Digital Payments and Monetary Policy Transmission*

Click here for the most recent version

Pauline Liang† Matheus Sampaio‡ Sergey Sarkisyan§

March 20, 2026

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

*We are grateful to Jorge Abad (discussant), Juliane Begenau, Greg Buchak, Tony Cookson, Nicolas Crouzet, Darrell Duffie, Isil Erel, Julia Fonseca, Rod Garratt (discussant), Benjamin Hebert, Sean Higgins, Juan Imbet, Naz Koont (discussant), Arvind Krishnamurthy, Martin Kuncl (discussant), Matteo Leombroni (discussant), Jiaqi Li (discussant), Jack Liebersohn, Marco Macchiavelli (discussant), Monika Piazzesi, Amiyatosh Purnanandam (discussant), Alexi Savov, Stefano Schiaffi (discussant), Martin Schneider, Peter Serene (discussant), Amit Seru, Xu Tian (discussant), Yufeng Wu, Yao Zeng, Jinyuan Zhang (discussant), and conference and seminar participants at the HEC Banking in the Age of Challenges Conference, Inter-Finance PhD Seminar, SFS Cavalcade, European Finance Association, IPA Research Gathering, Northern Finance Association, Cleveland Fed Financial Stability Conference, Midwest Finance Association, Philadelphia Fed/UD Fintech and Financial Institutions Research Conference, Annual Conference of the Central Bank of Brazil, Bank of Canada Payments and Securities Settlement Workshop, Philly Fed Day-Ahead Conference, Columbia/BPI Conference, The Ohio State Fisher, Stanford GSB, Wharton School, CAFRAL, Peking University NSD, Bocconi, and SFI Lugano for helpful suggestions. We thank Eric Liu for his outstanding research assistance.

†Department of Finance, Stanford GSB.
E-mail address: pliang20@stanford.edu

‡Department of Finance, Florida State University College of Business.
E-mail address: msampaio@fsu.edu

§Department of Finance, Fisher College of Business, The Ohio State University.
E-mail address: sarkisyan.1@osu.edu

1 Introduction

Monetary policy transmits to the real economy through banks' portfolio decisions. 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)). However, we lack compelling evidence on why deposit market power is so high. The reasons can be either institutional or related to consumer demand. In this paper, we show the significance of payments for market power and monetary transmission. We ask if digital payments can impact monetary transmission by reducing banks' market power and document increased pass-through to deposit rates and lending, resulting from banks' reduced 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 enables fast transfers and retail payments, possibly competing with existing payment methods.[1]. 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).[2] 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[3] with more than 75% of Brazilians actively using it.[4] Pix also requires a bank account to be used and is very cheap for small banks to join. Thus, Pix creates an excellent setting to study how monetary policy transmission changed due to a potential reduction in banks' market power.

To understand if Pix impacts deposit market power and monetary policy trans-

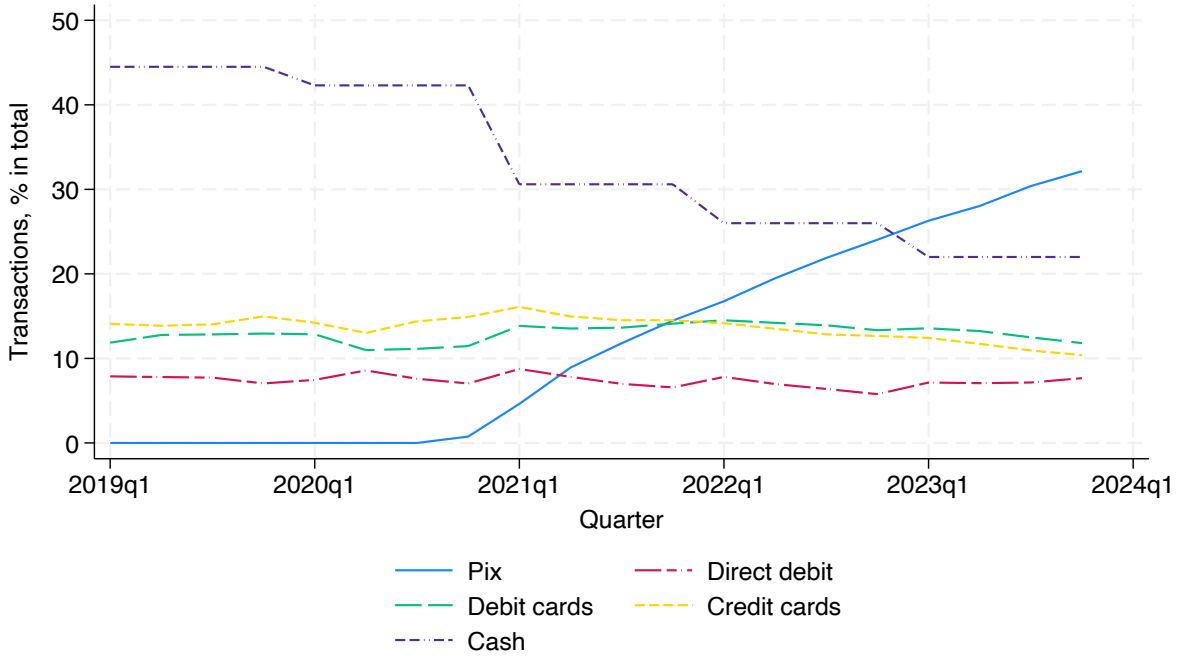
[1] Sampaio and Ornelas (2024) investigates further the competition and complementarities forces of payment methods in Brazil.

[2] 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.

[3] Based on the November 2024 exchange rate.

[4] 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 Wordplay and Consumer Insights Global survey. 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.

mission, we combine municipality-level monthly data on Pix transactions, 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 deposits controls 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 address unobserved differences between banks and local demand confounders, we run panel regressions, including bank and branch fixed effects. This way, we either compare branches of the same bank operating in areas with different Pix usage or track the same branch over time. We also address endogeneity of Pix itself – we use the introduction of the *Pix Saque* feature that allowed users to withdraw and deposit money using Pix. Since the feature is used primarily at small businesses (MEIs), we interact the post dummy with the municipality-level MEI concentration. We show the absence of pre-trends and a strong association between the instrument and the usage of Pix. The exclusion restriction implies that the new feature does not impact banking variables disproportionately in high-MEI areas for reasons other than Pix.

We find that in the areas with more Pix transactions, increases in policy rates lead to higher increases in deposit rates and larger loan contractions, consistent with the reduced local market power and intensified monetary policy transmission.[5] 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 rates by an additional 3.4 pp. Since banks pay more competitive deposit rates, they are able to retain more deposits, consistent with the deposit channel literature. We find that the effects are increasing over time, as Pix usage has grown. We also show that monetary policy transmission was not ex-ante more efficient in high-Pix areas, even without instrumenting.

Since banks retain more deposits, why does their lending still decline? Lending declines because banks' cost of funding rises, and they have to increase loan rates. The

[5]In Appendix D.5, we also consider identified high-frequency monetary surprises instead of full changes in policy rates. In Appendix D.8, we use monetary shocks to argue that monetary transmission becomes faster and more persistent with Pix.

new deposits that banks get are highly liquid, because they come from a marginal depositor and their inflows were caused by Pix. This leads to an increased flight risk on the liability side, which forces banks to invest in more liquid assets. Indeed, we find a significant increase in safe asset flows in high-Pix areas. This result is consistent with recent papers documenting flight risk and maturity transformation in the environment with fast payments (Blickle et al. (2024); Li et al. (2021)). To avoid confounding due to households moving deposits to FinTechs, we construct a proxy of branch-level balance sheet data for FinTechs in Brazil and include it in our sample. The results are robust to various proxy definitions and to excluding FinTechs altogether.

