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Digital Payments and Monetary Policy Transmission*

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Abstract

We examine the impact of digital payments on the transmission of monetary policy by leveraging administrative data on Brazil's Pix, a digital payment system. We find that Pix adoption reduces banks' market power, making them respond more to changes in policy rates. We estimate a dynamic banking model in which digital payments amplify deposit demand elasticity. Our counterfactual results reveal that digital payments intensify the monetary transmission by reducing banks' market power – banks respond more to policy rate changes, and loans decrease more after monetary policy hikes. We find that digital payments impact monetary transmission primarily through deposit market power.

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

JEL Codes: E42, G21, E52

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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 expect that banks will increase their deposit rates as well, which should lead to banks contracting lending. In reality, banks are able to keep their deposit rates below the market rate without losing all of their depositors (Drechsler et al. (2017)). Digital payments facilitate transactions between deposit accounts, potentially changing the interest rate elasticity of the deposit demand. This paper asks if digital payments facilitate the transmission of monetary policy. We argue that digital payments increase monetary policy pass-through on deposit rates and lending 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 in November 2020. Pix not only enables instant transfers but also boasts widespread acceptance as a merchant payment method due to its lower fees[1] and higher speed compared to existing payment methods. Since its launch, Pix has emerged as the 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 January 2024, Pix transactions reached R$ 17.2 trillion per year, equivalent to approximately $2.87 trillion[2] with more than 75% of Brazilians actively using it.[3]

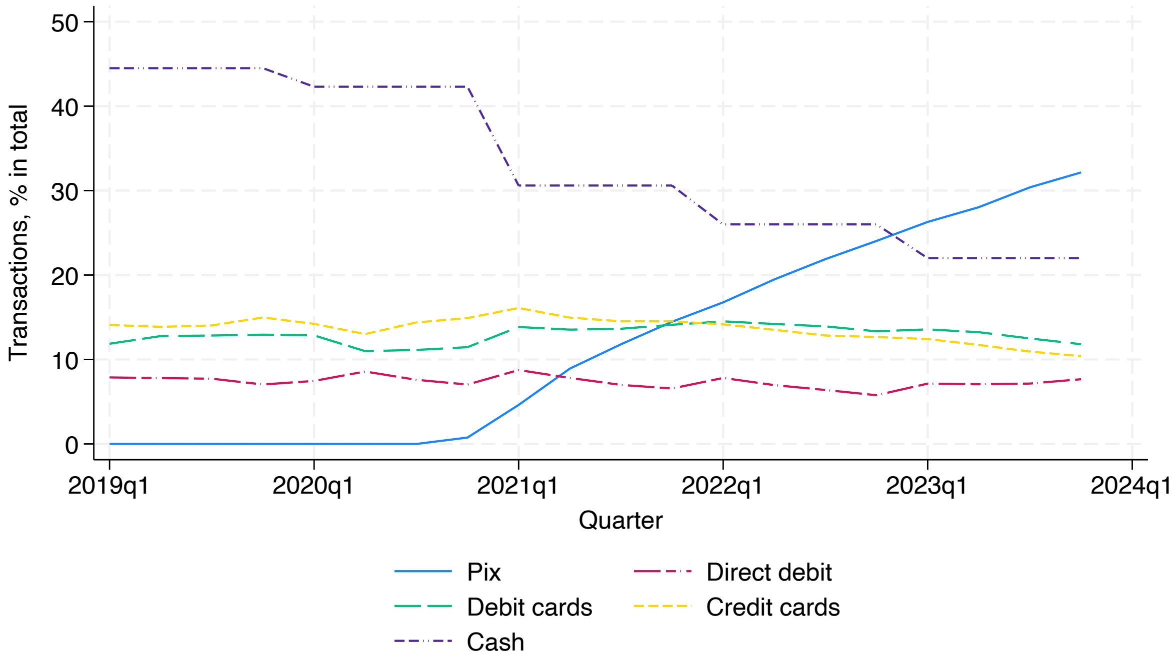
Although Pix surpasses traditional payment systems that rely on bank deposits, it requires a bank account to be used. Central Bank of Brazil required large and medium-sized banks (banks with more than 500,000 depositors) to join Pix. Entry costs for

[1]The Central Bank mandated that all transactions conducted by individuals and small businesses must be free of charge. On average, Pix costs banks only 0.01 BRL for every 10 transactions.

[2]Based on the November 2024 exchange rate.

[3]For comparison, debit card transactions amounted to R$664 billion in 2019. See https://paymentscmi.com/insights/pix-in-brazil-what-to-expect-in-2024-and-ahead/.

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



Note: The graph is based on Sarkisyan (2024) 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.

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 months, and transacting funds between the participating banks became free. Thus, Pix creates an excellent setting to study how monetary policy transmission changed due to a potential reduction in banks' market power.

Instant payment systems can impact deposit market power and monetary transmission 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)), 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. This channel would lead to an increase in deposit rates and outflows of deposits. Third, 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 (2024)) so that banks generally have to react more to the changes in policy rates. More generally, the digitalization of banking can have a positive impact on competition (Erel, Liebersohn, Yannelis, and Earnest (2023)). This last channel can lead to an inflow of deposits through the deposit channel (Drechsler et al. (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 (used in Fonseca and Matray (2022); Fonseca and Van Doornik (2022); Sarkisyan (2024); Ding et al. (2025)), bank-level interest rates, and municipality-level demographic and economic data, including number of bank accounts. 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 deposit accounts for banks' ability to utilize their local market power (Drechsler et al. (2021)) as well as includes branches that set their rates following the banks' headquarters (Begenau and Stafford (2022); D'Avernas et al. (2023)).

We start by documenting that banks' market power declines after the introduction of Pix, especially in areas with more Pix usage. Specifically, we compute the sensitivities of banks' 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) after contractionary monetary policy rate changes. We find that after Pix, deposit spread betas decrease, especially in areas with more Pix usage. In other words, banks respond more to policy rate changes after Pix is introduced by offering more competitive deposit rates.

To further argue that the drop in market power is due to the introduction of Pix, we estimate within-bank regressions, following Drechsler et al. (2017). We address two challenges – branches of banks being fundamentally different and unobservable local demand. We find that in the areas with more Pix transactions, increases in policy rates lead to higher increases in deposit rates, higher deposit outflows due to easier switching between banks, and larger loan contractions, consistent with the reduced local market power and intensified monetary policy transmission.[4] Specifically, in response to a 1 p.p. increase in monetary policy rate, banks in areas with 1 s.d. more per capita Pix transactions increase their deposit spreads only by 42 b.p. as opposed to an average of 59 b.p.

Regarding an outflow of deposits, there are two opposing effects – 1) depositors might be more willing to stay with the bank when the bank offers higher deposit rate (Erel et al. (2023); Kundu et al. (2024)) and 2) switching between bank accounts is easier (Buchak et al. (2024); Koont et al. (2023); Lu et al. (2024)). In our case, the latter effect dominates because Pix allows deposits to switch easily, including to digital banks that are not included in our sample. We indeed add supporting evidence for deposits in Brazil flowing out to digital banks, in addition to regular investments during high interest rates, such as mutual funds. Despite overall deposit outflows, consistent with Erel et al. (2023), we confirm that the more banks increase their deposit rates, the more deposits they are able to retain.

We further shed light on mechanisms and show that the decline in the market power of banks is driven by the fact that Pix provides an alternative to banks' physical branch services, to payments offered by banks, and facilitates opening new accounts. We show that the number of branches declines significantly in areas with more per capita Pix transactions. We also find that payment-related fees decline in Brazil, especially in areas with more Pix usage, and banks that operate in areas with more Pix transactions increase non-payment-related fees to extract rents in markets where Pix does not compete. Finally, we show that the number of bank accounts per person increases in areas with more Pix transactions. This result is in contrast with an alternative explanation of the decline in spread betas, which is that households raised holdings of their existing bank

[4]In Appendix C.4, we also consider identified high-frequency monetary surprises instead of full changes in policy rates. In Appendix C.7, we use monetary shocks to argue that monetary transmission becomes faster and more persistent with Pix.

accounts instead of opening new ones. We argue that this latter explanation cannot be the only driver of our findings, given an increase in the number of bank accounts.

To illustrate the channels that 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 distance, interest rates, and convenience (Park and Pennacchi (2009)). 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 adopt digital payments, the demand for their deposits also increases.

Cashless payments affect monetary transmission through various channels, and it is not straightforward to separate the effect of Pix and market power. 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 four types of agents – households, non-financial firms, banks, and a central bank with an exogenous interest rate process. Households choose 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 (they also have an option not to borrow at all). Finally, banks issue deposits, originate loans, and buy reserves and government securities. The model mainly follows Wang et al. (2022), Whited et al. (2022), and other papers that estimate models with banks (Van den Heuvel (2008); Corbae and D'Erasmo (2014); Egan et al. (2017); Xiao (2020)).

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. We assume that all banks offer Pix to their clients, which is consistent with the data. We indeed find that non-rate characteristics become a relatively less important determinant of deposit demand after the launch of Pix (i.e., interest rate becomes more important).

We use bank-level data from Brazil from 2014 to 2022 to estimate the model.[5] We combine rich bank-level balance sheet data with interest rates. We also collect data on salaries and employment from RAIS and by hand. We start by estimating demands for deposits and loans separately using the methods from the industrial organization literature (Berry et al. (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)). Specifically, we use fixed costs of assets, loan loss provision, and salaries (in Appendix C.12). 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 has a lower take-up – 50% of its actual value. 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. We ultimately find that loans decline more after the introduction of Pix when policy rates increase. The slopes of deposit rates, deposits, and lending also change, indicating an increase in monetary pass-through. These findings suggest that digital payments facilitate monetary policy transmission by making deposit rates more sensitive to policy rates. The findings in the model are also consistent, both qualitatively and quantitatively, with our empirical estimates.

Finally, we evaluate the impact of digital payments on the deposit channel of monetary policy transmission.[6] We do it by eliminating the market power in the deposit

[5]In Appendix C.13, we also estimate the state-level model for more granularity.
[6]Our model features three main channels: the reserve channel (Bernanke and Blinder (1988, 1992); Kashyap and Stein (2000)), the capital channel (Bolton and Freixas (2000); Brunnermeier and Sannikov (2014); Elenev et al. (2021)), and the deposit channel (Drechsler et al.

markets in the model and checking how deposits and loans respond with and without Pix at each policy rate. We find that Pix amplifies the transmission through the deposit channel by 20-45% on total deposits and 10% on bank lending. The reason is that Pix mainly impacts depositors' decisions rather than firms' borrowing choices or banks' capital issuance and reserve purchases.

We show several additional results to further argue that payment systems intensify monetary transmission. For example, we run local projections to show that monetary policy transmission is faster and more persistent after the introduction of Pix. This partly helps to address the concern that our results are driven by the COVID-19 pandemic or by the informality of the Brazilian economy. COVID-19 and informality contributed to the adoption of Pix, but it is unlikely to have a high persistence of monetary transmission up to three years after the pandemic started.

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 (Jiang et al. (2022); Erel et al. (2023); Koont et al. (2023); Cookson et al. (2023); Koont (2023)). These papers consider endogenous choice of the banks to digitalize, whereas we consider a policy implemented by the Central Bank that affects all banks. Theoretically, Abad et al. (2025) study how CBDC impacts monetary policy. The most closely related paper by Whited et al. (2022) shows that central bank digital currencies can also impact monetary policy by crowding out deposits and loans. To our knowledge, our paper is the first to show both empirically and structurally that monetary policy transmission is facilitated by digital payments. Unlike digital banking or CBDC, payment systems are imposed upon all banks (i.e., no choice to digitize) and are widely implemented.

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 et al. (2010); Aker and Mbiti (2010); Jack and Suri (2014);

(2017, 2021); Wang et al. (2022)).

Suri and Jack (2016); Muralidharan et al. (2016); Riley (2018); Duffie (2019); Ouyang (2021); Brunnermeier et al. (2019); Aker et al. (2020); Bachas et al. (2021); Garratt et al. (2022); Brunnermeier et al. (2023); Bian et al. (2023); Wang (2023); Haendler (2022); Higgins (2024); Dubey and Purnanandam (2023); Mariani et al. (2023); Crouzet et al. (2023); Sampaio and Ornelas (2024); Crouzet et al. (2024); Berg et al. (2023); Ding et al. (2025)). 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 et al. (2018); Erel and Liebersohn (2022); Ghosh et al. (2021); Chava et al. (2021); Di Maggio and Yao (2021); Gopal and Schnabl (2022); Parlour et al. (2022); Babina et al. (2022); Beaumont et al. (2022)).[7] More broadly, FinTech development is associated with more financial inclusion either directly (Philippon (2019)) or by increasing competition in banking (Célerier and Matray (2019); Brown et al. (2019)). We add to the literature by showing that cashless payments are an important facet of monetary policy transmission because they give households access to a more competitive banking industry.

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 et al. (2017); Li et al. (2023); Yannelis and Zhang (2023)). 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 et al. (2017, 2021); Gelman et al. (2022)). Wang et al. (2022) estimate a 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

[7] For the literature review, see Berg et al. (2022).

digital payments because they reduce banks' market power.

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

In this paper, we exploit a natural experiment from Brazil's Pix payment system – an instant 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,[8] phone number, email, or random key. The key uniquely identifies a bank account for the transaction to take place. The

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

Central Bank also required banks with more than 500,000 participants to join Pix and designed the costs to be shared among participants. 10 Pix transactions cost 0.01 BRL for Brazilian banks.

Pix was introduced to address several frictions in banking transfers and payments in Brazil. The first of these frictions is the delay in transfers. For example, in Brazil, the most common transfers could take several days to clear. For example, Bank Wires (TEDs) can take up to a day, Payment slips (Boletos)[9] transactions take up to 3 days, 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 is already a friction that maintains the market power of banks by making it harder to switch money from one account to another 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.

Another 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) show 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 153 million individuals and 12 million firms already using Pix by March 2024. Other papers showed that instant payments are popular in urban areas, state capitals, and in rich neighborhoods (Crouzet et al. (2024); Sarkisyan (2024)). 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

[9]Payment slips are commonly used to pay bills in Brazil.

became convenient to have multiple accounts for multiple purposes. We will argue that this is the main mechanism behind our results. 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 policy rates, they expect banks to increase deposit rates in response. This has two effects: first, higher deposit rates encourage saving over spending and lead to more deposit accounts being opened; second, to maintain profit margins, banks raise loan rates, which lowers investment. However, banks do not increase their deposit rates as much as the policy rates rise (Drechsler et al. (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 interest rate pass-through 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 raise them only modestly because their funding costs, driven by deposit rates, remain relatively low. 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 efficient.

2.3 Data

We collect administrative data on monthly Pix transactions from the Central Bank of Brazil. The data includes the municipality where the transaction is made, the total monthly value of transactions in Brazilian reals, the number of Pix transactions, and the number of users. We can then calculate per capita and per-user transactions for most of the 5,570 municipalities. Pix data starts in November 2020 (the month of Pix launch) and ends in January 2024.

We collect monthly balance sheet data for bank branches operating in Brazil from ESTBAN. The data covers 266 banks from August 1988 to September 2022.[10] The data includes bank identifiers (CNPJ) and balance sheet data – deposits by type, loans, financing, cash positions, reserves, interbank loans, etc. Data also contains municipalities where branches operate, which allows us to calculate deposit market concentrations (Herfindahl-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,

[10] At any point in time, there are no more than 120 banks. A full sample includes 266 banks because some banks existed before they left the market, and vice versa.

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 as proxies for deposit rates and interest income to use as proxies for loan rates.

We also collect rich municipality data that includes demographic and economic variables and the number of bank accounts in each municipality. We also observe the share of banked population in each municipality over time. We provide a detailed discussion of the data used in the paper in Appendix B.

