbet, and C. Schiller (2023). Social Media as a Bank Run Catalyst. *SSRN Electronic Journal*.

Crouzet, N., A. Gupta, and F. Mezzanotti (2023). Shocks and Technology Adoption: Evidence from Electronic Payment Systems.

Di Maggio, M. and V. Yao (2021). Fintech Borrowers: Lax Screening or Cream-Skimming? *The Review of Financial Studies 34*(10), 4565–4618.

Diebold, F. X. and S. A. Sharpe (1990). Post-Deregulation Bank-Deposit-Rate Pricing: The Multivariate Dynamics. *Journal of Business & Economic Statistics 8*(3), 281–291.

Drechsler, I., A. Savov, and P. Schnabl (2017). The Deposits Channel of Monetary Policy. *The Quarterly Journal of Economics 132*(4), 1819–1876.

Drechsler, I., A. Savov, and P. Schnabl (2021). Banking on Deposits: Maturity Transformation without Interest Rate Risk. *Journal of Finance LXXVI*(3).

Duarte, A., J. Frost, L. Gambacorta, P. Koo Wilkens, and H. S. Shin (2022). Central Banks, the Monetary System and Public Payment Infrastructures: Lessons from Brazil's Pix. *SSRN Electronic Journal*.

Dubey, T. S. and A. Purnanandam (2023). Can Cashless Payments Spur Economic Growth? *SSRN Electronic Journal*.

Duffie, D. (2019). Digital Currencies and Fast Payment Systems: Disruption is Coming. *Working Paper*.

Elenev, V., T. Landvoigt, and S. Van Nieuwerburgh (2021). A Macroeconomic Model With Financially Constrained Producers and Intermediaries. *Econometrica 89*(3), 1361–1418.

Erel, I. and J. Liebersohn (2022). Can FinTech reduce disparities in access to finance? Evidence from the Paycheck Protection Program. *Journal of Financial Economics 146*(1), 90–118.

Erel, I., J. Liebersohn, C. Yannelis, and S. Earnest (2023). Monetary Policy Transmission Through Online Banks. *SSRN Electronic Journal*.

Ferrari, S., F. Verboven, and H. Degryse (2010). Investment and Usage of New Technologies: Evidence from a Shared ATM Network. *American Economic Review 100*(3), 1046–1079.

Ghosh, P., B. Vallee, and Y. Zeng (2021). FinTech Lending and Cashless Payments.

Gopal, M. and P. Schnabl (2022). The Rise of Finance Companies and FinTech Lenders in Small Business Lending. *The Review of Financial Studies 35*(11), 4859–4901.

Hannan, T. H. and A. N. Berger (1991). The Rigidity of Prices: Evidence from the Banking Industry. *The American Economic Review 81*(4), 938–945.

Hannan, T. H. and J. M. McDowell (1990). The Impact of Technology Adoption on Market Structure. *The Review of Economics and Statistics 72*(1), 164.

Hauswald, R. and R. Marquez (2003). Information Technology and Financial Services Competition: Table 1. *Review of Financial Studies 16*(3), 921–948.

Ho, K. and J. Ishii (2011). Location and competition in retail banking. *International Journal of Industrial Organization 29*(5), 537–546.

Jack, W. and T. Suri (2014). Risk Sharing and Transactions Costs: Evidence from Kenya's Mobile Money Revolution. *American Economic Review 104*(1), 183–223.

Kashyap, A. K. and J. C. Stein (2000). What Do a Million Observations on Banks Say about the Transmission of Monetary Policy? *American Economic Review 90*(3), 407–428.

Koont, N., T. Santos, and L. Zingales (2023). Destabilizing Digital 'Bank Walks'. *SSRN Electronic Journal*.

Kwon, S. Y., Y. Ma, and K. Zimmermann (2021). 100 Years of Rising Corporate Concentration. *SSRN Electronic Journal*.

Mariani, L., J. R. H. Ornelas, and B. Ricca (2023). Banks' Physical Footprint and Financial Technology Adoption. *SSRN Electronic Journal*.

Muralidharan, K., P. Niehaus, and S. Sukhtankar (2016). Building State Capacity: Evidence from Biometric Smartcards in India. *American Economic Review 106*(10), 2895–2929.

Neumark, D. and S. A. Sharpe (1992). Market Structure and the Nature of Price Rigidity: Evidence from the Market for Consumer Deposits. *The Quarterly Journal of Economics 107*(2), 657–680.

Nevo, A. (2001). Measuring Market Power in the Ready-to-Eat Cereal Industry. *Econometrica 69*(2), 307–342.

Ouyang, S. (2021). Cashless Payment and Financial Inclusion. *SSRN Electronic Journal*.

Park, K. and G. Pennacchi (2009). Harming Depositors and Helping Borrowers: The Disparate Impact of Bank Consolidation. *Review of Financial Studies 22*(1), 1–40.

Parlour, C. A., U. Rajan, and H. Zhu (2022). When FinTech Competes for Payment Flows. *The Review of Financial Studies 35*(11), 4985–5024.

Riley, E. (2018). Mobile money and risk sharing against village shocks. *Journal of Development Economics 135*, 43–58.

Sarkisyan, S. (2022). Instant Payment Systems and Competition for Deposits. *SSRN Electronic Journal*.

Suri, T. and W. Jack (2016). The Long-Run Poverty and Gender Impacts of Mobile Money. *Science 354*(6317), 1288–1292.

Wang, L. (2023). Regulating Competing Payment Networks. *Working Paper*.

Wang, Y., T. M. Whited, Y. Wu, and K. Xiao (2022). Bank Market Power and Monetary Policy Transmission: Evidence from a Structural Estimation. *The Journal of Finance 77*(4), 2093–2141.

Whited, T. M., Y. Wu, and K. Xiao (2022). Central Bank Digital Currency and Banks.