We further shed light on mechanisms and show that the decline in the market power of banks is driven by the fact that Pix facilitates opening new accounts, provides an alternative to banks' physical branch services, and creates competition to the payments offered by banks. Importantly, 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 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. Finally, we show that the number of banked individuals does not increase significantly in high-Pix areas, suggesting that the results cannot be explained by financial inclusion.

An empirical analysis does not let us 1) estimate the deposit demand to understand its change after Pix, 2) study counterfactuals with a lower usage of Pix, 3) evaluate changes in different channels of monetary transmission one-by-one, and 4) consider several policy-relevant scenarios. To answer these questions, we estimate a dynamic banking model[6] with three frictions: imperfect competition, regulatory constraints, and financial fric-

[6]In Appendix C, 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.

tions. The model features four types of agents – households, non-financial firms, banks, and a central bank with an exogenous interest rate process. The model belongs to a family of dynamic banking models with the deposit demand that depends on rates and non-rate characteristics (Van den Heuvel (2008); Corbae and D'Erasmo (2014); Egan et al. (2017); Xiao (2020); Wang et al. (2022); Whited et al. (2022)).

A digital payment system enters households' problem through the demand for deposits. Specifically, households value non-rate characteristics, such as the number of branches, differently with digital payments. 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 supplemented by employment data from Brazil from 2014 to 2022 to estimate the model.[7] 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 D.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. Since banks pay higher deposit rates, they are able to retain more deposits. We ultimately find that loans decline more after the introduction

[7]In Appendix D.13, we also estimate the state-level model for more granularity.

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.

We also augment the model with FinTechs, such as NuBank. We first show that the effects of Pix become stronger as FinTechs create additional competition for large banks. We then consider a counterfactual scenario without FinTechs. We find that deposit rates are higher with FinTechs, and the difference between deposit rates with and without FinTechs is bigger when Pix take-up is full. We also show that whether FinTechs attract deposits depends crucially on the take-up of Pix.

Next, we evaluate the impact of digital payments on three channels of monetary policy transmission.[8] We do it by eliminating the market power in the deposit markets, the capital constraints, and the reserve requirements, 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 80-130% on total deposits and limits the transmission by 20-80% on bank lending. The impact on other channels is more limited. The reason is that Pix mainly impacts depositors' decisions rather than firms' borrowing choices or banks' capital issuance and reserve purchases.

Finally, we consider several policy-relevant counterfactuals. The presence of the regulated fixed savings deposit rates forces banks to pay higher deposit rates, but at the expense of a more limited deposit supply. The fact that Pix increases demand elasticities makes deposits and deposit betas higher. We also consider potential interchange or user fees to Pix – they would increase the value of cash, reduce deposits, and force banks to pay higher deposit rates.

Our paper contributes to several strands of the literature. This paper is the first

[8]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. (2017, 2021); Wang et al. (2022)).

to show that banks' market power and, hence, monetary transmission are significantly impacted by cashless payments. 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)). For example, Erel et al. (2023) and Koont et al. (2023) consider the endogenous choice of banks to digitalize and split banks into digital and non-digital. To our knowledge, no paper has studied how a ubiquitously available payment technology impacts banks' market power and monetary transmission. We do it by studying a payment system imposed on nearly all banks in the economy in an experiment where Pix adoption was enforced, so by design, we can separate the effect of technology from the selection into adoption, unlike other papers. Benefits of payments do not come merely from digitalization, but also from increased convenience of deposits, impacting not just rate-sensitive depositors in digital banks but all depositors and banks in the economy. Pix is also not just a new interface. With a close-to-full adoption, Pix changes an entire payment settlement infrastructure, possibly affecting liquidity, branch relevance, and account proliferation. There is also a body of theoretical literature on a topic. For example, 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.

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); 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)).[9] 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)). Several papers have argued that financial technology benefits large incumbents and hence, increases banks' market power (Hannan and McDowell (1990); Hauswald and Marquez (2003)). 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. Sarkisyan (2024) shows that Pix increases deposit market competition in a tight window around the launch of Pix, but does not measure longer-term changes in market power, deposit rates, deposits, and lending, all of which can be affected by multiple channels, not just increased competition. We contribute by

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

documenting a persistent reduction in market power and an increase in pass-through to rates and flows using policy shocks and a structural model.

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 the dynamic banking model and discusses the identification and estimation. Section 5 presents results from the model estimation and counterfactual analyses. Section 6 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,[10] phone number, email, or random key. The key uniquely identifies a bank account for the transaction to take place. The

[10]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)[11] 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

[11] 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.

We also stress that market power is not necessarily equal to deposit market competition (D'Avernas et al. (2023)). Even though Sarkisyan (2024) shows that deposit competition rises in a short window around the launch of Pix, it does not imply a decline in market power or intensified monetary transmission. For example, Bertrand oligopoly allows for price setting, but the market is fully competitive.

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.[12] 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

[12] 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.

(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, 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 on 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. For example, the HHI for municipalities is very large, implying concentrated markets.

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

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$)	0.84	0.004	4.8	2.6	0.08	11.3
Savings deposits (bn. R$)	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			
Municipality HHI	0.63	0.56	0.31			
Income per capita	475.2	480	211.8			
GDP per capita (th.)	31.6	24.8	29.9			
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.

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

3.1 Cross-sectional evidence

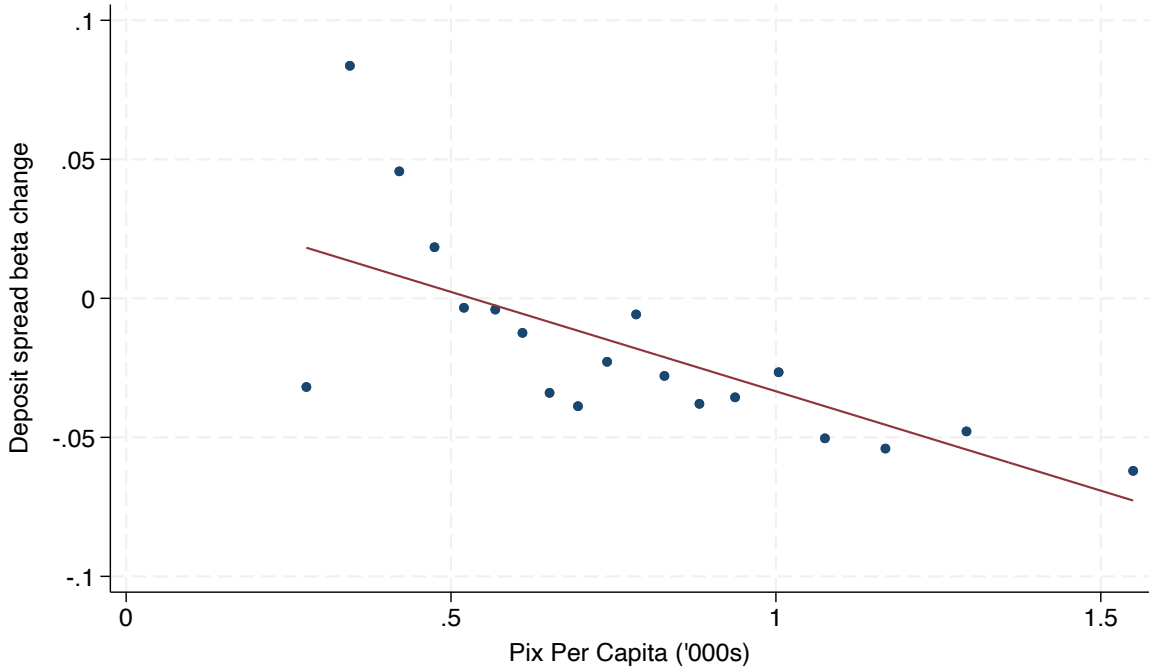
We follow Drechsler et al. (2017) and construct a measure of the deposit market power – deposit spread betas, i.e., the sensitivity of deposit spreads (policy rate minus deposit rate) to policy rates. Specifically, for each branch of a bank we run the following sets of regressions:

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

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 policy. 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

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.