Table 1 contains summary statistics. Panel A shows statistics for banks. Generally, banking has grown over time, with bank assets more than doubling in size. The number of branches declines, indicating economy's digitalization and less dependence of physical offices. Deposit rates before Pix were significantly higher than deposit rates after Pix, which is consistent with the policy rate changes (Panel B). Banks also generally charge positive deposit spreads. Panel C shows statistics on Pix and demographics for 3,975 municipalities, for which we have data.

3 Empirical results

We start by showing that the introduction of digital payments is associated with 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 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-bank evidence that banks

Table 1: Summary Statistics

	Pre-Pix			Post-Pix		
	Mean	Median	Std. dev.	Mean	Median	Std. dev.
Panel A: Bank variables (ESTBAN and IF)						
Checking deposits (bn. R$)	0.84	0.004	4.8	2.6	0.08	11.3
Saving deposits (bn. R$)	2.6	0	17.9	8.6	0	43.8
Time deposits (bn. R$)	3.9	0.13	20.1	16.6	0.91	60.2
Total loans (bn. R$)	3.3	0.11	16.6	12	0.62	42.5
Total assets (bn. R$)	211.6	6.1	1223.2	592.8	29.3	2335
Deposit rates (%)	7.3	4	11.1	4.9	2.7	9.3
Branches		10,161			8,944	
Panel B: Macro variables (BCB)						
Policy rate (%)	13.1	12.4	6.7	7.5	7.8	4.4
Panel C: Municipality variables (IBGE and BCB)						
Pix usage (mn. R$)				80.3	13.1	600.7
Pix usage per capita (th. R$)				0.83	0.71	0.65
Population (th.)	62.3	21.8	298			
Share of urban population	71.9	75.7	20.2			
Share of male population	50.2	50	1.5			
Share of illiterate population	14.4	10.9	9.5			
Municipalities			3,975			

Note: This table provides descriptive statistics for the bank data used in the main analysis of the paper. Panel A shows statistics for banks. Panel B provides means, medians, and standard deviations for macro variables. Panel C documents statistics for municipal variables. The columns are split into pre-Pix (before November 2020) and post-Pix (after November 2020) periods. The bank numbers sum up across branches with available balance sheet data and do not include branches without available data. The time period is from January 2019 to September 2022. Demographic data is based on the 2010 Census.

respond more to policy rate changes in areas with higher Pix take-up.

3.1 Cross-sectional evidence

We follow Drechsler et al. (2017) and construct a measure of the deposit market power – deposit spread betas, i.e., the sensitivity of deposit spreads (policy rate minus deposit rate) to policy rates. Specifically, for each branch of a bank we run the following sets of regressions:

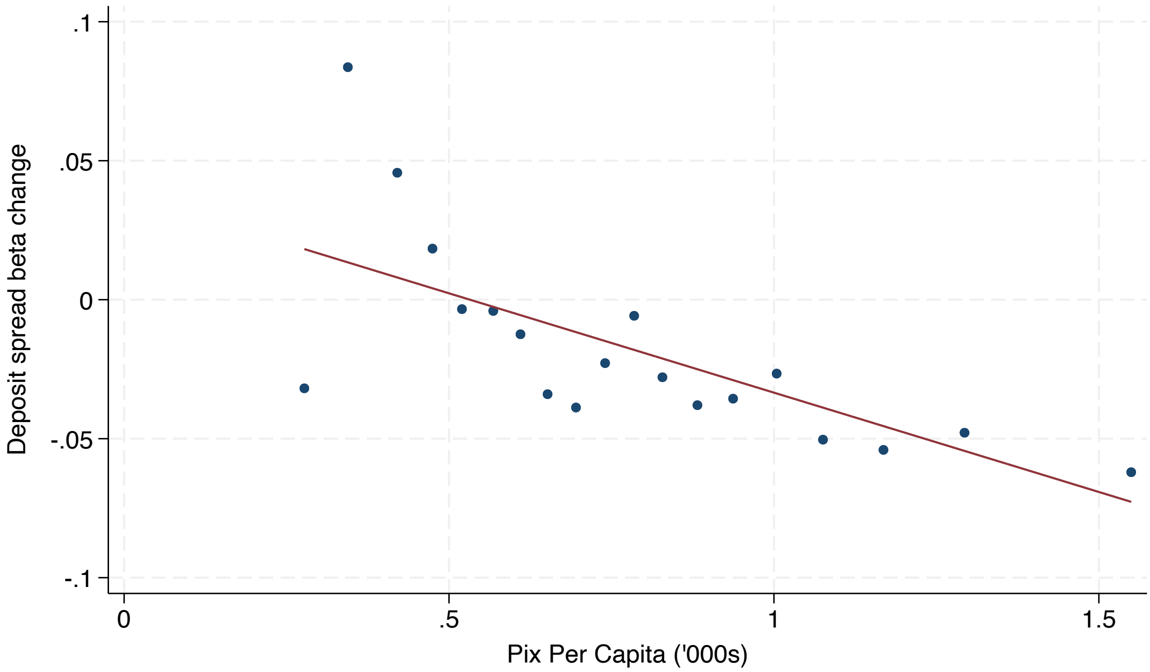
$$y_{it} = \beta_i MS_t + u_{it} \tag{2}$$

where y_{it} is a change in deposit spreads of branch i, defined as the Selic rate less the deposit rate, and MS_t is a change in the policy rate. Central Bank does not provide deposit rates for each municipality office but conversations with bankers in Brazil confirm that unlike in the US banks in Brazil do not base their time deposit rates on the location. In other words, they follow a uniform pricing. Hence, we follow D'Avernas et al. (2023) to assume that each branch of a bank would pay the same deposit rate, so we effectively run municipality-level regressions.

For each branch i, we can interpret β_i as the branch i's elasticity of deposit spreads to monetary policy changes. We refer to β_i as *spread betas.* High spread betas mean that banks respond less to policy rate changes, and hence, they have higher deposit market power. To conduct this exercise, we estimate deposit betas using Equation (2) twice: once before the introduction of Pix and once after. We then calculate the change in deposit betas and examine whether these changes vary across municipalities based on their level of Pix usage.

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 betas are lower – banks change their deposit rates more in response to policy rate changes after Pix is introduced, and generally offer more competitive rates. Moreover, the deposit betas change more for banks that operate in areas with more per capita

Figure 2: Changes in Spread Betas



Note: The graph shows the changes in deposit spread betas in Brazil after the introduction of Pix. The X-axis shows the value of Pix transactions divided by the population. Deposit spread betas are measured as sensitivities of deposit spreads to monetary policy rates.

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. In Appendix C.1, we also plot deposit flow betas.

One concern with the results is that people in richer areas might have higher values of Pix transactions as their spending volume is larger. In other words, the value of Pix transactions can be correlated with income. In Appendix C.2, we propose two ways to address the concern. First, we directly control for income per capita when estimating deposit betas from the set of equations 2. Second, instead of measuring Pix usage as the value of Pix transactions per capita (the measure that depends on income), we measure Pix usage as *quantity* of transactions per capita. Our results are robust to both modifications.

The cross-sectional 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 should fall less following contractionary monetary policy actions, which we formally show below. The cross-sectional analysis has a number of identification issues, which we also address next.

3.2 Within-bank 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 banks. For example, tech firms are more affected by policy rate hikes, and they are more likely to borrow from specific (large) banks. The cross-sectional analysis does not account for such possibilities. We address the concern by including branch fixed effects in our regressions, that account for the location and a bank. 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.

The second challenge is differences across banks. For example, large and small banks can respond to policy hikes and introduction of payment systems differently. To address that challenge, we include bank-time fixed effects in regressions with deposit flows because we observe them at the branch level. For deposit rates (bank-level) and loan flows (branch-level but determined by head offices), we include bank fixed effects.

We test if the reaction of changes in deposit spreads and deposit flows to policy rate changes is different with Pix by estimating a within-bank panel regression. Specifically, we limit the sample to two years before the launch of Pix and two years after and run the following panel regression (from January 2019 to September 2022):

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

where Y_{imt} is either a change in deposit spreads, deposit flows, or loan flows, $PixPerCap_{mt}$ is the value of Pix transactions per person, α_{im} is branch fixed effects, η_i is a bank fixed effect, and θ_{it} is bank-time fixed effects. The vector of controls includes all interaction terms. We follow Drechsler et al. (2017) and include bank-time fixed effects in the deposit flow regressions to account for bank-level differences between branches. We cannot include bank-time fixed effects in loan flow regressions because loans are generally originated by the banks' headquarters. Similarly, we only observe deposit spreads at the bank level and assume uniform pricing, so we cannot include bank-time fixed effects in the spread regressions. We also set $PixPerCap_{mt}$ equal to 0 before introduction of Pix to make sure we do not throw out the pre-period.

Table 2 reports the results. Columns 1 and 2 show the results for deposit spreads. We find that deposit spreads are increasing less with policy rates in areas with more Pix usage. Specifically, a 1 p.p. increase in the policy rate generally increases banks' deposit spreads by 73 b.p., but in areas with R$ 1000 higher per capita Pix transactions, spreads increase only by 19 b.p. At the same time, Columns 1 and 2 of Table 3 show that bank deposits flow out more because Pix makes it easier to move from bank to bank or outside of the banking system. The results suggest that banks' market power declines and monetary policy becomes more efficient. A reduction in spreads is economically very large. We stress that a 53.9 b.p. reduction is after a R$ 1000 increase in the value of Pix transactions per capita. A standard deviation of increase in Pix value is smaller than R$ 1000, so to have a more representative interpretation of the results, we z-score Pix per capita (subtract the mean and divide by standard deviation) in Appendix C.8 and find that after a one s.d. increase in the value of Pix transactions, deposit spreads decline by 16.7 b.p. Consistent with a decline in spreads, we show in Appendix C.10 that banks' profitability declines.

Movement in deposits is driven by at least two countervailing forces. First, since banks offer more competitive deposit rates, many households will decide to stay in the banking sector (Drechsler et al. (2017); Erel et al. (2023); Kundu et al. (2024)). Second, the simplicity of switching from bank to other banks and non-banks (many Brazilians indeed opened accounts at FinTech banks such as NuBank after the introduction of Pix, which are not in our sample) can lead to outflows of deposits (Buchak et al. (2024); Koont et al. (2023); Lu et al. (2024)). In our case, the latter effect dominates, especially with included bank-time fixed effects, where most of the effects are driven by out-of-bank movements. In what follows, when we argue that monetary policy intensifies, we refer to changes in deposit rates and loans, not deposit flows, given many equilibrium forces that influence deposits.

If the channel studied in Erel et al. (2023) is present in our case, then banks that increase their deposit rates more should see fewer outflows of deposits. We test it by running a 2SLS regression of deposit flows on deposit spreads:

$$Y_{imt} = \beta \Delta \widehat{DepSpread}_{imt} + \gamma X_{imt} + \alpha_{im} + \theta_{it} + \varepsilon_{imt} \tag{4}$$

where the first-stage regression is equation (3) with changes in deposit spreads as a dependent variable. We include all relevant interactions and fixed effects in the first stage to keep the 2SLS estimates consistent. Column 3 of Table 3 shows that the banks that reduce spreads more (i.e., increase deposit rates more) see fewer outflows of deposits, consistent with Erel et al. (2023) and Kundu et al. (2024).

It is also important to discuss where the deposits in Brazil flow out to. Similar to the US, money market mutual funds are one option for depositors to earn a higher interest rate when policy rates are high. However, Brazil in recent years has witnessed a growth in FinTech banks, such as NuBank, Neon, and Inter. These banks attract many clients from traditional banks. Figure 3 shows that, unlike traditional bank deposits, digital

Table 2: Impact of Pix on Deposit Spreads and Loan Flows

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

	Deposit spread change		Loan flows	
	(1)	(2)	(3)	(4)
Pix Per Capita × MS	-0.539^{***}	-0.532^{***}	-1.604^{***}	-1.566^{***}
	(0.038)	(0.037)	(0.122)	(0.120)
Pix Per Capita	0.419^{***}	0.430^{***}	-0.048	0.250^{***}
	(0.027)	(0.028)	(0.087)	(0.085)
MS	0.731^{***}	0.721^{***}	1.760^{***}	1.694^{***}
	(0.011)	(0.009)	(0.065)	(0.063)
Branch FE	Yes	No	Yes	No
Bank FE	Yes	Yes	Yes	Yes
Obs.	126,945	126,970	388,323	388,345
R^2	0.129	0.127	0.063	0.012

Note: This table provides results of within-bank estimation of the effect of Pix on loan flows and deposit spreads – equation (3). Columns 1 and 2 show the results for deposit spreads. Columns 3 and 4 correspond to changes in lending flows. 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.

bank[11] deposits do not decline after the rise in Selic rates. Moreover, the intensity of the rise in deposits of digital banks increases after Pix. This graph suggests that the deposit outflows partly go into digital banks.

We also test the implications of the introduction of Pix for lending flows. Columns 3 and 4 of Table 2 show that lending declines more in high-Pix areas following contractionary monetary policy change. This is consistent with an intensified monetary transmission. Since banks increase their deposit rates more after Pix, they also potentially need to adjust their loan rates, thus contracting their lending more. In Appendix C.6, we also aggregate lending to the bank level and show that the results are robust. In Appendix C.3, we show that banks' equity also declines.

There is a classic identification concern when studying how monetary policy impacts banks – policy rates are not exogenous since they are set based on economic conditions. In Brazil, the monetary authority (Copom) holds meetings approximately every six weeks to determine the policy rate. Variables such as inflation and investments impact both bank

[11] Defined as NuBank, Inter, C6, and Neon, including subsidiaries.

Table 3: Impact of Pix on Deposit Flows

$$Y_{imt} = \beta MS_t \cdot PixPerCap_{mt} + \gamma X_{imt} + \alpha_{im} + \theta_{it} + \varepsilon_{imt}$$
$$Y_{imt} = \beta \Delta \widehat{DepSpread}_{imt} + \gamma X_{imt} + \alpha_{im} + \theta_{it} + \varepsilon_{imt}$$

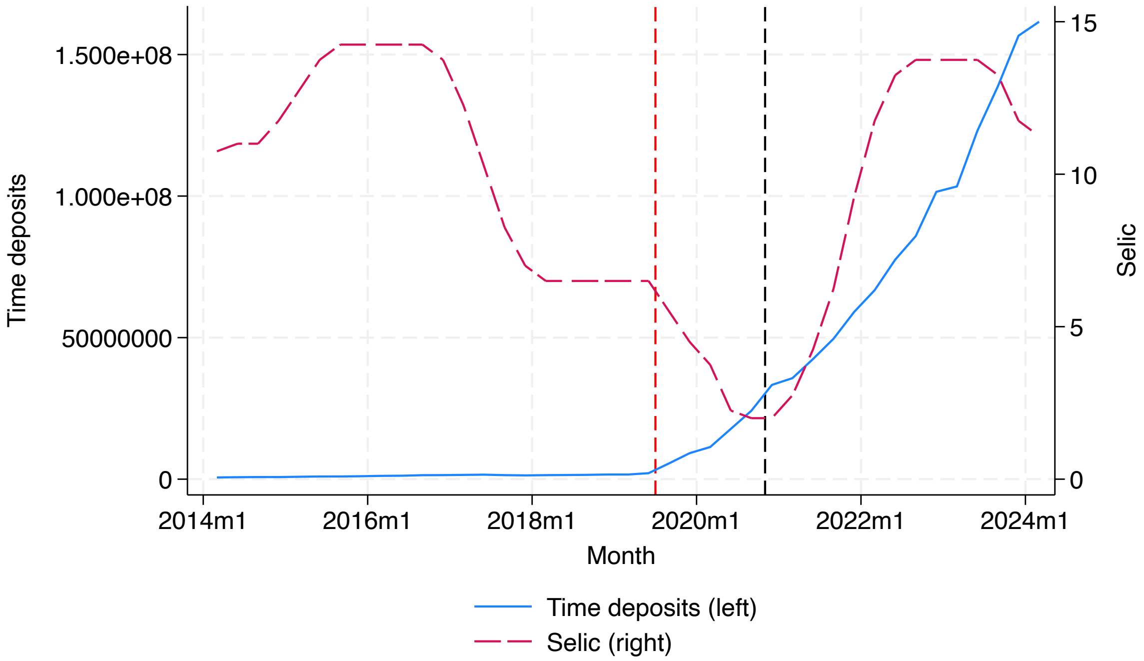
	Deposit flows		
	(1)	(2)	(3)
Pix Per Capita × MS	-0.468^{**}	-0.456^{**}	
	(0.228)	(0.228)	
Pix Per Capita	0.734^{***}	0.699^{***}	
	(0.196)	(0.179)	
Deposit spread change			-1.675^{***}
			(0.159)
Specification	OLS	OLS	IV
Branch FE	Yes	No	Yes
Bank FE	Yes	Yes	Yes
Bank-Time FE	Yes	Yes	Yes
Obs.	365,090	365,113	119,444
R^2	0.066	0.043	0.001

Note: This table provides results of within-bank-time estimation of the effect of Pix on deposit flows – equation (3). Column 3 runs a 2SLS specification where deposit spread change is instrumented with Pix Per Capita interacted with the change in policy rates. All relevant interactions are included. Standard errors are clustered at the municipality level and displayed in parentheses. Bank-time, bank and branch fixed effects are included. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

lending and policy rates, thus creating potential biases. In Appendix C.4, we address this concern by using identified high-frequency monetary policy surprises instead of actual changes in Selic rate. We find that our results are robust – deposit rates increase while lending declines more after the introduction of Pix. In Appendix C.7, we further use monetary shocks to argue that monetary transmission becomes faster and more persistent with Pix by using local projections. In addition, in Appendix C.9, we run a placebo test to show that deposit spreads, deposit flows and loan flows were not declining in high-Pix areas already before the introduction of Pix. Finally, we consider a different measure of the Pix variable – the number of users per capita. We show in Appendix C.5 that both the IV and OLS results are robust to the definition.