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 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.

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 D.1, 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 discuss next.

3.2 Identification concerns

The branch-level cross-sectional analysis has at least three identification challenges. The first challenge is related to differences between municipalities and banks in Brazil. For example, different areas can have investment opportunities, which would in turn impact both banks' decisions and deposit demand after changes to policy rates. Branches of banks of different sizes can also have their own policies. To address this concern, we run within-bank and within-branch panel regressions, where we include bank and branch (bank-municipality) fixed effects. 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. OLS results using this method are in Appendix D.4.

The second concern is endogeneity of Pix. Although the roll-out of Pix was preannounced before COVID, so it was not related to the pandemic itself, the usage of Pix can be correlated with variables that can also impact deposits and loans. For example, as Sarkisyan (2024) shows, Pix was especially popular in large and high-income areas, which also tend to be more financially sophisticated. We address this concern by implementing an IV strategy, where we use the introduction of a new feature into Pix.

The third concern is the absence of digital banks, since they do not have branches. Digital banks such as Nubank attracted a lot of attention recently, and they were able

to successfully compete with large banks, partly thanks to Pix. Hence, missing digital banks can understate the actual causal estimates.[13] We proxy for municipality-level data on digital banks by using the Pix usage as a share of digital bank variables in a given municipality. We collect bank-level balance sheet data on digital banks from COSIF. As a robustness test, we also use direct data on state-level Pix payments made to digital banks as an additional share in Appendix D.3.

3.3 Identified results

We test if the reaction of changes in deposit spreads, deposit flows, and lending flows to policy rate changes is different with Pix by estimating a within-bank and within-branch panel regression. Specifically, we limit the sample to after 2019 and run the following regression:

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

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, and η_i is a bank fixed effect. The vector of controls includes all interaction terms and deposit flows in the regressions of lending flows. We also set $PixPerCap_{mt}$ equal to 0 before the introduction of Pix to make sure we do not throw out the pre-period.

Including bank fixed effects helps with concerns related to banks being fundamentally different. For example, large banks in Brazil received government support in expansion (Fonseca and Matray (2022)), which puts them at an advantage relative to small banks when it comes to local lending. By including bank fixed effects, we effectively compare branches of the same bank located in areas with different Pix usage. Including branch fixed effects further helps to account for local investment opportunities – we compare banks in the same area across time.

The fixed effect regression above does not address the endogeneity of Pix itself. Al-

[13]The results are robust when digital banks are not included, as we show in Appendix D.2.

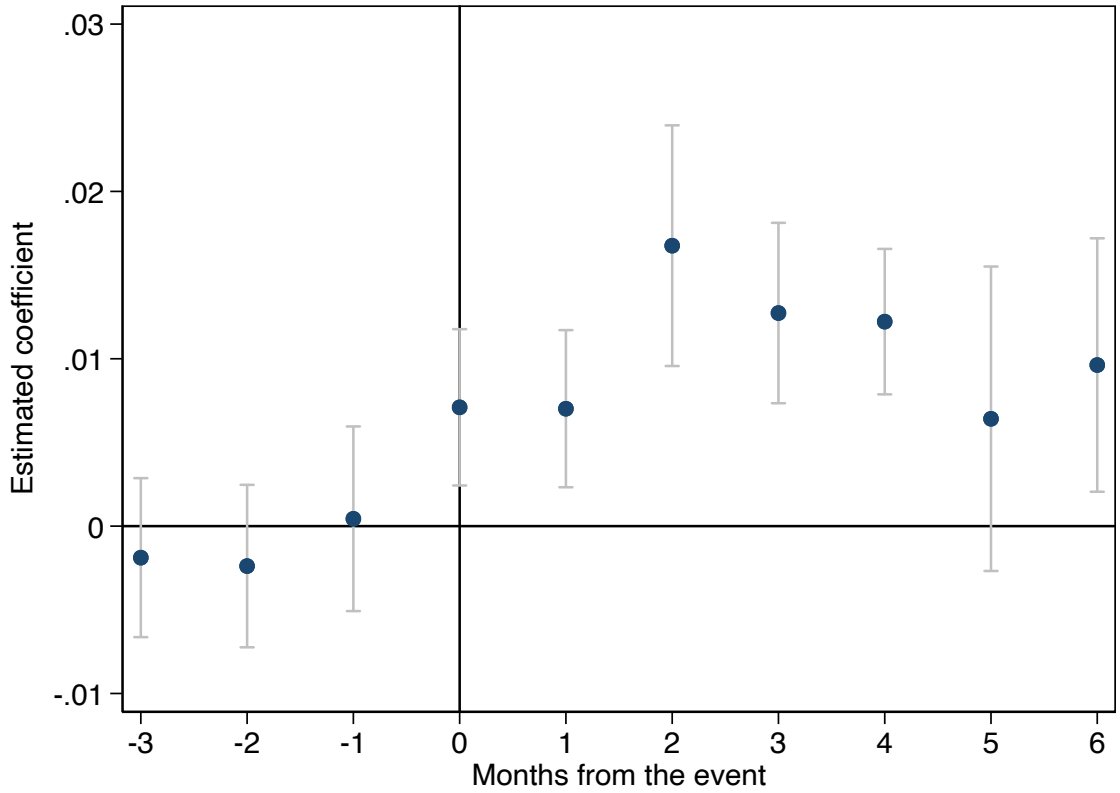
though the timing of Pix was not influenced by COVID-19 pandemic, the degree of rollout in each municipality can. To address the issue, we are exploiting a plausibly exogenous variation in Pix coming from the introduction of a new feature – *Pix Saque* and *Pix Troco* late in October of 2021. The feature allowed customers to use Pix for money deposits and withdrawals, just as they would use ATMs with debit cards.

Given a general positive trend in Pix usage, simply using the date of Pix Saque introduction would not satisfy the exclusion restriction. To further address the issue, we use an empirical observation – Pix Saque and Pix Troco are predominantly available at small enterprises (henceforth, MEIs). This is analogous to purchasing money orders and depositing money at convenience stores in the US. We collect data on the number of MEIs in Brazil in 2021 from Simples Nacional and the total number of enterprises from IBGE, to calculate the concentration of MEIs in each municipality in Brazil. We then interact the MEI concentration with the post dummy of Pix Saque. Since the regressions include the interaction between Pix and changes to policy rates, we also include the second instrument – our original instrument interacted with the changes in policy rates. The relevance of the instrument stems from the fact that Pix Saque was popular and led to an increase in Pix usage, especially in areas with a high concentration of MEIs. Figure 3 shows that the use of Pix increased significantly in high-MEI areas following the introduction of Pix Saque, with no significant pre-trends. Note that when we run the 2SLS, we include the same control variables in both the first and the second stages of the regressions.