Overall, the empirical results suggest that banks' market power declines 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

Figure 3: Deposits of Digital Banks



Note: The graph shows time deposits of digital banks (left panel) and Selic rate in Brazil (right panel). The blue line shows time deposits collected from IF, and the red line shows Selic rate. The vertical black line shows the date of the launch of Pix. The vertical red line shows the date of the announcement of Pix.

increase their deposit rates more following contractionary monetary policy decisions. 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 NuBank or Matera. Small banks in Brazil also gained a significant deposit share relative to large banks after the launch of Pix (Sarkisyan (2024)), which is consistent with our findings.

3.3 Mechanisms

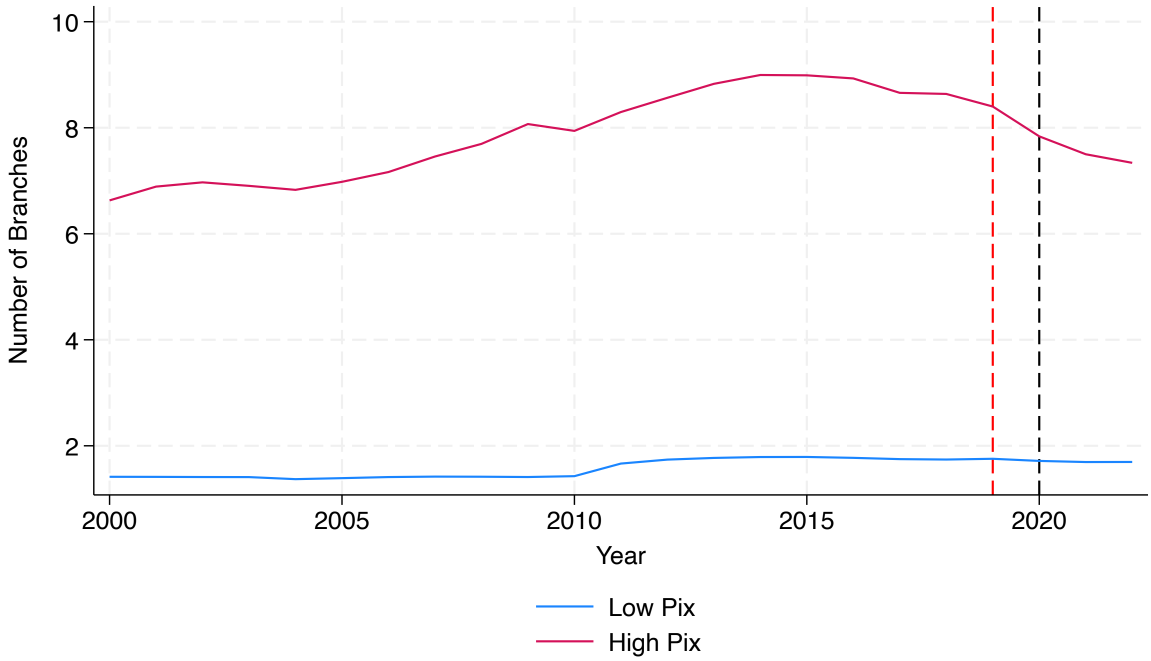
So far, we have shown that after the launch of Pix, banks started offering more competitive deposit rates, resulting in a larger reduction in lending. We interpret such a change as an increase in monetary transmission. In this section, we dig deeper into potential mechanisms underlying our results. Specifically, we argue that banks' deposit market power declines because Pix allows depositors to move easily from bank to bank and provides alternatives to bank payment services and branches – two of several reasons for banks' market power. In other words, depositors become more alert (Lu et al. (2024)), and they're choosing banks more based on interest rates rather than convenience (Sarkisyan (2024)).

Since Pix provides opportunities to transfer money and make payments digitally, the value of physical branches can decline in Brazil. A decline in the number of branches can be associated with reduced bank franchise value (Benmelech et al. (2023)). We collect data on the number of branches from IF and ESTBAN to show how the number of branches changed in areas with high Pix usage and areas with low Pix usage. We hence split municipalities in Brazil into those where Pix use per capita is above the median and the ones where the use of Pix is below the median.

Figure 4 shows the results. First, Pix is used more in areas with more branches, potentially reflecting that those are more developed and urbanized areas. However, the number of branches declined steadily in high-Pix areas both before the introduction of Pix and after the announcement and the launch. The former reflects the fact that the demand for digital payment is higher in areas where physical branches are being replaced. The latter implies that with Brazilians using Pix to make payments and transfer money, the need for physical branches is lower, consistent with Mariani et al. (2023).

Pix also provides alternatives to bank-supplied payment services like wire transfers, credit cards, checks, etc. Since Pix competes with these services, banks might lose market power because they cannot extract as much rent from payment services anymore. To see how banks respond, we source bank fees from the Central Bank and split services into payment-related ones (such as credit cards) and non-payment-related ones (such as help with pensions). We split areas into high-Pix and low-Pix to see how the fees change for banks that face more competition from Pix.

Figure 4: Number of Branches in Brazil



Note: The graph shows the number of bank branches in Brazil separately for areas with high Pix use and low Pix use. The blue line shows branches in low Pix areas (where per capita Pix usage is below the median), and the red line shows branches in high Pix areas. The vertical black line shows the date of the launch of Pix. The vertical red line shows the date of the announcement of Pix.

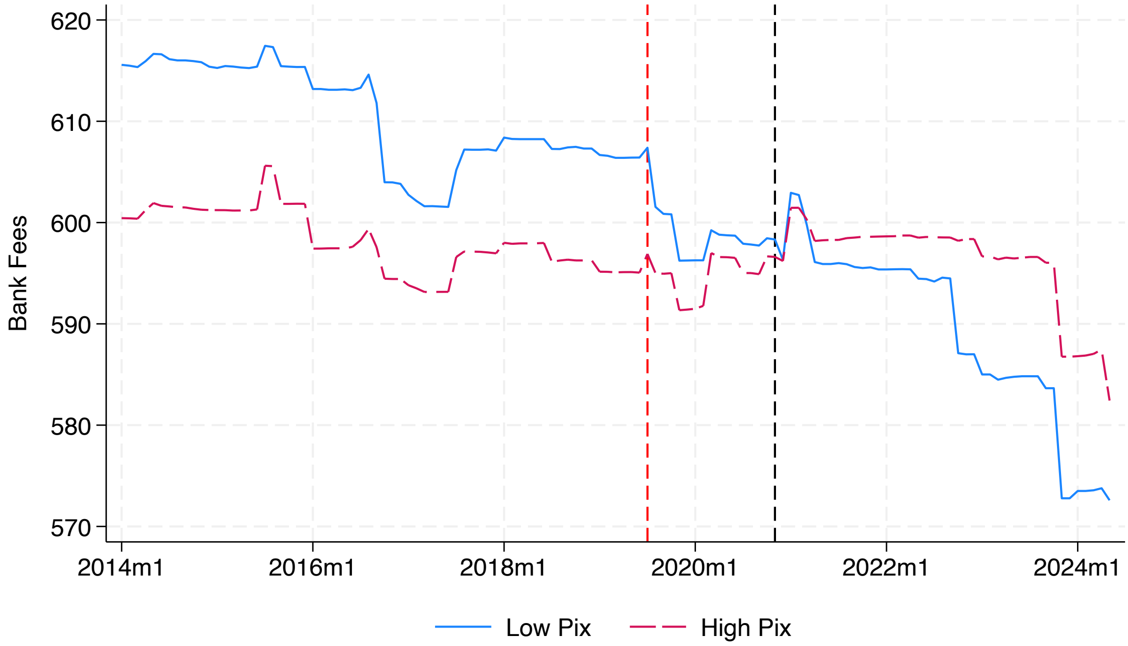
Figure 5 shows the results. Panel A shows fees that are not related to payments and, hence, do not face direct competition from Pix. Panel B includes payment-related services. The graphs imply that payment-related fees dropped significantly for all banks after the announcement of Pix, potentially to be able to compete. The drop in payment-related fees is more pronounced in high-Pix areas. At the same time, banks in high-Pix areas increase non-payment-related fees to extract rent from something that does not get competition from Pix. Competing with Pix, which has zero fees, is very challenging for banks, so they decide to extract rents elsewhere.

Finally, using data from the Central Bank of Brazil, we study how the number of bank accounts changes in Brazil after Pix. Figure 6 shows the results.[12] We find that the total number of bank accounts increases relatively more in areas with more Pix transactions.

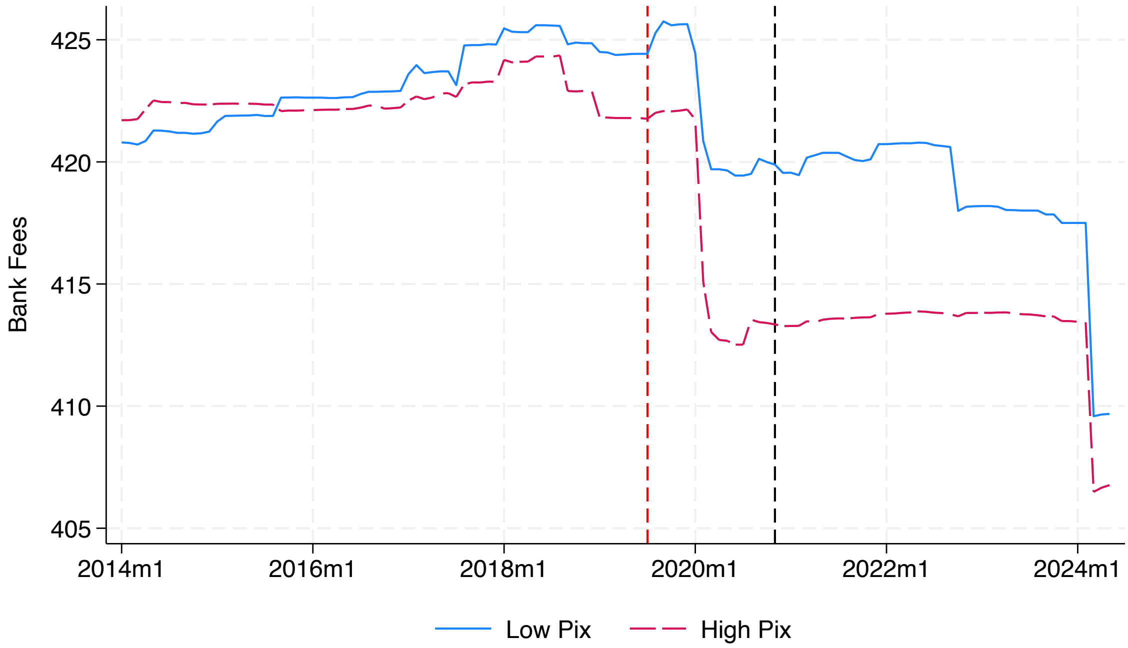
[12]Based on Sampaio and Ornelas (2024) – Matheus Sampaio is one of the authors of this paper.

Figure 5: Bank Fees in Brazil

Panel A: Non-Payment Services



Panel B: Payment Services



Note: This figure plots fees for services provided by banks separately for banks that operate in high-Pix areas (red line) and banks that operate in low-Pix areas (blue line). Panel A shows services that are not related to payments. Panel B shows services that are related to payments. The vertical black line shows the date of the launch of Pix. The vertical red line shows the date of the announcement of Pix.

More importantly, an increase in bank accounts per person is also larger in high-Pix areas. The finding is consistent with our proposed mechanism – Pix allows households to easily transfer money between bank accounts and to be banked at smaller banks. The result also speaks to a competing mechanism – an increase in usage of existing accounts. An increase in the number of accounts implies that an increase in usage of existing accounts cannot fully explain our results.

Another possible interpretation of the results is that banks get new clients who were previously unbanked. That can potentially change the rate structure by altering the composition of bank deposits in Brazil by crowding out paper currency. We argue that the extensive margin interpretation is unlikely for at least two reasons. First, the decline in the number of unbanked people is an increase in demand for bank deposits, which is not consistent with an increase in deposit rates. Second, Sarkisyan (2024) shows that in areas where there was a larger share of the unbanked population prior to November 2020, deposits of the largest banks in Brazil increased relative to smaller banks, implying that the unbanked population mostly opened accounts at larger banks. This would also be inconsistent with the reduction in banks' deposit market power.

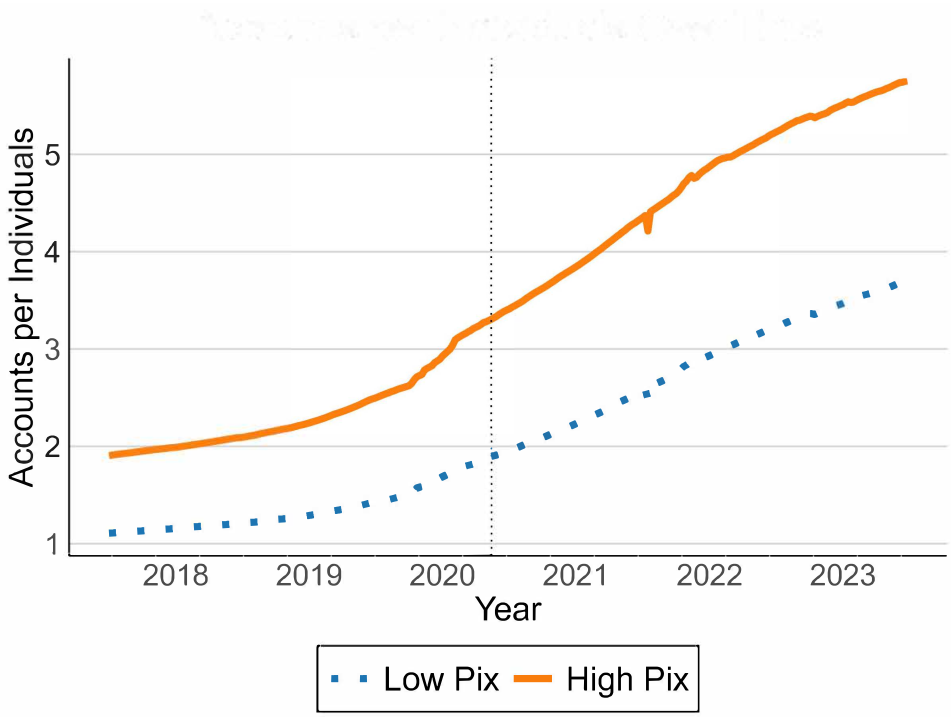
The empirical results motivate us to understand how underlying channels interact. For example, how does the introduction of Pix change the demand for deposits from the household sector? Which channel of monetary policy transmission makes the pass-through more complete after the introduction of Pix? Also,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

4 Simple model

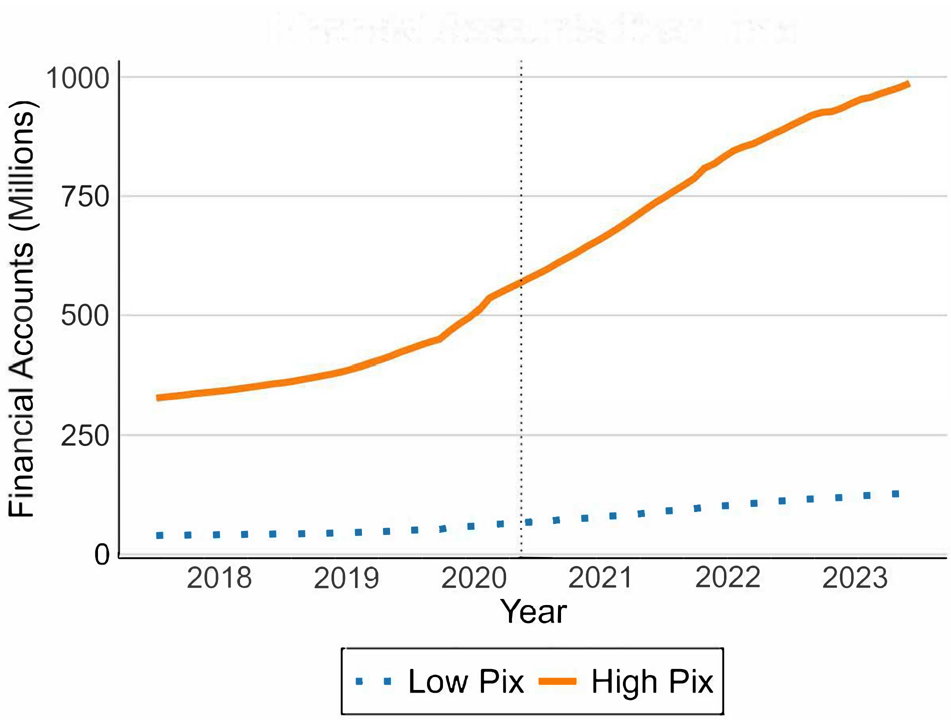
We start by providing a simple model to illustrate the main mechanisms highlighted in our paper. To set the stage for analyzing the households' decision on banking, we present a circular city model that is similar to Park and Pennacchi (2009). We then perform

Figure 6: Number of Bank Accounts in Brazil

Panel A: Number of Accounts Per Capita



Panel B: Total Number of Accounts



Note: This figure is based on analysis of Sampaio and Ornelas (2024). It plots the number of bank accounts separately for high-Pix areas (orange line) and low-Pix areas (blue line). Panel A shows the number of accounts per capita. Panel B shows the total number of accounts. The vertical black line shows the date of the launch of Pix.

comparative statics on the impact of the introduction of Pix on deposit demand.

4.1 Settings

Consider a continuum D of households that 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 a 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 linear 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 across more than one bank account, and they receive the maximum of the auxiliary services across their banks. 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_-. If a household decides to deposit with two banks, we fix the share of deposit allocated to bank i to be $\alpha_- \in (0,1)$. The subscript "$_-$" denotes that parameters correspond to the region to the left of bank i. The household's utilities from the three options are

$$v_-(\text{Bank } i) = r_i + u_i - t_d x_-, \tag{5}$$

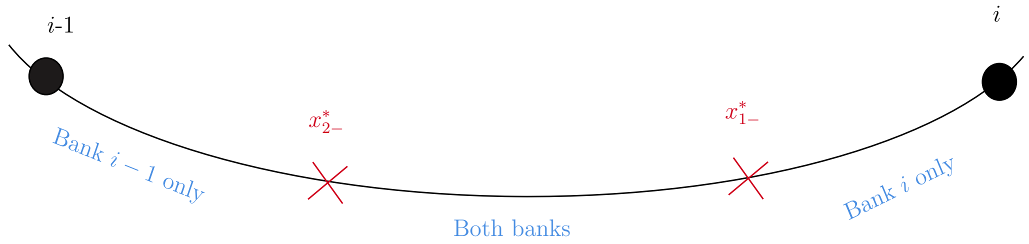
$$v_-(\text{Bank } i-1) = r_{i-1} + u_{i-1} - t_d(\frac{1}{n} - x_-), \tag{6}$$

$$v_-(\text{Mix}) = \alpha_- r_i + (1-\alpha_-)r_{i-1} + \underbrace{\frac{u_i + u_{i-1} + |u_i - u_{i-1}|}{2}}_{\max(u_i, u_{i-1})} - t_d\frac{1}{n}, \tag{7}$$

4.2 Household's deposit decision

Intuitively, the household's deposit decision depends on their location in the city. Figure 7 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.

Figure 7: Households' Deposit Decision



We derive the expression for the two thresholds x^*_{1-} and x^*_{2-} using the utilities from (5)-(7). At x^*_{1-}, households are indifferent between choosing bank i and a mixed strategy. Similarly, at x^*_{2-}, households are indifferent between choosing bank $i-1$ and a mixed strategy. The two thresholds are

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

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

The share of households that will deposit with both banks is

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

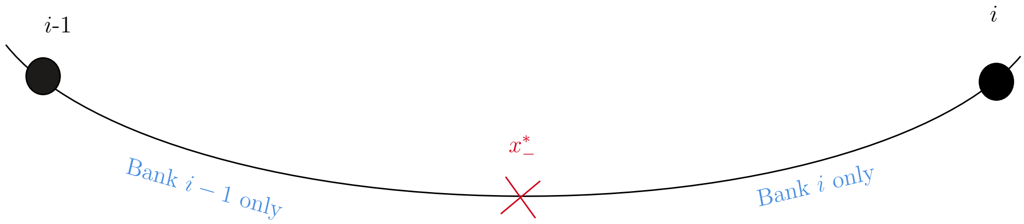
Of course, if the travel cost is large relative to the additional benefits gained from having another bank account, the middle region will shrink until it reaches zero. Figure 8 shows the scenario where no households choose the mixed strategy. Households located within x^*_- from bank i find it optimal 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,

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

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

Figure 8: No Mixed Strategy



conditions 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

$$\frac{1}{n}t_d \geq (2\alpha_- - 1)(r_i - r_{i-1}) + |u_i - u_{i-1}|. \tag{12}$$

This condition implies that if the additional auxiliary banking services and interest rate gained from splitting deposits into two banks 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 $i+1$. If the household chooses to deposit with both banks, α_+ is the share of deposits allocated to bank i. Their expressions are

$$x_{1+}^* = \frac{1-\alpha_+}{t_d}(r_i - r_{i+1}) + \frac{1}{2t_d}(u_i - u_{i+1}) - \frac{1}{2t_d}|u_i - u_{i+1}| + \frac{1}{n}, \tag{13}$$

$$x_{2+}^* = \frac{\alpha_+}{t_d}(r_i - r_{i+1}) + \frac{1}{2t_d}(u_i - u_{i+1}) + \frac{1}{2t_d}|u_i - u_{i+1}|, \tag{14}$$

$$x_+^* = \frac{1}{2t_d}(r_i - r_{i+1}) + \frac{1}{2t_d}(u_i - u_{i+1}) + \frac{1}{2n}. \tag{15}$$

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 rates 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 receives all deposits from households choosing bank i only. In the mixed strategy region, bank i receives α_- of the deposits from households choosing mixed strategy from the left side, and receives α_+ from the right side i. The deposit share of bank i from the left side is

$$DepShare_{i-} = \begin{cases} x_{1-}^* + \alpha_-(x_{2-}^* - x_{1-}^*), & \text{Mix region exists} \\ x_-^*, & \text{No mix region} \end{cases}$$

which yields

$$DepShare_{i-} = \begin{cases} \frac{1}{t_d}\overbrace{[(2\alpha_-^2 - 2\alpha_- + 1)(r_i - r_{i-1}) + \frac{1}{2}(u_i - u_{i-1}) + (\alpha_- - \frac{1}{2})|u_i - u_{i-1}|]}^{\text{Competitiveness}} + \overbrace{\frac{1-\alpha_-}{n}}^{\text{Market concentration}}, & \text{Mix region exists} \\ \frac{1}{t_d}\underbrace{[\frac{1}{2}(r_i - r_{i-1}) + \frac{1}{2}(u_i - u_{i-1})]}_{\text{Competitiveness}} + \underbrace{\frac{1}{2n}}_{\text{Market concentration}}, & \text{No mix region} \end{cases} \tag{16}$$

Similarly, the deposit share of bank i from the right side is

$$DepShare_{i+} = \begin{cases} \frac{1}{t_d}\overbrace{[(2\alpha_+^2 - 2\alpha_+ + 1)(r_i - r_{i+1}) + \frac{1}{2}(u_i - u_{i+1}) + (\alpha_+ - \frac{1}{2})|u_i - u_{i+1}|]}^{\text{Competitiveness}} + \overbrace{\frac{1-\alpha_+}{n}}^{\text{Market concentration}}, & \text{Mix region exists} \\ \frac{1}{t_d}\underbrace{[\frac{1}{2}(r_i - r_{i+1}) + \frac{1}{2}(u_i - u_{i+1})]}_{\text{Competitiveness}} + \underbrace{\frac{1}{2n}}_{\text{Market concentration}}, & \text{No mix region} \end{cases} \tag{17}$$

The total deposit share of bank i is

$$DepShare_i = DepShare_{i-} + DepShare_{i+}. \tag{18}$$

From the expressions above, 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 that 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

$$\begin{aligned} MixDepositors_i &= (x^*_{2-} - x^*_{1-}) + (x^*_{2+} - x^*_{1+}) \\ &= \frac{1}{t_d} \underbrace{\Big((2\alpha_- - 1)(r_i - r_{i-1}) + (2\alpha_+ - 1)(r_i - r_{i+1}) + |u_i - u_{i-1}| + |u_i - u_{i+1}| \Big)}_{\geq 0 \text{ by assumption}} - \frac{2}{n}. \end{aligned} \tag{19}$$

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 deposit share in (16) and (17) with respect to transportation costs. If the competitiveness term is positive, then the derivative $\frac{\partial DepShare_i}{\partial t_d} < 0$.

When transportation costs decline, households are more likely to have two bank accounts. This can be inferred from the mixed strategy condition from (12), as well as the share of mixed strategy depositors from (19).

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 (16), we see that the uniform non-monetary benefit makes the bank service component in the competitiveness term go away in both cases. 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 (19),

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

Secondly, the demand for deposits of bank i generally decreases. We see this from the derivative of (16) and (17), both $\frac{\partial DepShare_{i-}}{\partial n} < 0$ and $\frac{\partial DepShare_{i+}}{\partial n} < 0$ regardless of the existence of the mix region. 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 among multiple banks, so demand for any individual bank decreases.

5 Dynamic model

To understand the mechanism behind the impact of digital payment on monetary policy transmission, we follow Wang et al. (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 and 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.[13] Given that households face a static problem, we drop the subscript t for convenience, but in the actual estimation, we include time fixed effects. Each market consists of J banks, each of which offers a differentiated deposit product. Households allocate their endowments (R$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. In addition to the data described in Section 2, we also collect Brazilian Treasury holdings by households from the Central Bank of Brazil to model the outside option.

Each investment option is characterized by the interest rate r^d and a vector of non-rate characteristics x^d. The interest rate on cash is zero, whereas the interest rate on bonds is the policy rate f (*Selic rate*). The households choose the best investment option to maximize utility

$$\max_{j \in \mathcal{A}^d} u_{i,j} = \alpha^d r_j^d + \beta^d p_j^d r_j^d + \gamma^d x_j^d + \mu_j^d + \epsilon_{i,j}^d, \tag{20}$$

where $u_{i,j}$ is the utility from household i choosing investment option j. The coefficient α^d is the sensitivity to the interest rate r_j^d. β^d is an additional sensitivity to deposit rate after the introduction of Pix. The variable p_j^d measures the size of the Pix transactions in the locations where bank j operates.[14] We include the Pix variable on its own as well.

[13] We estimate the state-level model in Appendix C.13).

[14] In Appendix C.11, we introduce Pix as a dummy variable and show that our results are robust.

Bonds and cash have a Pix transaction size of zero. The coefficients γ^d are sensitivities to non-rate characteristics that include number of branches and time fixed effects. 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

$$\mathbb{I}_{i,j}^d = \begin{cases} 1, & \text{if } u_{i,j} \geq u_{i,k}, \quad j,k \in \mathcal{A}^d \\ 0, & \text{otherwise} \end{cases} \tag{21}$$

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:

$$\begin{aligned} s_j^d(r_j^d | f, p_j^d) &= \int \mathbb{I}_{i,j}^d dF(\epsilon) \qquad (22) \\ &= \frac{\exp(\alpha^d r_j^d + \beta^d p_j^d r_j^d + \gamma^d x_j^d + \mu_j^d)}{\exp(Bonds) + \exp(Cash) + \sum_{n=1}^{J} \exp(Banks)} \end{aligned}$$

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

where the numerator is the utility of choosing bank j, and the denominator is the sum of the utilities of all investment options. The total market size for household savings is denoted by W_t, so the deposit demand function for bank j is

$$D_{j,t}(r_{j,t}^d | f_t, p_{j,t}^d) = s_{j,t}^d(r_{j,t}^d | f_t, p_{j,t}^d) \cdot W_t. \tag{23}$$

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_t. As before, we drop the subscript t since which year a separate market. 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. We collect data on bond issuance by Brazilian corporations from FRED.[15]

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^l_j. 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

$$\bar{f} = \eta f_t + \mathbb{E}_t \left[\sum_{n=1}^{\infty} \eta(1-\eta)^n f_{t+n} \right] \tag{24}$$

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

$$\max_{j \in \mathcal{A}^\ell} \pi_{i,j} = \alpha^\ell r^\ell_j + \gamma^\ell x^\ell_j + \xi^\ell_j + \epsilon^\ell_{i,j} \tag{25}$$

where $\pi_{i,j}$ is the utility from firm i choosing financing option j. The coefficient α^ℓ is the sensitivity to the interest rate r^ℓ_j, γ^ℓ are sensitivities to bank-level non-rate characteristics. We let ξ^ℓ_j denote the product invariant demand shock. The last term $\epsilon^\ell_{i,j}$ is the relationship shock specific to the household-bank combination. Firm i's optimal

[15] FRED is maintained by the Federal Reserve Bank or St. Louis, so data entries are in USD. We collect data on USD-BRL exchange rates over time from Yahoo Finance to convert USD into BRL.

choice of financing is then

$$\mathbb{I}^{\ell}_{i,j} = \begin{cases} 1, & \text{if } \pi_{i,j} \geq \pi^{h}_{i,k}, \quad j,k \in \mathcal{A}^{\ell} \\ 0, & \text{otherwise} \end{cases} \tag{26}$$

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 $\epsilon^{\ell}_{i,j}$ follows a type II extreme-value distribution. The loan share of each bank is

$$\begin{aligned} s^{\ell}_{j}(r^{\ell}_{j}|f) &= \int \mathbb{I}^{\ell}_{i,j} dF(\epsilon) \qquad (27) \\ &= \frac{\exp(\alpha^{\ell} r^{\ell}_{j} + \beta^{\ell} x^{\ell}_{j} + \xi^{\ell}_{j})}{\underbrace{\exp(\alpha^{\ell}(\overline{f} + \overline{\delta}) + \beta^{\ell} x^{\ell}_{J+1} + \xi^{\ell}_{J+1})}_{Bonds} + \underbrace{\exp(\beta^{\ell} x^{\ell}_{n} + \xi^{\ell}_{n})}_{NotBorrowing} + \underbrace{\sum_{s=1}^{J} \exp(\alpha^{\ell} r^{\ell}_{s} + \beta^{\ell} x^{\ell}_{s} + \xi^{\ell}_{s})}_{Banks}} \end{aligned}$$

where the numerator is the utility of choosing bank j, and the denominator is the sum of the utilities of all financing options. The total market size for firm financing is denoted by K_t, so the loan demand function for bank j at time t is

$$B_{j,t}(r^{\ell}_{j,t}|f_t) = s^{\ell}_{j,t}(r^{\ell}_{j,t}|f_t) \cdot K_t. \tag{28}$$

5.3 The banking sector

There are J banks in the market. Each bank simultaneously chooses the deposit rate r^{d}_{j} and lending rate r^{ℓ}_{j}. Banks raise funds from deposits and wholesale markets and invest in loans and securities. There is no bank default in the economy. In each period, banks make decisions to maximize future cash flows for their equity holder. Next, we describe the asset and liability sides of the banks separately.