Before showing the results of the second-stage estimation, we discuss why the exclusion restriction is plausible in this case. The exclusion restriction states that the only way Pix Saque can impact bank variables more in high-MEI areas is through the usage of Pix. This is justified because Pix Saque is the feature that only applies to Pix, and not to other bank-based apps. MEI concentration by itself also does not seem to increase the usage of Pix, as Figure 3 clearly suggests. Finally, we keep bank and branch fixed effects included to address potential issues in which certain areas are more exposed to

Figure 3: Pix Usage after Pix Saque in Areas with High MEI Concentration

$$PixPerCap_{mt} = \sum_{s=-2}^{6} \delta_s 1\{t = s\} \cdot MEI_m + \gamma X_{imt} + \eta_m + \varepsilon_{mt}$$



Note: This figure plots the results of event-study estimation of Pix usage, where the event is the introduction of Pix Saque in late October of 2021, interacted with the MEI concentration. The vector of controls relevant interaction terms, and changes in tax regulations, given their relevance for the use of Pix Saque. Municipality fixed effects are included. The 95% confidence intervals are based on errors clustered at the municipality level.

withdrawing and depositing money at MEIs.

Finally, we address the concern of the absence of digital banks from our sample. Digital banks attracted many Brazilians after Pix, but they do not have physical branches, and hence, they are not in our sample. We use bank-level balance sheet data for FinTech banks and split it into the branch-level data by using Pix shares in each municipality as the shares of deposits of FinTech banks. As a robustness test, we also use direct data on state-level Pix payments made to digital banks as an additional share in Appendix D.3.

Table 2 reports the results from the second stage. 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. If Pix per capita increases by 1 s.d., a 1 p.p. increase in the policy rate would move deposit rates by 3.4 pp more. At the same time, Columns 5 and 6 show that bank deposits flow out less because banks retain more depositors. The results suggest that banks' market power declines and monetary policy becomes more efficient. Consistent with a decline in spreads, we show in Appendix D.10 that banks' profitability declines. Appendix D.4 shows the results without instrumenting.

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 D.7, we also aggregate lending to the bank level and show that the results are robust.

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 one bank to another 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 former effect dominates, especially since we include FinTech banks in the sample. The results are robust if we exclude them in Appendix D.2. The magnitudes of changes in deposit spreads are larger there, because FinTechs already had higher betas before Pix, so their inclusion reduces the effects on spreads. We also provide a falsification test in Table 3 below, by showing for both IV and OLS that savings deposits either increase by little or do not increase at all. This is because savings deposits in Brazil have a regulated deposit rate, and as a result, they should not be affected by changes in market power brought upon by Pix. Note that time deposits in Brazil do not have to be very long-term. Accounts such as *caixinhas* often only require locking money for a few weeks. Yet, the time deposit rate is not regulated,

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

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

	Deposit spread change		Loan flows		Deposit flows	
	(1)	(2)	(3)	(4)	(5)	(6)
Pix Per Capita × MS	−0.034***	−0.034***	−2.824***	−2.829***	0.522***	0.522***
	(0.005)	(0.005)	(0.051)	(0.052)	(0.067)	(0.067)
Pix Per Capita	−0.065***	−0.064***	−0.764***	−0.720***	−0.852***	−0.900***
	(0.001)	(0.001)	(0.010)	(0.010)	(0.022)	(0.023)
MS	1.025***	1.026***	3.766***	3.795***	−3.068***	−3.088***
	(0.005)	(0.005)	(0.046)	(0.046)	(0.084)	(0.084)
Branch FE	Yes	No	Yes	No	Yes	No
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	269,313	269,252	895,474	895,453	867,815	867,794
R^2	0.245	0.246	0.012	0.009	0.006	0.006

Note: This table provides results of the second-stage within-bank estimation of the effect of Pix on loan flows, deposit 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. Columns 5 and 6 correspond to changes in deposit flows. Z-scored Pix per capita is instrumented with the interaction of the time dummy for the introduction of Pix Saque and municipality-level concentration of MEIs. Interaction terms are also instrumented. 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.

so banks can compete.

Banks are able to retain more deposits because they increase deposit rates, and yet, lending declines. Table 4 shows where the new deposits go. Columns 1-4 indicate that the reserves and government securities do not respond much to Pix, but safe assets rise. Safe assets are defined as the sum of cash holdings, deposits, and interbank placements, so they include highly liquid assets. This means that rather than lending, banks invest newly retained deposits in liquid safe assets. This is because of the type of deposits that Pix brings – depositors who would move out of the banking system after policy rate hikes, absent Pix. Since Pix makes deposits more liquid, such deposits have an increased flight risk. Banks then want to match the liquidity of new liabilities to the liquidity of new assets by investing in highly liquid safe assets. These results are consistent with the evidence in Blickle et al. (2024) and Li et al. (2021) that use data from the US.

One concern can be that high-Pix and low-Pix areas had different monetary policy

Table 3: Impact of Pix on Savings Deposit Flows

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

	Saving deposit flows			
	(1)	(2)	(3)	(4)
Pix Per Capita × MS	−0.171***	−0.171***	0.190***	0.017
	(0.028)	(0.027)	(0.013)	(0.014)
Pix Per Capita	−1.181***	−1.231***	−0.723***	−0.883***
	(0.016)	(0.016)	(0.013)	(0.014)
MS	−1.193***	−1.209***	−1.626***	−1.438***
	(0.034)	(0.032)	(0.022)	(0.022)
Specification	IV	IV	OLS	OLS
Bank FE	Yes	Yes	Yes	Yes
Branch FE	No	Yes	No	Yes
Obs.	879,028	879,008	879,442	879,422
R^2	0.017	0.023	0.055	0.079

Note: This table provides results of the second-stage within-bank estimation of the effect of Pix on savings deposits – equation (3). Columns 1 and 2 show the IV. Columns 3 and 4 correspond to the OLS results. Z-scored Pix per capita is instrumented with the interaction of the time dummy for the introduction of Pix Saque and municipality-level concentration of MEIs. Interaction terms are also instrumented. 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.

transmission even before Pix. We provide an additional piece of evidence to address the concern. Specifically, in Appendix D.9, we run a placebo test to show that deposit spreads and loan flows were not declining and deposit flows were not rising in high-Pix areas already before the introduction of Pix, without instrumentation. The results support the claim that high-Pix and low-Pix areas would be on a similar track in terms of monetary transmission, absent Pix, even if we do not use an instrumental variable.

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 lending and policy rates, thus creating potential biases. In Appendix D.5, 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

Table 4: Impact of Pix on Safe Asset Flows

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

	Reserve flows		Gov flows		Safe flows	
	(1)	(2)	(3)	(4)	(5)	(6)
Pix Per Capita × MS	4.372	4.374	−0.281	−0.201	2.283***	2.277***
	(2.994)	(2.985)	(0.338)	(0.338)	(0.172)	(0.173)
Pix Per Capita	0.242	0.245	0.344***	−0.042	−0.159***	−0.188***
	(0.323)	(0.357)	(0.104)	(0.098)	(0.027)	(0.027)
MS	−6.431	−6.407	0.547	0.443	−3.675***	−3.686***
	(9.099)	(9.133)	(0.615)	(0.624)	(0.241)	(0.243)
Branch FE	Yes	No	Yes	No	Yes	No
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	5,318	5,318	86,999	86,963	531,675	531,652
R^2	0.001	0.001	0.001	0.000	0.000	0.000

Note: This table provides results of the second-stage within-bank estimation of the effect of Pix on reserve flows, government securities flows, and safe asset flows – equation (3). Safe assets are defined as the sum of cash holdings, deposits, and interbank placements. Columns 1 and 2 show the results for reserve flows. Columns 3 and 4 correspond to changes in government security flows. Columns 5 and 6 correspond to changes in safe asset flows. Z-scored Pix per capita is instrumented with the interaction of the time dummy for the introduction of Pix Saque and municipality-level concentration of MEIs. Interaction terms are also instrumented. 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.

while lending declines more after the introduction of Pix. In Appendix D.8, we further use monetary shocks to argue that monetary transmission becomes faster and more persistent with Pix by using local projections. This result also underscores that the effects were gradually increasing over time. Finally, we consider a different measure of the Pix variable – the number of users per capita. We show in Appendix D.6 that both the IV and OLS results are robust to the definition.