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

$$I_{j,t} = \sum_{n=0}^{\infty} \frac{(1-\eta)^n B_{j,t} r^{\ell}_{j,t}}{(1+\gamma)^n} \tag{29}$$

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

$$L_{j,t+1} = (1-\eta)(L_{j,t} + B_{j,t}). \tag{30}$$

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 $\delta_t \eta (L_t + B_t)$ in each period. Banks incur a servicing cost of ϕ^{ℓ} per unit of loans. Besides loans, banks can choose to invest in government securities G, with a return equal to the policy rate f_t. Banks keep a portion of funds in reserves R_t at the central bank. Reserves do not pay interest.

Liabilities: On the liability side, banks can borrow from insured retail deposits $D_{j,t}$ or uninsured non-reservable funding $N_{j,t}$. Retail deposits follow the household demand function in (23). Since households can hold cash which has an interest rate of zero, deposit rate r^d_j has a zero lower bound:

$$r^d_j \geq 0. \tag{31}$$

Banks incur a servicing cost of ϕ^d per unit of deposits. Uninsured non-reservable funding faces a quadratic cost:

$$\Phi^N(N_{j,t}) = \left(f_t + \frac{\phi^N}{2} \cdot \frac{N_{j,t}}{D_{j,t}} \right) N_{j,t}. \tag{32}$$

Profit and equity: In each period, bank j's profit is

$$\Pi_{j,t} = I_{j,t} - (L_{j,t} + B_{j,t})(\eta\delta_t + \phi^\ell) + G_{j,t} f_t - (r^d_{j,t} + \phi^d) D_{j,t} - \Phi^N(N_{j,t}) N_{j,t} - \psi \bar{E}_j, \quad (33)$$

where ψ is the fixed operating costs per unit of bank equity and $\bar{E}$ is the steady-state equity. The fixed operating costs are associated with rent on premises, salaries, and other fixed costs. The bank chooses the amount of cash dividends $C_{j,t}$ paid to equity holders and injects the remaining of the profits into equity for next period. We assume that banks cannot raise capital externally, so cash dividends must be non-negative

$$C_{j,t} \geq 0, \forall t.$$

Finally, the evolution of bank's equity is

$$E_{j,t+1} = E_{j,t} + (1 - \tau)\Pi_{j,t} - C_{j,t+1}, \quad (34)$$

where τ is the corporate tax rate.

Constraints Banks are subject to several constraints. First, the balance sheet constraint must hold in each period

$$L_{j,t} + B_{j,t} + R_{j,t} = D_{j,t} + N_{j,t} + E_{j,t}, \quad (35)$$

Deposits are subject to the reserve requirement

$$R_{j,t} \geq \theta D_{j,t}. \quad (36)$$

Finally, the government imposes capital requirements on banks

$$E_{j,t} \geq \kappa A_{j,t}. \quad (37)$$

5.4 Monetary Policy

Government sets 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

$$\begin{bmatrix} \ln \delta_{t+1} - \mathbb{E}(\ln \delta) \\ \ln f_{t+1} - \mathbb{E}(\ln f) \end{bmatrix} = \begin{bmatrix} \rho_\delta & \rho_{\delta f} \\ 0 & \rho_f \end{bmatrix} \cdot \begin{bmatrix} \ln \delta_t - \mathbb{E}(\ln \delta) \\ \ln f_t - \mathbb{E}(\ln f) \end{bmatrix} + \begin{bmatrix} \sigma_\delta & 0 \\ 0 & \sigma_f \end{bmatrix} \varepsilon_{t+1}. \quad (38)$$

The policy rate directly affects banks' cost of borrowing from uninsured non-reservable 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 Banks' problem and equilibrium

Banks choose loan and deposit rates according to the demand functions in (23) and (28). There are five state variables at the beginning of the period. The policy rate f_t and charge-off rate δ_t are exogenous state variables. The next two state variables are bank's equity E_t and outstanding loans L_t at the beginning of the period. The last state variable is the cross-sectional distribution of bank states Γ_t. This is because each bank's optimal choice depends on all other banks' states and decisions. The law of motion for the cross-sectional distribution is governed by

$$\Gamma_{t+1} = P^\Gamma(\Gamma_t)$$

Each bank j chooses the optimal policy to maximize expected discounted cash dividends to shareholders. We drop subscript j in the bellman equation for simplicity.

$$V(f_t, \delta_t, L_t, E_t|\Gamma_t) = \max_{\{r_t^l, r_t^d, G_t, N_t, R_t, C_{t+1}\}} \frac{1}{1+\gamma} \Big\{ C_t + 1 + \mathbb{E}V(f_{t+1}, \delta_{t+1}, L_{t+1}, E_{t+1}|\Gamma_{t+1}) \Big\} \tag{39}$$

$$\begin{aligned}
s.t. \quad & D_t = s_t^d(r_t^d|f_t, p_t^d) \cdot W_t, \quad \text{Deposit demand} \\
& B_t = s_t^\ell(r_t^\ell|f_t) \cdot K_t, \quad \text{Loan demand} \\
& r_t^d \geq 0, \quad \text{Non-negative deposit rate} \\
& I_t = \sum_{n=0}^{\infty} \frac{(1-\eta)^n B_t r_t^\ell}{(1+\gamma)^n}, \quad \text{Loan interest income} \\
& L_{t+1} = (1-\eta)(L_t + B_t), \quad \text{Loan evolution} \\
& E_{t+1} = E_t + (1-\tau)\Pi_t - C_{t+1}, \quad \text{Equity evolution} \\
& C_{t+1} \geq 0, \forall t, \quad \text{Non-negative cash dividend} \\
& L_t + B_t + R_t + G_t = D_t + N_t + E_t, \quad \text{Balance sheet} \\
& E_t \geq \kappa(L_t + B_t), \quad \text{Capital requirement} \\
& R_t \geq \theta D_t, \quad \text{Reserve requirement} \\
& \Pi_t = I_t - (L_t + B_t)(\eta\delta_t + \phi^\ell) + G_t f_t \\
& \qquad - (r_t^d + \phi^d)D_t - \Phi^N(N_t)N_t - \psi\bar{E}, \quad \text{Profits} \\
& \text{Equation (38)}, \quad \text{Law of motion for monetary policy} \\
& \Gamma_{t+1} = P^\Gamma(\Gamma_t), \quad \text{Law of motion for cross-sectional distribution}
\end{aligned}$$

A stationary equilibrium occurs when

1. All banks solve their problem according to equation (39), given other banks' choices of deposit and loan rates
2. Households and firms maximize utility given banks' deposit and loan rates
3. Deposit and loan markets clear
4. Law of motion for cross-sectional distribution P^Γ is consistent with banks' optimal choices

To reduce the dimensions in the estimation, we conjecture that the cross-sectional distribution P^{Γ} a function of the policy rate f_t. At the last step of the numerical method, we verify that the aggregate equilibrium deposit and loan rates are consistent with the bank choices.

5.6 Estimation

We calibrate the parameters and estimate the model in four steps. The estimation uses the national market as the market definition, with each quarter as 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 4 presents the estimated parameters.

In Step 1, we set the bank's discount rate to be 5%, which is a common calibration value in the literature. The tax rate is 34%, consistent with the corporate tax rate in Brazil. The capital ratio is 6% according to the 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 is only one type of deposit in the model, we set the 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, we set the number of banks to be five in the market. In Brazil, the average number of banks in a municipality is around five.

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 4. The 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 charge-offs, as

Table 4: Parameter Estimates

Panel A: Calibrated parameters			
γ	Discount rate	0.05	
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	0.012	[0.018]
β^d	Additional sensitivity to deposit rate from Pix	0.004	[0.002]
α^ℓ	Borrowers' sensitivity to loan rates	-0.032	[0.021]
Panel D: Parameters estimated from SMD			
W/K	Relative deposit market size	1.2958	[0.273]
q_n^ℓ	Value of firms' outside option	-0.912	[0.43]
ϕ^N	Quadratic cost of non-reservable borrowing	0.1683	[0.040]
ϕ^d	Cost to service deposits	0.0066	[0.013]
ϕ^ℓ	Cost to service loans	0.0004	[0.012]
ψ	Net fixed operating cost	0.0048	[0.184]

Note: This table 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.

well as the correlation of Selic rate innovation and loan charge-offs. We estimate these parameters according to Equation (38) using aggregate data from 1976 to 2022.

Next, in Step 3, we estimate the loan and deposit demand functions following the method in Berry et al. (1995). Recall Equations (23) and (28). Using them, we can express the deposit and loan demands as logit functions and obtain the fitted values of the parameters from the right-hand sides,

$$D_j\left(r_j^d \mid f, p_j^d\right)=\frac{\exp\left(\hat{\alpha}^d r_j^d+\hat{\beta}^d p_j^d r_j^d+q_j^d\right)}{\exp\left(\hat{\alpha}^d f\right)+\exp\left(q_c^d\right)+\sum_{m=1}^{\hat{J}} \exp\left(\hat{\alpha}^d r_m^d+\hat{\beta}^d p_m^d r_m^d+q_m^d\right)} W, \tag{40}$$

$$B_j\left(r_j^{\ell} \mid f\right)=\frac{\exp\left(\hat{\alpha}^{\ell} r_j^{\ell}+q_j^{\ell}\right)}{\exp\left(\hat{\alpha}^{\ell}(\bar{f}+\bar{\delta})\right)+\exp\left(q_n^{\ell}\right)+\sum_{m=1}^{\hat{J}} \exp\left(\hat{\alpha}^{\ell} r_m^{\ell}+q_m^{\ell}\right)} K, \tag{41}$$

where q_c^d is the quality value or convenience of holding cash. The variable 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 zero. We also assume homogeneous sensitivity of deposit and loan rates. Finally, the BLP method does not allow us to estimate the 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 the BLP method is the 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 and provisions for loan losses 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. In Appendix C.12, we include salaries as an instrument instead of the loan loss provision. Data on salaries in Brazil is very scarce and mostly has to be hand-collected. For the loan BLP, we only use fixed costs as an instrument since the loan loss provision depends on the amount of loans.

Panel C of Table 4 presents the estimate from the BLP method. Depositors' uniform sensitivity to deposit rate α^d is 0.012, and the additional deposit rate sensitivity from Pix

β^d is 0.004. To interpret the magnitude, for an initial deposit market share of 10%, a 100 bps increase in the deposit rate raises the share by 0.12 percentage points. Moreover, if Pix transaction size rises by 1%, the deposit share increases by an additional 0.04 percentage points per 100 bps increase in the deposit rate. On the lending side, the firms' sensitivity to bank loan rate is -0.032. For an initial loan market share of 10%, the share drops by 0.32 percentage points on average if banks raise their loan rate by 100 bps.

Finally, in Step 4, we assume banks take into account the demand functions (40) and (41) as estimated from BLP and choose the optimal deposit and loan rate to maximize the future stream of cash dividends. We estimate the rest of the bank characteristics via a simulated minimum distance (SMD) method. Specifically, we use eight moments to estimate six parameters and two free moments (deposits-to-assets and market-to-book) for model fits. The model is over-identified.

To identify the quadratic cost of uninsured non-reservable funding, we use the mean and standard deviation of the non-reservable to retail deposit ratio. A higher cost of non-reservable borrowing discourages banks from using wholesale funding as a substitute for retail deposits. Then, we use deposit spread and loan spread to identify costs to service deposits and loans, respectively. The intuition is that higher service costs incentivize banks to charge a higher spread on their deposit or loan products. Net fixed operating cost is pinned down by two moments: the average net non-interest 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 follow the intuition that banks with higher fixed costs operate with a lower leverage ratio. Next, we jointly identify the relative size of the 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 total credit to the Selic rate. On the one hand, a higher deposit-to-asset ratio indicates a larger deposit market. On the other hand, the sensitivity of deposits 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 options. 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 reflects accurate monetary policy transmission. The sensitivity of bank lending to the Selic rate and the sensitivity of deposits to the Selic rate are estimated using a vector autoregression with aggregate data.

Panel D of Table 4 presents the estimate from the SMD method. The deposit servicing cost is 0.7%, whereas the loan servicing cost is 0.04%. The quadratic cost of non-reservable borrowing is 0.168, a much higher value compared to the deposit and loan servicing costs. This number is also on the higher end compared to the estimate for the US banking sector in Wang et al. (2022). A potential explanation is that Brazilian banks have less access to the wholesale market and, therefore, it is more costly for them to raise non-reservable funds. Table 5 reports the main actual and simulated moments in the SMD estimations, along with the t-statistics and standard errors. We match sensitivities well, which is very important given that we study monetary transmission. The model, however, generates lower deposit rates than Brazilian banks pay, which is a consequence of low deposit-taking costs. Higher deposit spreads also result in lower leverage ratios. We acknowledge this limitation of the estimation procedure and think that the likely reason is that Brazilians prior to Pix had large demand for cash and USD, which results in the demand being skewed towards cash rather than the bond. A separate problem is that Brazil's bonds are as risky as the sovereign, which is likely not risk-free. Given matched elasticities and consistent empirical results, we do not view this limitation as crucial to our findings.

Table 5: Moment Conditions

	Actual	Sample	S.E.
Deposit spread	0.0185	0.0674	[0.003]
Loan spread	0.1678	0.3539	[0.011]
Net non-interest expense/Assets	0.007	−0.0111	[0.001]
Leverage	16.9	8.6	[2.528]
Credit - Selic rate sensitivity	−0.578	−0.384	[0.243]
Bank loan - Selic rate sensitivity	−0.789	−0.377	[0.338]
Non-reservable/deposits	2.28	0.25	[0.246]
SD of Non-reservable/deposits	1.83	0.026	[0.234]

Note: This table reports the actual and simulated moments in the SMD estimations, along with the sample standard errors. Deposit spread is defined as Selic rate minus deposit rate. Leverage ratio is defined as assets over book equity. We estimate the sensitivities of total credit and bank loans to the Selic rate via vector autoregressions.