A final remaining concern is that deposit rates react asymmetrically to increases and decreases in policy rates. Since Brazil's Selic rate was increasing post-Pix, the asymmetry can be problematic. Identified shocks and cross-sectional variation add credibility to our findings. Even holding policy rates fixed, areas with more Pix transactions experience greater change to monetary transmission than other areas. Unlike the US, Brazil is also not close to the zero lower bound, which makes the deposit betas more symmetric.

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 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. 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.

3.4 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. We discuss the channels of monetary transmission in Section 4. In this section, we dig deeper into potential mechanisms underlying a reduction in market power. 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)). We also discuss how financial inclusion affects the results.

First, using data from the Central Bank of Brazil, we study how the number of bank accounts changes in Brazil after Pix. Figure 4 shows the results.[14] We find that the total number of bank accounts increases relatively more in areas with more Pix transactions. More importantly, an increase in bank accounts per person is also larger in high-Pix

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

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.

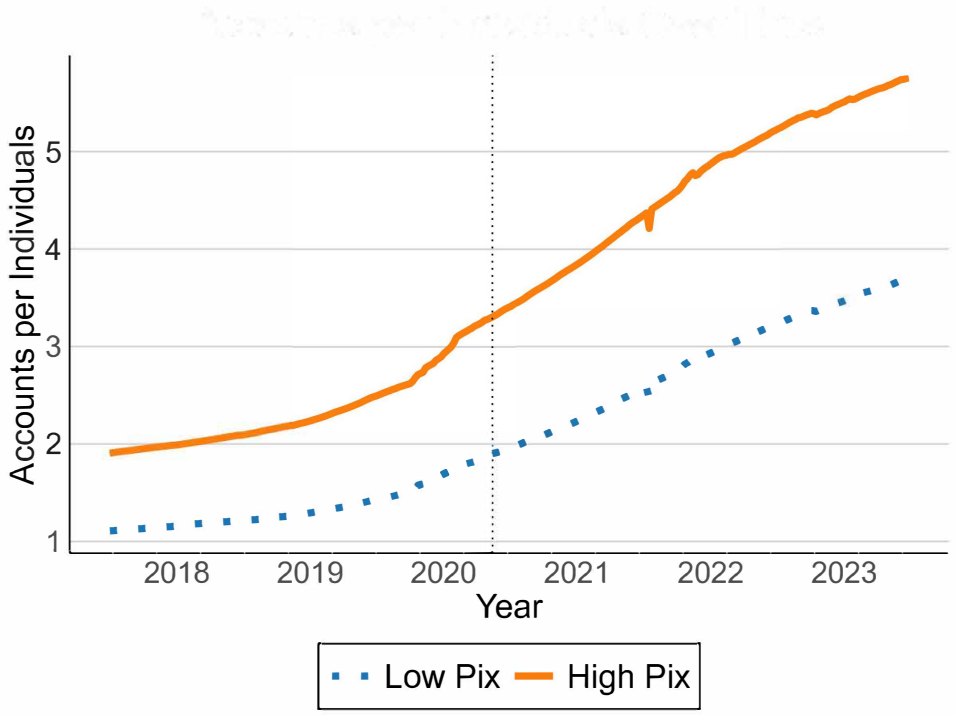
Another possible interpretation of the results is that banks get new clients who were previously unbanked. That can potentially change the rate structure by altering the composition of bank deposits in Brazil by crowding out paper currency. We argue that the extensive margin interpretation is unlikely 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 before 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. They do it because accounts at larger banks are free and because they often do not have enough funds to save, so they do not benefit from high deposit rates.

Next, 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.

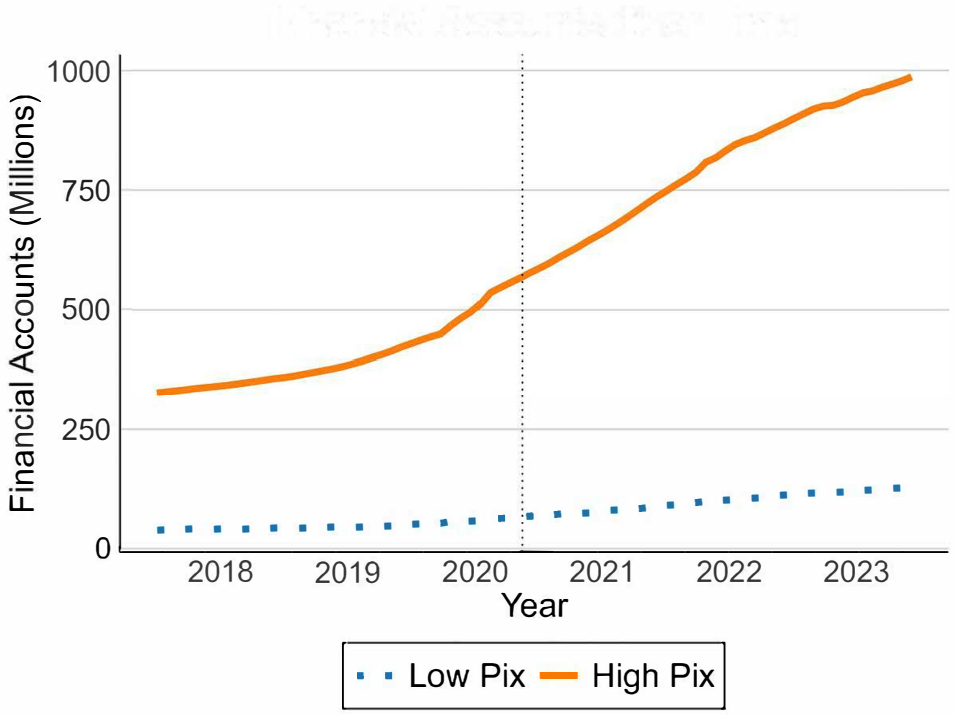
Figure 5 shows the results. First, Pix is used more in areas with more branches, potentially reflecting that those are more developed and urbanized areas. However, the number of branches declined steadily in high-Pix areas both before the introduction of Pix and after the announcement and the launch. The former reflects the fact that the demand for digital payment is higher in areas where physical branches are being replaced.