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. Panel A of Figure 9 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. Panel B of Figure 9 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 et al. (2017)

We also show the trajectories for loan rates and lending. Because banks increase deposit rates, their loan rates also go up. Loan rates tend to follow policy rates more closely than deposit rates. In a fritionless economy, bank lending declines because deposits are the main source of funding for banks. Panel C of Figure 9 has a hump shape: lending increases until policy rate reaches 4% and then decreases as policy rate increases. The shape is consistent with the loan result in Wang et al. (2022) where the authors find that financial frictions such as market power and bank regulation generate a hump shape in bank's lending solution. This is referred to in the literature as a reversal rate – initially, lending increases because interest rates are low, but once interest rates are high, lending demand declines.[16]

6.2 *Counterfactual: reduced take-up of Pix*

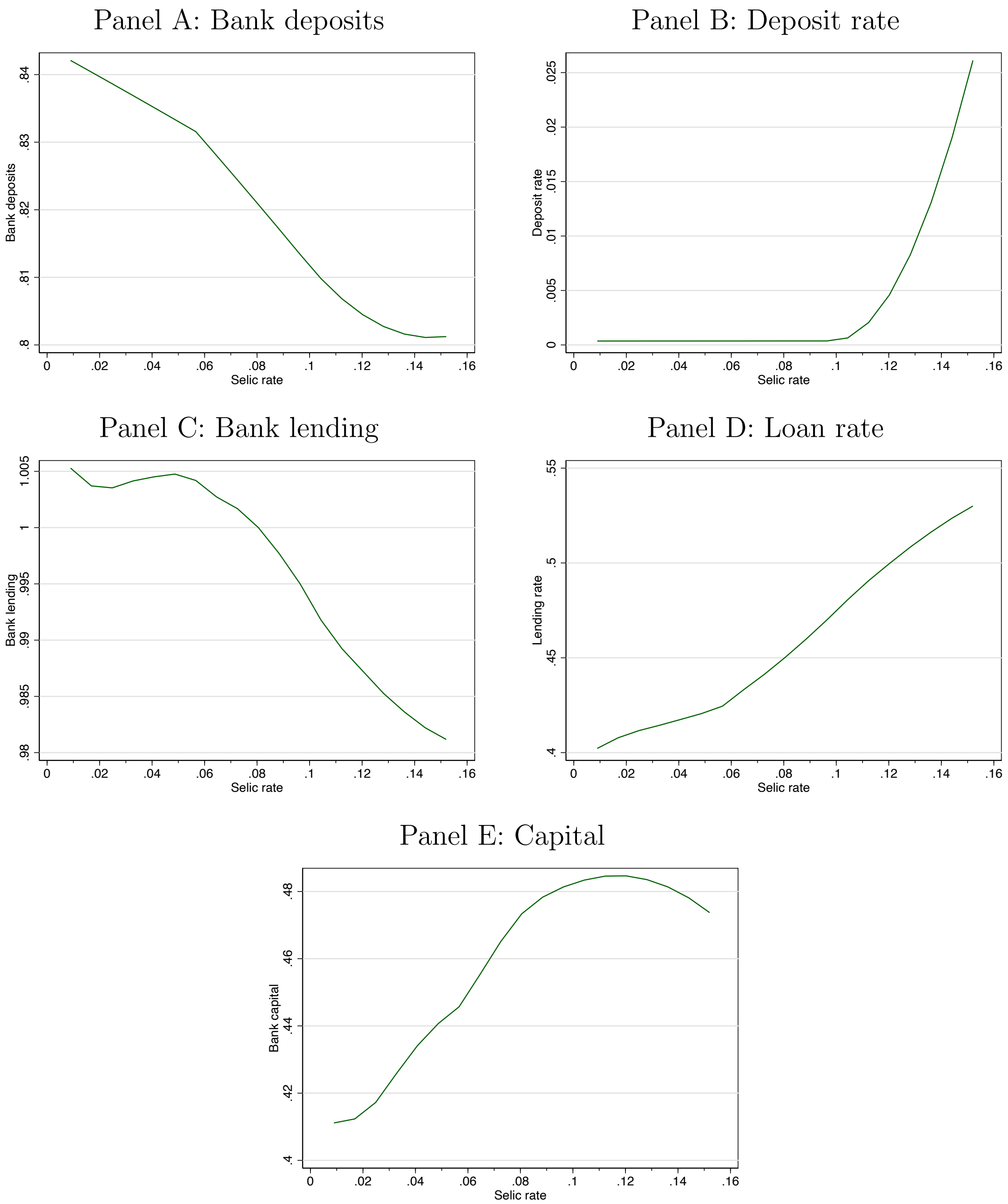
With the baseline model in mind, we now examine the effect of the introduction of Pix on the monetary transmission. Our theoretical model suggests that with less Pix usage, banks should have higher market power, and hence, their deposit rates should be lower. Similarly, less efficient payment methods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

To analyze the counterfactual, we set the take-up of Pix to 50% of its original value by reducing β^d in households' utility function. The reduction 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 10 plots the results. Panel C shows the optimal deposit rate when Pix is reduced and when Pix is fully used. The blue shaded area indicates the difference between the two solutions. Banks generally pay lower deposit rates with lower Pix because, with less usage of digital payments, banks have higher market power, and hence, they can charge higher deposit spreads. The shape also becomes steeper, indicating the change in the pass-through. Panel A shows the bank deposits with full Pix usage and reduced usage. Bank deposits are larger with less Pix because it is less common to move out when interest rates are high, if the take-up of Pix is lower. This is an indication that Pix is used by Brazilian households to move their deposits across banks and out of the banking sector. Since deposits flow out more after the introduction of Pix, banks have less funding for lending, as shown in Panel B. Overall, lending with Pix is lower. The estimation results are fully consistent with the empirical findings of the paper.

[16] Note that our reversal rate is slightly higher than the one in Wang et al. (2022). This is because Brazil is a high-interest-rate economy.

Figure 9: Policy Functions

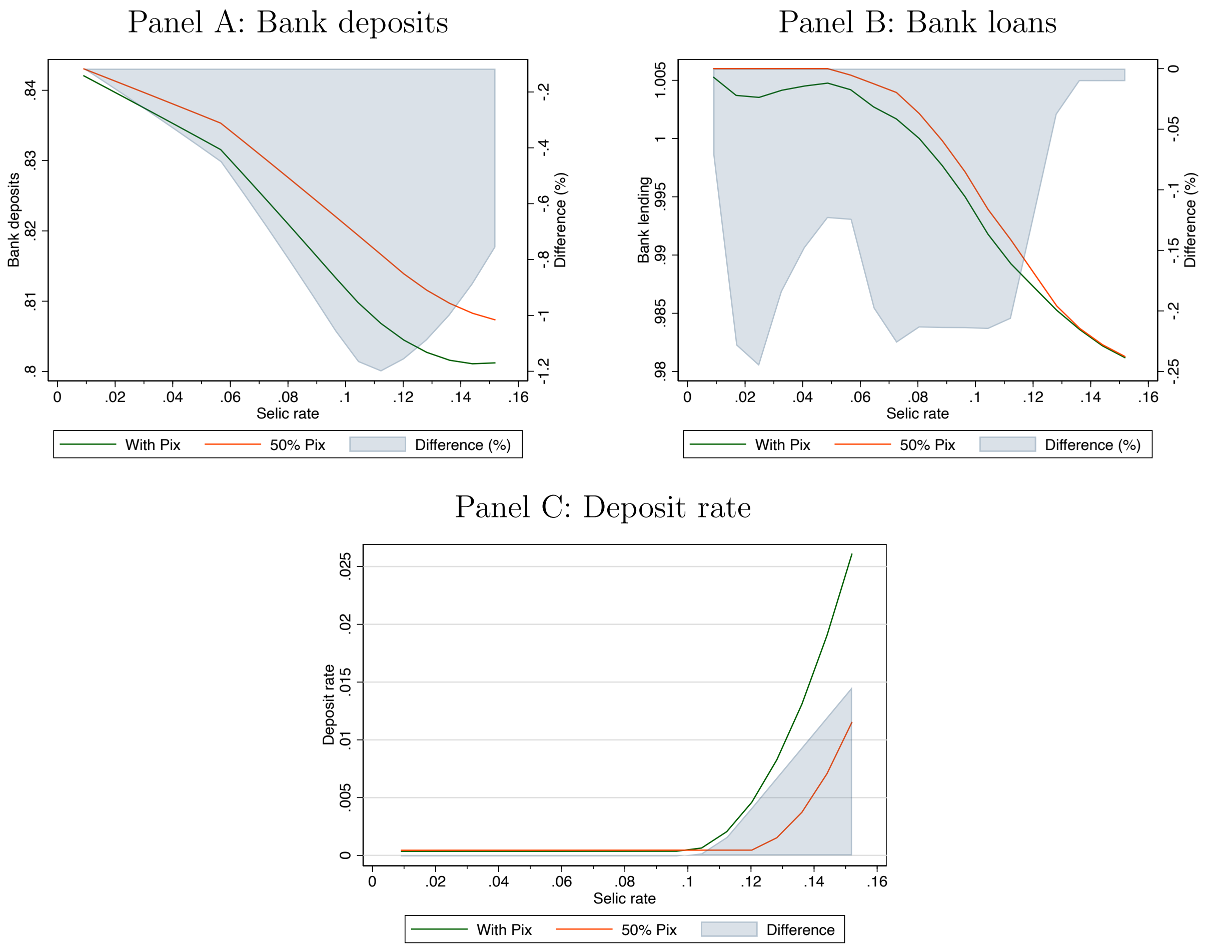


Note: This figure shows policy functions of bank deposits, deposit rates, loans, loan rates, and bank capital from the baseline model. Deposit, loan, and capital amounts are scaled by the steady-state bank loan amount.

6.3 *Counterfactual: Pix's effect through deposit channel*

Now, we investigate the quantitative forces that shape the relationship between digital payment and monetary policy. We focus on the deposit channel because Pix affects

Figure 10: Counterfactual with Lower Pix Take-up

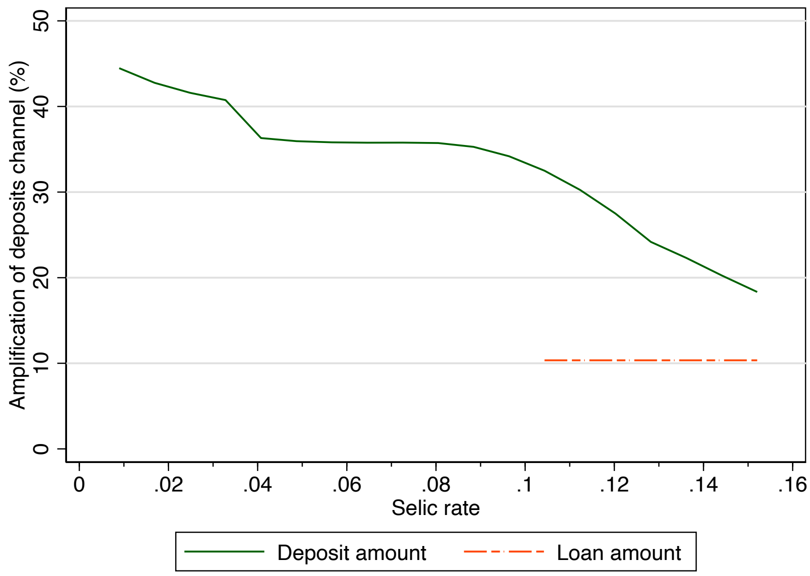


Note: This figure shows the counterfactual results with 50% of Pix take-up. The green lines correspond to the baseline solutions with Pix, whereas the orange lines correspond to the counterfactual solution where the take-up of Pix is reduced to 50% of the original value. The blue-shaded areas indicate the difference between the baseline and counterfactual solutions. Bank deposit and loan amounts are scaled by steady-state bank loan amounts from the baseline model.

the banking sector through the household deposit demand. Specifically, we eliminate the effect of the deposit channel in the model and check how deposits react to changes in policy rates. We perform the analysis in two scenarios, one with full Pix usage and another with 50% of actual Pix usage. We then check how much Pix amplifies the deposit channel in the monetary policy transmission.

Figure 11 shows the results. The solid green line plots the amplification effect of Pix on aggregate deposit amount through the deposit market power channel. Specifically, we consider the counterfactual where banks do not hold market power over bank deposits.

Figure 11: The Effect of Pix through the Deposit Channel



Note: This figure shows Pix's effect on deposit and loan amounts through the deposit channel. The solid green line shows how much Pix amplifies the deposit channel effect on the deposit amounts, whereas the dashed orange line shows Pix's amplification effect on bank lending. We construct the amplification effects by estimating the counterfactual solutions with full Pix take-up and a 50% of actual Pix take-up, and with and without deposit market power.

We then compare the cases with full and reduced Pix usage. Larger numbers mean that Pix has a higher impact on the deposit channel's contribution to bank deposits. On average, Pix enhances the deposit channel by 20 - 45% on aggregate deposits. Similarly, the orange line plots the amplification effect of Pix on bank lending. Pix enhances the deposit channel by 10% on total lending. The results show that Pix has a significant impact on the monetary policy transmission through the deposit channel, i.e., through the reduction in banks' market power.

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 75% 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, deposit outflows, and lending contractions.

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, which results in higher deposit rates and lending contractions following policy rate increases.

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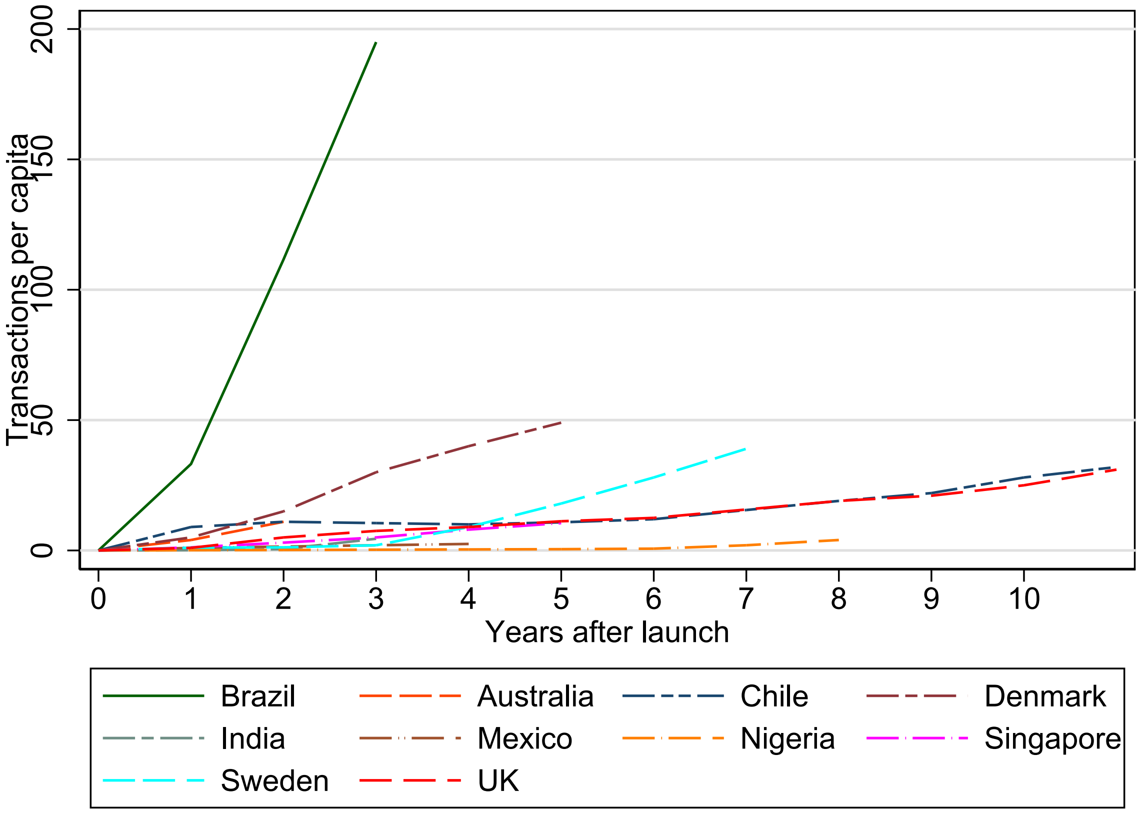
Internet Appendix

A Additional figures

Figure A.1: Use of Payments in Different Countries



Note: The graph shows the development of payment systems around the world. The data used is collected from Statista and is based on Duarte et al. (2022).

B Data definitions and sources

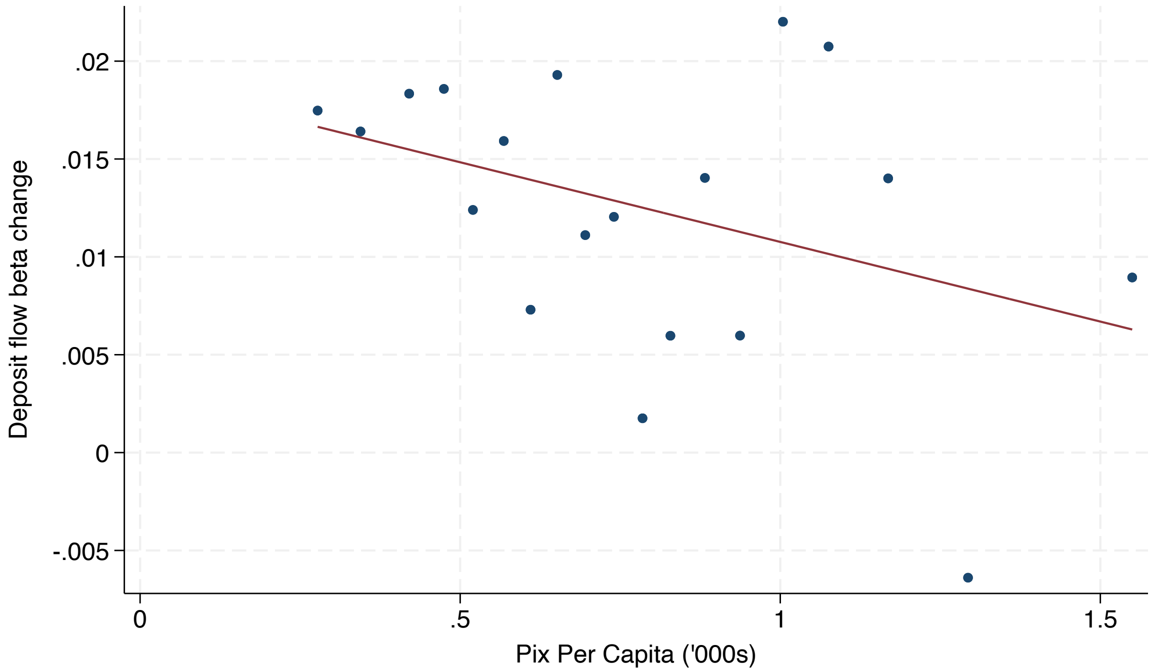
Table B.1 shows sources of the data and simple definitions. Specifically, Column 3 provides frequencies, and Column 4 depicts points of observation. Most of the data used for empirical tests is monthly and municipality-level. Bank data is branch-level and also monthly. Most of the data for the model is bank-level and quarterly.

Table B.1: Data Definitions and Sources

Name	Source	Frequency	Point of observation
Pix volume	Banco Central	Monthly	Municipality
Pix transactions	Banco Central	Monthly	Municipality
Assets	ESTBAN and IF	Monthly and Quarterly	Branch and Bank
Deposits	ESTBAN and IF	Monthly and Quarterly	Branch and Bank
Loans	ESTBAN and IF	Monthly and Quarterly	Branch and Bank
Reserves	ESTBAN and IF	Monthly and Quarterly	Branch and Bank
Fixed costs	ESTBAN	Monthly	Branch
Salaries	RAIS and hand-collected	Quarterly	Bank
Deposit rates	IF	Quarterly	Bank
Loan rates	IF	Quarterly	Bank
Equity	IF	Quarterly	Bank
GDP per capita	IBGE	Annual	Municipality
Demographics	IBGE	Only 2010	Municipality
Inflation	Banco Central	Monthly	Country
Exchange rates	Banco Central	Monthly	Country
Unemployment	Banco Central	Monthly	Country
Number of bank accounts	Banco Central	Monthly	Municipality
Bank fees	Banco Central	Monthly	Bank

Note: This table provides data definitions and sources. Columns 1 and 2 contain names and sources. Columns 3 and 4 show frequencies and points of observation. The term "Branch" refers to a municipal office. For example, we observe the balance sheet of Banco do Brasil's Rio de Janeiro office in January 2021. ESTBAN also has branch-level data (municipalities usually have multiple branches of the same bank). We choose to use the municipality office one because of the quality of branch-level data and misreporting (Fonseca and Matray (2022); Sarkisyan (2024)).

Figure C.1: Changes in Flow Betas



Note: The graph shows the changes in deposit flow betas in Brazil after the introduction of Pix. The X-axis shows the value of Pix transactions divided by the population. Deposit flow betas are measured as sensitivities of deposit flows to monetary policy rates.

C Additional results

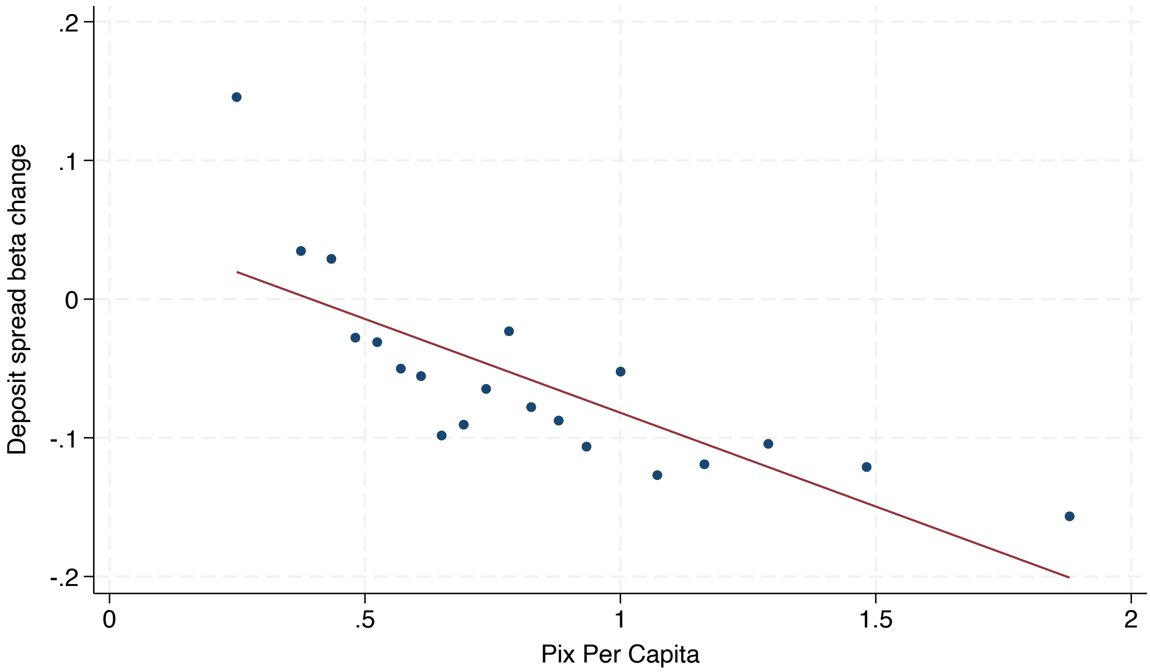
C.1 Changes in flow betas

In Section 3, we showed how deposit spread betas change in Brazil. We argue that banks start paying more competitive rate and at the same time, bank deposits flow out more because Pix makes it easier to move from bank to bank or outside of the banking system. Our results imply lower flow betas because there are more transfers between banks. Figure C.1 shows that flow betas decreases in areas with more Pix transactions.

C.2 Changes in spread betas: accounting for income

In Sectio 3, we argue that deposit spread betas decline more in the areas with higher value of Pix transactions per capita. One concern with the results is that people in richer

Figure C.2: Changes in Spread Betas: Controlling for Income



Note: The graph shows the changes in deposit spread betas in Brazil after the introduction of Pix. The X-axis shows the quantity of Pix transactions divided by the population. Deposit spread betas are measured as sensitivities of deposit spreads to monetary policy rates controlling for income per capita.

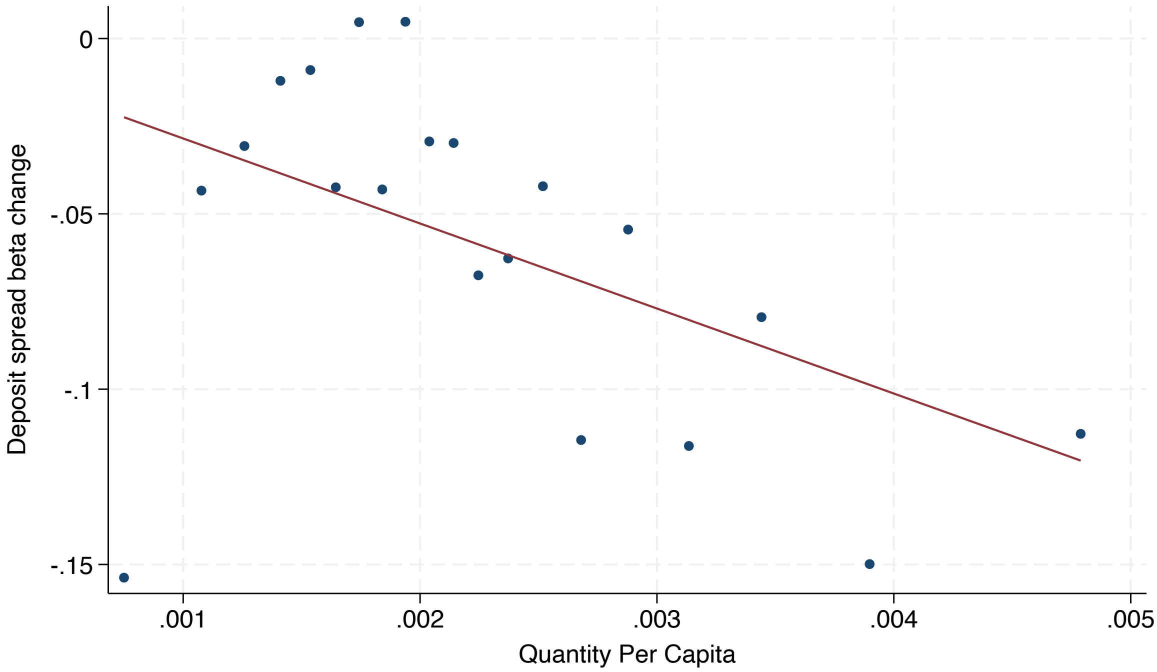
areas might have higher values of Pix transactions as their spending volume is larger. In other words, the value of Pix transactions can be correlated with income. In this section, we propose two ways to address the concern. First, we estimate spread betas but instead of doing it by estimating equation (2), we run the following sets of regressions that include income per capita:

$$y_{it} = \beta_i MS_t + \gamma_i IncomePC_m + u_{imt} \tag{C.1}$$

where $IncomePC_m$ is income per capita in municipality m. We do not observe this value across years, but we do observe a municipality-level cross-section from the 2010 Census. The estimation results are shown in Figure C.2 – our results are robust to accounting for income.

Even though controlling for income leaves our deposit spread graph unchanged, there

Figure C.3: Changes in Spread Betas: Quantity of Pix Transactions



Note: The graph shows the changes in deposit spread betas in Brazil after the introduction of Pix. The X-axis shows the quantity of Pix transactions divided by the population. Deposit spread betas are measured as sensitivities of deposit spreads to monetary policy rates.

are concerns about third variables that could impact both Pix per capita and income. To address the concern, we next plot deposit spreads in different areas in Brazil, but instead of measuring Pix usage as the value of transactions per capita, we measure it as the *quantity* of transactions per capita. Unlike the value of transactions, the quantity does not necessarily depend on income. Figure C.3 shows that deposit spread betas decline in areas with a larger number of Pix transactions.

C.3 Changes in equity, alternative financing, and derivatives

Within-bank evidence in Table 2 suggests that banks retain more deposits after Pix, but they lose loans. In this section, we take a closer look at banks' balance sheets to understand which items move to create a discrepancy between assets and liabilities. Table C.1 shows how equity flows, alternative funding flows, and derivative flows change

Table C.1: Impact of Pix on Equity, Alternative Financing, and Derivatives

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

	Equity flows		Alternative funding flows		Derivative flows	
	(1)	(2)	(3)	(4)	(5)	(6)
Pix Per Capita × MS	−2.489***	−2.619***	2.333***	2.082***	0.136	0.106
	(0.610)	(0.639)	(0.653)	(0.637)	(0.442)	(0.439)
Pix Per Capita	3.661***	3.644***	0.351	0.346	0.055	0.039
	(0.775)	(0.727)	(0.386)	(0.378)	(0.228)	(0.227)
MS	−1.486*	−1.416*	−2.392***	−2.120***	−0.177	−0.133
	(0.889)	(0.834)	(0.413)	(0.379)	(0.237)	(0.228)
Branch FE	Yes	No	Yes	No	Yes	No
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	9,646	9,658	373,191	373,230	65,804	65,806
R^2	0.324	0.294	0.016	0.008	0.012	0.010

Note: This table provides results of within-bank estimation of the effect of Pix on equity flows, alternative funding flows, and derivative flows – equation (3). Columns 1 and 2 show the results for equity flows. Columns 3 and 4 correspond to changes in alternative funding flows. Columns 5 and 6 correspond to derivative flows. 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.

after the introduction of Pix conditional on banks' asset flows. Bank equity changes significantly – banks lose equity after the introduction of Pix, as their assets shrink. It is possible that banks are able to hold more deposits and less equity because reduced assets relax banks' capital constraints. We do not find any decline in alternative funding or significant change in derivatives.

C.4 Monetary shocks

The results in the main section used changes to the policy rate as a measure of monetary policy change. However, such measure might be endogenous because it is correlated with economic conditions (Nakamura and Steinsson (2018)). In this section we re-run regression (3) but use high-frequency monetary surprises instead of policy rate changes (Gertler and Karadi (2011); Paul (2020)).[17] The surprises are constructed using changes

[17]We thank the authors of B. P. Gomes et al. (2023) for sharing their monetary shock data with us.

Table C.2: Impact of Pix on Deposit Flows, Loan Flows, and Deposit Spreads: Identified Monetary Shocks

$$\text{First stage: } MS_t = a + b \text{ Identified } MS_t + \epsilon_t$$

$$\text{Second stage: } Y_{imt} = \beta \widehat{MS}_t \cdot PixPerCap_{mt} + \gamma X_{imt} + \theta_{it} + \eta_i + \alpha_{im} + \varepsilon_{imt}$$

	Deposit spread change		Loan flows		Deposit flows	
	(1)	(2)	(3)	(4)	(5)	(6)
Pix Per Capita × MS	-0.54^{***}	-0.36^{***}	-1.60^{***}	-1.66^{***}	-0.47^{**}	-0.98^{***}
	(0.04)	(0.04)	(0.12)	(0.14)	(0.23)	(0.31)
Pix Per Capita	0.42^{***}	0.20^{***}	-0.05	-0.20^{***}	0.73^{***}	1.06^{***}
	(0.03)	(0.03)	(0.09)	(0.07)	(0.20)	(0.24)
MS	0.73^{***}	0.80^{***}	1.76^{***}	2.13^{***}		
	(0.01)	(0.01)	(0.06)	(0.15)		
Method	OLS	IV	OLS	IV	OLS	IV
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank-Time FE	No	No	No	No	Yes	Yes
Obs.	126,945	126,945	388,323	388,323	365,090	365,090
R^2	0.129		0.063		0.066	
Wald $F-$stat		5.1		106.9		5,243.8

Note: This table provides results of within-bank estimation of the effect of Pix on deposit and loan flows and spread betas – equation (3). The odd columns present OLS results from equation (3). In the even columns, we use high-frequency identified monetary surprises sourced from B. P. Gomes et al. (2023) to instrument for the change in Selic rate. Columns 1 and 2 show the results for deposit spreads. Columns 3 and 4 correspond to changes in lending flows. Columns 5 and 6 correspond to changes in deposit flows. 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.

in policy rate expectations around monetary meetings (Copom meetings – analogous to FOMC meetings). By assumption, the shocks do not contain confounders – any change in the shock after the meeting reflects the surprise and can be used as an exogenous measure of monetary policy. Table C.2 shows that our results are robust to using high-frequency monetary shocks as a measure of monetary policy.