Figure 4: Number of Bank Accounts in Brazil

Panel A: Number of Accounts Per Capita

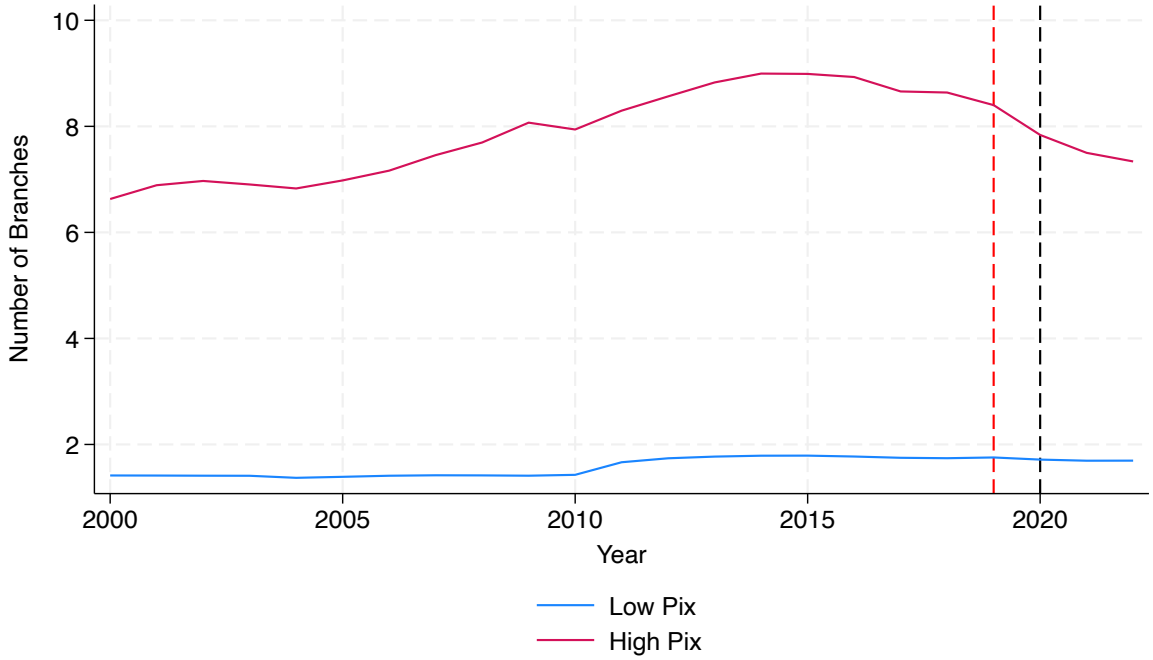


Panel B: Total Number of Accounts



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.

Figure 5: 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.

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).

Finally, 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 6 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

Table 5: Impact of Pix on Number of Banked People

	Bank accounts per capita	
	(1)	(2)
Pix Per Capita		0.058***
		(0.006)
Post Pix	0.132***	0.132***
	(0.001)	(0.001)
Pix Per Capita × Post Pix	0.007	0.007
	(0.008)	(0.008)
Controls	Yes	Yes
Municipality FE	Yes	No
Obs.	49,797	49,797
R^2	0.887	0.371

Note: This table provides results of regressing the number of bank accounts per capita on Pix, controls, and fixed effects. Standard errors are clustered at the municipality level and displayed in parentheses. Municipality fixed effects are included. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

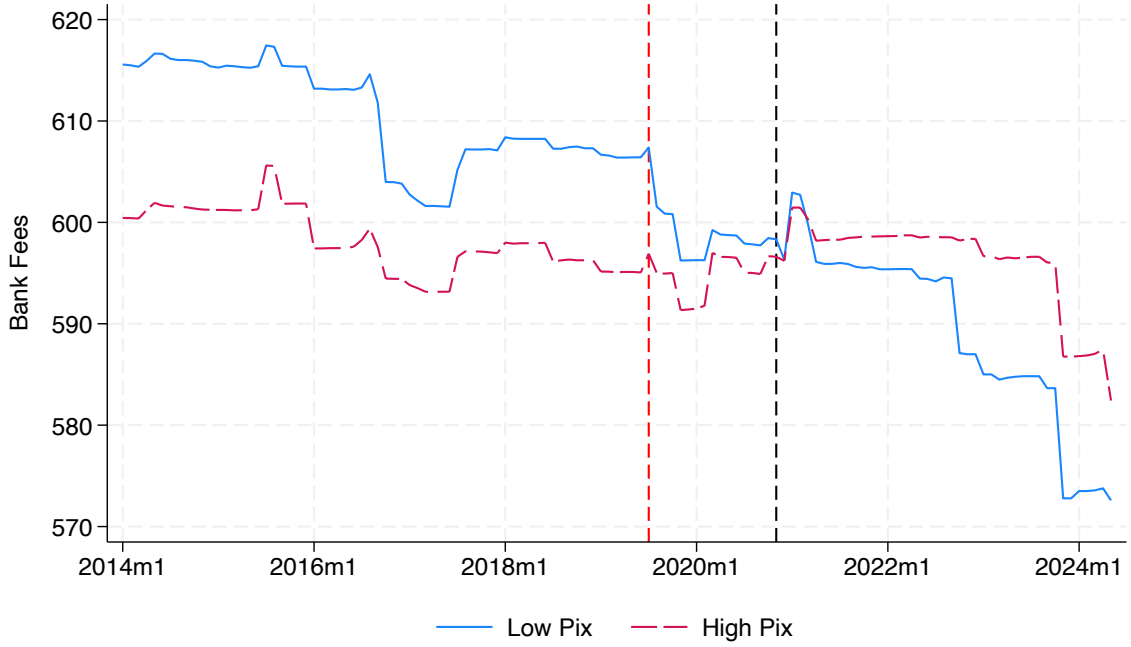
after the announcement of Pix, potentially to be able to compete. The drop in payment-related fees is more pronounced in high-Pix areas. At the same time, banks in high-Pix areas increase non-payment-related fees to extract rent from something that does not get competition from Pix. Competing with Pix, which has zero fees, is very challenging for banks, so they decide to extract rents elsewhere.

Another mechanism that can be at play is financial inclusion – Pix incentivizes Brazilians to open more bank accounts. If that is the case, we should see more depositors per capita in high-Pix areas after the introduction of Pix, conditional on controls and fixed effects. Table 5 shows that the effects are insignificant. This is consistent with the evidence in Sarkisyan (2024) showing that Brazilians who were previously unbanked prefer to open accounts at large banks, to save on fees and collect stimuli. Another reason is that to benefit from high interest rates that smaller banks pay, depositors need to have enough savings, which financially constrained Brazilians are less likely to do.

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

Figure 6: 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.

less efficient if Pix were not introduced? In the next section, we build and estimate a dynamic banking model to further investigate these questions.

4 Dynamic model

Empirical analysis allows us to show that Pix enhances monetary pass-through by reducing banks' market power. However, the limitations of our empirical approach do not allow us to answer three additional questions. First, how does the demand for deposits react to Pix? Second, what would deposit and lending betas be in the world with a lower usage of Pix? Finally, which channel of monetary transmission is affected by Pix the most? Reduced-form analysis cannot shed light on these questions, so we build and estimate a dynamic model.

We consider an infinite-horizon dynamic equilibrium model with three sectors: households, firms, and banks. The model is close to Wang et al. (2022) with an important addition of digital payments and several features to make the model compatible with a high-interest-rate economy. 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.

4.1 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.[15] 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

[15]We estimate the state-level model in Appendix D.13.

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. Non-rate characteristics play an important role, ensuring that households can prefer banks with lower rates if non-rate characteristics are good enough. 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

$$\max_{j \in \mathcal{A}^d} u_{i,j} = \alpha^d r_j^d + \beta^d p_j^d r_j^d + \theta^d p_j^d + \gamma^d x_j^d + \mu_j^d + \epsilon_{i,j}^d, \tag{4}$$

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 rates after the introduction of Pix. The variable p_j^d measures the size of the Pix transactions in the locations where bank j operates.[16] We include the Pix variable on its own as well.[17] 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

$$\mathbb{I}_{i,j}^d = \begin{cases} 1, & \text{if } u_{i,j} \geq u_{i,k}, \quad j,k \in \mathcal{A}^d \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

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

[17] It is important to note that Pix does not reduce frictions to zero. There are still various reasons why households would prefer larger banks or banks in their neighborhoods. The estimates of γ^d are economically significant with the presence of Pix, confirming the point.

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 $\epsilon^d_{i,j}$ follows a type II extreme-value distribution. We can then derive the market share of each bank from a logit model:

$$\begin{aligned} s^d_j(r^d_j|f,p^d_j) &= \int \mathbb{I}^d_{i,j} dF(\epsilon) \\ &= \frac{\exp(\alpha^d r^d_j + \beta^d p^d_j r^d_j + \theta^d p^d_j + \gamma^d x^d_j + \mu^d_j)}{\exp(Bonds) + \exp(Cash) + \sum_{n=1}^{J} \exp(Banks)} \end{aligned} \tag{6}$$

$$\begin{aligned} Bonds &= \alpha^d f + \gamma^d x^d_{J+1} + \mu^d_{j+1} \\ Cash &= \gamma^d x^d_c + \mu^d_c \\ Banks &= \alpha^d r^d_n + \beta^d p^d_n + \theta^d p^d_n + r^d_n + \gamma^d x^d_n + \mu^d_n \end{aligned}$$

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

$$D_{j,t}(r^d_{j,t}|f_t, p^d_{j,t}) = s^d_{j,t}(r^d_{j,t}|f_t, p^d_{j,t}) \cdot W_t. \tag{7}$$

4.2 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 the year in which 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.[18]

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

$$\bar{f} = \eta f_t + \mathbb{E}_t \left[\sum_{n=1}^{\infty} \eta(1-\eta)^n f_{t+n} \right] \tag{8}$$

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

$$\max_{j \in \mathcal{A}^\ell} \pi_{i,j} = \alpha^\ell r_j^\ell + \gamma^\ell x_j^\ell + \xi_j^\ell + \epsilon_{i,j}^\ell \tag{9}$$

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_j^ℓ, γ^ℓ are sensitivities to bank-level non-rate characteristics. We let ξ_j^ℓ denote the product invariant demand shock. The last term $\epsilon_{i,j}^\ell$ is the relationship shock specific to the firm-bank match. Firm i's optimal choice of financing is then

$$\mathbb{I}_{i,j}^\ell = \begin{cases} 1, & \text{if } \pi_{i,j} \geq \pi_{i,k}, \quad j,k \in \mathcal{A}^\ell \\ 0, & \text{otherwise} \end{cases} \tag{10}$$

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

$$s_j^\ell(r_j^\ell | f) = \int \mathbb{I}_{i,j}^\ell dF(\epsilon) \tag{11}$$

[18]FRED is maintained by the Federal Reserve Bank of 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.

$$= \frac{\exp(\alpha^\ell r_j^\ell + \gamma^\ell x_j^\ell + \xi_j^\ell)}{\underbrace{\exp(\alpha^\ell(\overline{f}+\delta) + \gamma^\ell x_{J+1}^\ell + \xi_{J+1}^\ell)}_{Bonds} + \underbrace{\exp(\gamma^\ell x_n^\ell + \xi_n^\ell)}_{NotBorrowing} + \underbrace{\sum_{s=1}^{J} \exp(\alpha^\ell r_s^\ell + \gamma^\ell x_s^\ell + \xi_s^\ell)}_{Banks}}$$

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

$$B_{j,t}(r_{j,t}^\ell | f_t) = s_{j,t}^\ell(r_{j,t}^\ell | f_t) \cdot K_t. \tag{12}$$

4.3 The banking sector

There are J banks in the market. Each bank simultaneously chooses the deposit rate r_j^d and lending rate r_j^ℓ. 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

$$I_{j,t} = \sum_{n=0}^{\infty} \frac{(1-\eta)^n B_{j,t} r_{j,t}^\ell}{(1+\gamma)^n} \tag{13}$$

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

$$L_{j,t+1} = (1-\eta)(L_{j,t} + B_{j,t}). \tag{14}$$

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 preference shifter ϕ^ℓ per unit of loans, which can be either negative or positive. 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 (7). Since households can hold cash which has an interest rate of zero, deposit rate r_j^d has a zero lower bound:

$$r_j^d \geq 0. \tag{15}$$

Since Brazil's savings deposit rate is regulated and set by the central bank, we impose the restriction that banks have to pay the rate above the savings rate in Brazil. Banks incur a preference shifter of ϕ^d per unit of deposits. Uninsured non-reservable funding faces a quadratic cost:

$$\Phi^N(N_{j,t}) = \left(f_t + \frac{\phi^N}{2} \cdot \frac{N_{j,t}}{D_{j,t}} \right) N_{j,t}. \tag{16}$$

Since lending involves maturity transformation, we also impose a quadratic constraint $\Phi^L(L_{j,t} + B_{j,t})$ on lending.

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

$$\Pi_{j,t} = I_{j,t} - (L_{j,t} + B_{j,t})(\eta\delta_t + \phi^\ell) + G_{j,t} f_t - (r_{j,t}^d + \phi^d) D_{j,t} - \Phi^N(N_{j,t}) - \Phi^L(L_{j,t} + B_{j,t}) - \psi \bar{E}_j, \tag{17}$$

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 profits into equity for the 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

$$E_{j,t+1} = E_{j,t} + (1-\tau)\Pi_{j,t} - C_{j,t+1}, \tag{18}$$

where τ is the corporate tax rate.

Finally, to incorporate the financial inclusion discussion into the model, we assume that Pix increases the depositor base at the 10% rate. This is relevant for the counterfactual exercises.

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

$$L_{j,t} + B_{j,t} + R_{j,t} = D_{j,t} + N_{j,t} + E_{j,t}, \tag{19}$$

Deposits are subject to the reserve requirement

$$R_{j,t} \geq \theta D_{j,t}. \tag{20}$$

Finally, the government imposes capital requirements on banks

$$E_{j,t} \geq \kappa A_{j,t}. \tag{21}$$

4.4 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

$$\begin{bmatrix} \ln \delta_{t+1} - \mathbb{E}(\ln \delta) \\ \ln f_{t+1} - \mathbb{E}(\ln f) \end{bmatrix} = \begin{bmatrix} \rho_\delta & \rho_{\delta f} \\ 0 & \rho_f \end{bmatrix} \cdot \begin{bmatrix} \ln \delta_t - \mathbb{E}(\ln \delta) \\ \ln f_t - \mathbb{E}(\ln f) \end{bmatrix} + \begin{bmatrix} \sigma_\delta & 0 \\ 0 & \sigma_f \end{bmatrix} \varepsilon_{t+1}. \quad (22)$$

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.