C.5 Different measure of Pix

Table C.3 replicates the main results with IV and OLS but instead of Pix value per capita, it uses Pix users per capita.

Table C.3: Impact of Users of Pix per Capita on Deposit Flows, Loan Flows, and Deposit Spreads: Identified Monetary Shocks

First stage: $MS_t = a + b$ Identified $MS_t + \epsilon_t$

Second stage: $Y_{imt} = \beta \widehat{MS}_t \cdot PixUPerCap_{mt} + \gamma X_{imt} + \theta_{it} + \eta_i + \alpha_{im} + \varepsilon_{imt}$

	Deposit spread change		Loan flows		Deposit flows	
	(1)	(2)	(3)	(4)	(5)	(6)
Pix Users Per Capita × MS	-2.48^{***}	-1.15^{***}	-9.10^{***}	-9.05^{***}	-1.06	-5.45^{***}
	(0.13)	(0.14)	(0.45)	(0.80)	(1.30)	(1.79)
Pix Users Per Capita	2.03^{***}	0.55^{***}	-0.09	-1.24^{***}	1.75	4.57^{***}
	(0.08)	(0.12)	(0.34)	(0.31)	(1.14)	(1.38)
MS	0.74^{***}	0.81^{***}	2.53^{***}	2.99^{***}		
	(0.01)	(0.01)	(0.08)	(0.24)		
Method	OLS	IV	OLS	IV	OLS	IV
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank-Time FE	No	No	No	No	Yes	Yes
Obs.	126,945	126,945	388,323	388,323	365,090	365,090
R^2	0.131		0.063		0.066	
Wald $F-$stat		3,251.5		79.9		4.6

Note: This table provides results of within-bank estimation of the effect of Pix (users per capita) on deposit and loan flows and spread betas – equation (3). The odd columns present OLS results from equation (3). In the even columns, we use high-frequency identified monetary surprises sourced from B. P. Gomes et al. (2023) to instrument for the change in Selic rate. Columns 1 and 2 show the results for deposit spreads. Columns 3 and 4 correspond to changes in lending flows. Columns 5 and 6 correspond to changes in deposit flows. 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.

C.6 Bank-level lending

In this section, we follow Drechsler et al. (2017), construct deposit-weighted bank-level measures of the variables in equation (3), and run the loan flow regression at the bank level. Table C.4 shows that our results are robust.

C.7 Speed and persistence of monetary transmission

In the paper, we show that the introduction of Pix increased monetary policy transmission – i.e., the pass-through to interest rates and loans is more complete. In this section, we study if monetary policy is also faster and more persistent with Pix. To do so, we use Jordà (2005) local projections. Specifically, we evaluate how bank lending reacts to

Table C.4: Loan Flows and Pix: Bank-Level Analysis

	Loan flows
Pix Per Capita × MS	-0.098^{*}
	(0.053)
Pix Per Capita	0.100^{**}
	(0.041)
MS	0.136^{*}
	(0.077)
Bank FE	Yes
Obs.	8,250
R^2	0.820

Note: This table provides results of bank-level estimation of the effect of Pix on loan flows. We use deposits as weights to aggregate branch-level variables to the bank level. We use the Pix value per capita in the regression estimations. Robust standard errors are displayed in parentheses. Bank fixed effects are included. *,**, and *** correspond to 10-, 5-, and 1% significance level, respectively.

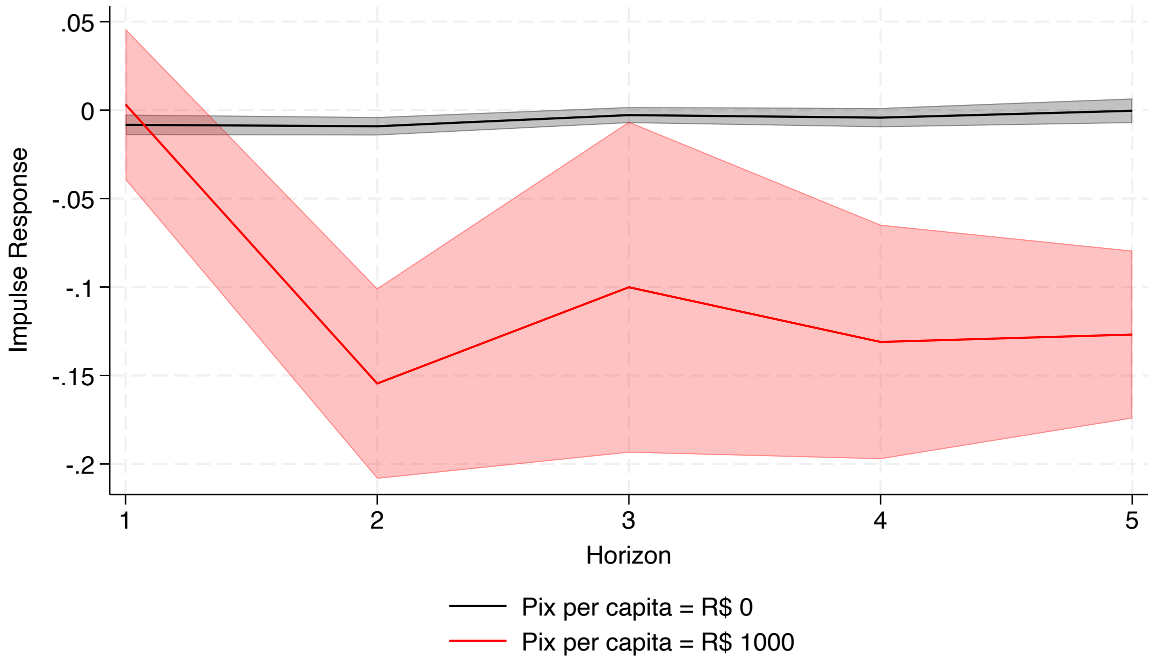
monetary shocks over time. In other words, we plot impulse response functions of bank lending to the monetary policy shocks.

Figure C.4 shows the results. There is always a reduction in bank lending following monetary policy shocks, which persists for two months after the meeting (the black line). The red line (corresponds to Pix per capita equal to $R 1000) shows that lending responds to monetary shocks more with higher Pix usage, so the effects of monetary policy on lending are potentially faster. The effects remain significantly negative even after five months, implying that monetary transmission is also more persistent with Pix.

C.8 Interpretations with standard deviations

In the main analysis, we interpret changes in deposit spreads after a R$ 1000 increase in the value of Pix transactions per capita. Such an increase is very large and not typical in Brazil, so in this section, we normalize the value of Pix transactions by subtracting the mean and dividing by the standard deviation. We find that a one s.d. increase in the value of Pix transactions per capita leads to a 16.7 b.p. reduction in deposit spreads. The results are presented in Table C.5.

Figure C.4: Impact of Monetary Shocks on Bank Lending: Local Projections



Note: The graph plots impulse response functions of bank lending to the monetary policy shocks. The impulse responses are calculated using Jordà (2005) local projections. Monetary shocks are defined using high-frequency monetary surprises around Brazilian monetary policy meetings. The black line corresponds to Pix per capita equal to 0. The red line corresponds to Pix per capita equal to $R 1000. The horizon is in months following the shock.

C.9 Placebo test with lagged effects

In this section, we test if deposit flows, loan flows, and deposit spreads decline in areas with more Pix transactions following a contractionary monetary policy change even before Pix was introduced. Table C.6 shows that deposit spreads were the same across areas with more or less Pix usage. Deposit flows and loan flows also do not decline – if anything, there is an increase in deposit flows and loan flows. The evidence is consistent with Pix driving changes in deposit spreads, deposit flows, and loan flows.

C.10 Impact on profitability

Since deposit spreads increase less following contractionary policy rate changes following the introduction of Pix, we should also expect banks to become less profitable. In this

Table C.5: Impact of Pix on Deposit Flows, Loan Flows, and Deposit Spreads: Z-Scored Pix Variable

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

	Deposit spread change		Loan flows		Deposit flows	
	(1)	(2)	(3)	(4)	(5)	(6)
Pix Per Capita (Z-score) × MS	-0.17^{***}	-0.17^{***}	-0.50^{***}	-0.49^{***}	-0.15^{**}	-0.14^{**}
	(0.01)	(0.01)	(0.04)	(0.04)	(0.07)	(0.07)
Pix Per Capita (Z-score)	0.13^{***}	0.13^{***}	-0.02	0.08^{***}	0.23^{***}	0.22^{***}
	(0.01)	(0.01)	(0.03)	(0.03)	(0.06)	(0.06)
MS	0.70^{***}	0.69^{***}	1.66^{***}	1.59^{***}		
	(0.01)	(0.01)	(0.06)	(0.06)		
Branch FE	Yes	No	Yes	No	Yes	No
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank-Time FE	No	No	No	No	Yes	Yes
Obs.	126,945	126,970	388,323	388,345	365,090	365,113
R^2	0.129	0.127	0.063	0.012	0.066	0.043

Note: This table provides results of within-bank estimation of the effect of Pix on deposit and loan flows and spread betas – equation (3). The independent variable is the z-scored value of Pix transactions per capita. Columns 1 and 2 show the results for deposit flows. Columns 3 and 4 correspond to changes in lending flows. Columns 5 and 6 correspond to changes in 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.

section, we analyze how return on assets and interest return on assets (net interest income divided by assets) change. Table C.7 shows that ROA declines for banks more affected by Pix following a contractionary policy change. The effect is mostly driven by changes in interest income, which is why the results in Columns 3 and 4 are stronger.

C.11 Estimation with Pix as a dummy variable

We estimate the model by allowing Pix to vary over time and across banks' locations to capture important heterogeneities. To address potential construction concerns, we estimate the model by treating Pix as a dummy variable that is equal to one after November 2020. Another interpretation of the approach is that we allow estimates to change before and after Pix. The results of the demand estimation using BLP are presented in Table C.8. As in our main specifications, deposit demand becomes more elastic after the launch of Pix.

Table C.6: Impact of Pix on Lagged Deposit Flows, Loan Flows, and Deposit Spreads

$$Y_{imt-12} = \beta MS_{t-12} \cdot PixPerCap_{mt} + \gamma X_{imt-12} + \theta_{it} + \eta_i + \alpha_{im}\varepsilon_{imt}$$

	Deposit spread change		Deposit flows		Loan flows	
	(1)	(2)	(3)	(4)	(5)	(6)
Pix Per Capita × MS	0.273	0.179	2.193***	2.226***	2.196***	2.084***
	(0.337)	(0.330)	(0.312)	(0.328)	(0.770)	(0.765)
Pix Per Capita	0.711***	0.583**	0.680***	1.076***	0.807**	0.898***
	(0.255)	(0.245)	(0.150)	(0.150)	(0.338)	(0.339)
MS	1.254***	1.218***	1.747***	1.688***		
	(0.022)	(0.019)	(0.116)	(0.117)		
Branch FE	Yes	No	Yes	No	Yes	No
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank-Time FE	No	No	Yes	Yes	No	No
Obs.	91,017	91,046	264,528	264,551	281,798	281,822
R^2	0.085	0.079	0.041	0.019	0.091	0.017

Note: This table provides results of within-bank estimation of the effect of Pix on lagged deposit flow and spread betas – a placebo test. Columns 1 and 2 show the results for deposit spreads. Columns 3 and 4 correspond to changes in lending flows. Columns 5 and 6 correspond to changes in deposit flows. Standard errors are clustered at the municipality level and displayed in parentheses. Bank and branch fixed effects are included. Bank-time fixed effects are included in deposit flow regressions but not in loan flow and deposit spread regressions because loans and deposit spreads in our data are determined at the bank level every period, so they are collinear with bank-time fixed effects. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

C.12 Estimation with salaries in the instrument set

In this section, we add salaries to our instrument set instead of the loan loss provision. Data on salaries in Brazil is very scarce and has to be hand-collected from bank statements. The results of the demand estimation using BLP are presented in Table C.9. As in our main specifications, deposit demand becomes more elastic after the launch of Pix.

C.13 State-level demand estimation

In this section, we relax the assumption that the market is Brazil as a whole and instead define markets as state-time combinations. This allows us to consider the possibility that some banks do not operate outside of their states. Table C.10 shows that the demand estimation produces qualitatively similar and economically larger results.

Table C.7: Impact of Pix on Profitability

$$ROA_{it} = \beta MS_t \cdot PixPerCap_{mt} + \gamma X_{imt} + \eta_i + \varepsilon_{imt}$$

	ROA		Interest ROA	
	(1)	(2)	(3)	(4)
Pix Per Capita × MS	-0.030^{***}	-0.026^{***}	-0.364^{***}	-0.347^{***}
	(0.004)	(0.003)	(0.008)	(0.010)
Pix Per Capita	0.025^{***}	0.034^{***}	0.188^{***}	0.213^{***}
	(0.002)	(0.004)	(0.005)	(0.007)
MS	0.018^{***}	0.010^{**}	0.300^{***}	0.272^{***}
	(0.002)	(0.004)	(0.006)	(0.010)
Bank FE	Yes	No	Yes	No
Obs.	128,683	128,683	128,683	128,683
R^2	0.459	0.002	0.462	0.116

Note: This table provides results of within-bank estimation of the effect of Pix on profitability. Columns 1 and 2 measure profitability as return on assets, i.e., net income divided by assets. Columns 3 and 4 define profitability as net interest income divided by assets. Bank fixed effects and bank-level balance sheet controls are included. Standard errors are clustered at the municipality level and displayed in parentheses. *,**, and *** correspond to 10-, 5-, and 1% significance level, respectively.

Table C.8: Demand Estimation Results: Pix as a Dummy Variable

Parameter	Symbol	Estimate	Standard error
Sensitivity to deposit rates	α^d	0.027	(0.019)
Sensitivity to deposit rate with Pix	β^d	0.127^{***}	(0.048)
Observations		6,584	
R^2		0.934	

Note: This table provides results of the estimation of the deposit demand where the Pix variable is binary – equal to one after November 2020. The method used is GMM following the random coefficient logit procedure described in Berry et al. (1995). The estimated time period is from January 2015 to December 2021. Bank and time fixed effects are included. Deposit rates are instrumented with supply shifters. Standard errors are clustered at the bank level and displayed in Column 4 of the table. *,**, and *** correspond to 10-, 5-, and 1% significance level, respectively.

Table C.9: Demand Estimation Results: Salaries in the Instrument Set

Parameter	Symbol	Estimate	Standard error
Sensitivity to deposit rates	α^d	0.037	(0.022)
Sensitivity to deposit rate with Pix	β^d	0.002***	(0.001)
Observations		7,679	
R^2		0.924	

Note: This table provides results of the estimation of the deposit demand. The method used is GMM following the random coefficient logit procedure described in Berry et al. (1995). The estimated time period is from January 2015 to December 2021. Bank and time fixed effects are included. Deposit rates are instrumented with supply shifters – fixed costs and salaries over assets. Standard errors are clustered at the bank level and displayed in Column 4 of the table. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

Table C.10: Demand Estimation Results: State Level

Parameter	Symbol	Estimate	Standard error
Sensitivity to deposit rates	α^d	0.4456***	(0.0563)
Sensitivity to deposit rate with Pix	β^d	0.0961***	(0.0265)
Observations		22,356	
R^2		0.936	

Note: This table provides results of the estimation of the deposit demand. The method used is GMM following the random coefficient logit procedure described in Berry et al. (1995). The estimated time period is from January 2015 to December 2021. The data used is state-level. Bank and time fixed effects are included. Deposit rates are instrumented with supply shifters – fixed costs and provision for loan losses. Standard errors are clustered at the bank level and displayed in Column 4 of the table. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.