4.5 Banks' problem and equilibrium

Banks choose loan and deposit rates according to the demand functions in (7) and (12). 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 the subscript j in the Bellman equation for simplicity.

$$V(f_t, \delta_t, L_t, E_t|\Gamma_t) = \max_{\{r_t^l, r_t^d, G_t, N_t, R_t, C_{t+1}\}} \frac{1}{1+\gamma} \Big\{ C_{t+1} + \mathbb{E}V(f_{t+1}, \delta_{t+1}, L_{t+1}, E_{t+1}|\Gamma_{t+1}) \Big\} \quad (23)$$

$$\begin{aligned} s.t. \quad & D_t = s_t^d(r_t^d|f_t, p_t^d) \cdot W_t, \quad \text{Deposit demand} \\ & B_t = s_t^\ell(r_t^\ell|f_t) \cdot K_t, \quad \text{Loan demand} \\ & r_t^d \geq 0, \quad \text{Non-negative deposit rate} \end{aligned}$$

$$I_t = \sum_{n=0}^{\infty} \frac{(1-\eta)^n B_t r_t^{\ell}}{(1+\gamma)^n}, \quad \text{Loan interest income}$$

$$L_{t+1} = (1-\eta)(L_t + B_t), \quad \text{Loan evolution}$$

$$E_{t+1} = E_t + (1-\tau)\Pi_t - C_{t+1}, \quad \text{Equity evolution}$$

$$C_{t+1} \geq 0, \forall t, \quad \text{Non-negative cash dividend}$$

$$L_t + B_t + R_t + G_t = D_t + N_t + E_t, \quad \text{Balance sheet}$$

$$E_t \geq \kappa(L_t + B_t), \quad \text{Capital requirement}$$

$$R_t \geq \theta D_t, \quad \text{Reserve requirement}$$

$$\Pi_t = I_t - (L_t + B_t)(\eta\delta_t + \phi^{\ell}) + G_t f_t$$
$$- (r_t^d + \phi^d)D_t - \Phi^N(N_t)N_t - \Phi^L(L_{j,t} + B_{j,t}) - \psi\bar{E}, \quad \text{Profits}$$

$$\text{Equation (22)}, \quad \text{Law of motion for monetary policy}$$

$$\Gamma_{t+1} = P^{\Gamma}(\Gamma_t), \quad \text{Law of motion for cross-sectional distribution}$$

A stationary equilibrium occurs when

1. All banks solve their problem according to equation (23), 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.

4.6 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 6 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.[19] 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 6. 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 well as the correlation of Selic rate innovation and loan charge-offs. We estimate these parameters according to Equation (22) using aggregate data from 1976 to 2022.

Next, in Step 3, we estimate the loan and deposit demand functions following the

[19] In Appendix D.14, we show that our results are robust if we calibrate the discount rate to 4%, which would make banks more patient.

Table 6: 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	
χ_B	Lending cost	1	
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	1.5816	[0.04]
q_n^ℓ	Value of firms' outside option	3.993	[0.192]
ϕ^N	Quadratic cost of non-reservable borrowing	1.545	[0.839]
ϕ^d	Deposit preference shifter	-0.0013	[0.002]
ϕ^ℓ	Loan preference shifter	-0.0094	[0.002]
ψ	Net fixed operating cost	0.0002	[0.0001]

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

method in Berry et al. (1995). Recall Equations (7) and (12). 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,

$$D_j\left(r_j^d \mid f, p_j^d\right) = \frac{\exp\left(\hat{\alpha}^d r_j^d + \hat{\beta}^d p_j^d r_j^d + q_j^d\right)}{\exp\left(\hat{\alpha}^d f\right) + \exp\left(q_c^d\right) + \sum_{m=1}^{\hat{J}} \exp\left(\hat{\alpha}^d r_m^d + \hat{\beta}^d p_m^d r_m^d + q_m^d\right)} W, \quad (24)$$

$$B_j\left(r_j^\ell \mid f\right) = \frac{\exp\left(\hat{\alpha}^\ell r_j^\ell + q_j^\ell\right)}{\exp\left(\hat{\alpha}^\ell(\bar{f}+\bar{\delta})\right) + \exp\left(q_n^\ell\right) + \sum_{m=1}^{\hat{J}} \exp\left(\hat{\alpha}^\ell r_m^\ell + q_m^\ell\right)} K, \tag{25}$$

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 D.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 6 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 (24) and (25) 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 deposits-to-assets ratio and sensitivities of deposit rates to the policy rate. Then, we use deposit spread and loan spread to identify preference shifter to service deposits and loans, respectively. The intuition is that higher preference shifters (resembling higher servicing 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 – the mean and standard deviation of the non-reservable borrowing to retail deposits ratio. Panel D of Table 6 presents the estimate from the SMD method.

Table 7 reports the main actual and simulated moments in the SMD estimations,

Table 7: Moment Conditions

	Actual	Sample	S.E.
Deposit spread	0.0185	0.0173	[0.003]
Loan spread	0.1678	0.4932	[0.011]
Deposits/Assets	0.3301	0.4811	[0.040]
Net non-interest expense/Assets	0.007	−0.0149	[0.001]
Leverage	16.9	17.2	[2.528]
Credit - Selic rate sensitivity	−0.578	−0.4445	[0.243]
Bank loan - Selic rate sensitivity	−0.789	−0.4463	[0.338]
Market-to-book ratio	1.447	10	[0.409]

Note: This table reports the actual and simulated targeted 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.

along with the t-statistics and standard errors. We match sensitivities well, which is very important given that we study monetary transmission. We also match deposit rates, leverage, and the deposits/assets ratio relatively well. One limitation of our model is the simple lending side, which does not allow us to match loan spreads precisely. We acknowledge this issue, but since the model focuses on the deposit side, lending moments are unlikely to cause issues for inference.

5 Estimation results and counterfactuals

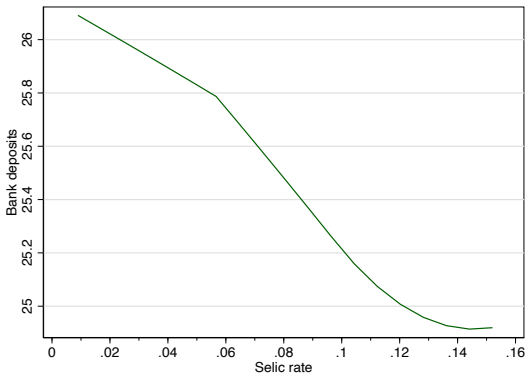
5.1 Baseline results

We present the policy functions of deposits and loans for an average bank from the baseline estimation in this section. Panel A of Figure 7 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 7 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)

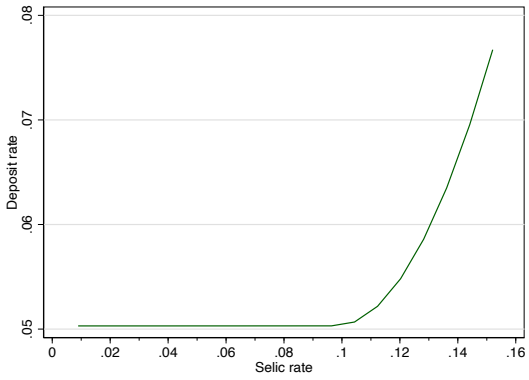
We also show the trajectories for loan rates and lending. Because banks increase deposit rates, their loan rates also go up. Loan rates tend to follow policy rates more closely than deposit rates. Panel C shows that bank lending declines because deposits are the main source of funding for banks.

Figure 7: Policy Functions

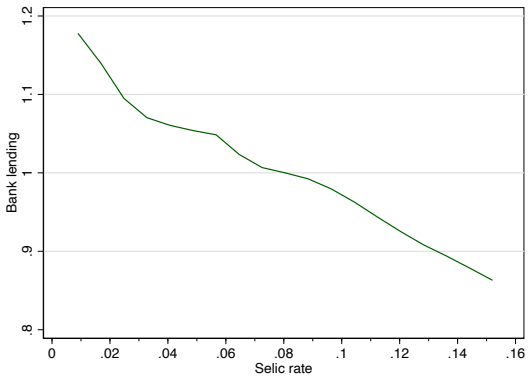
Panel A: Bank deposits



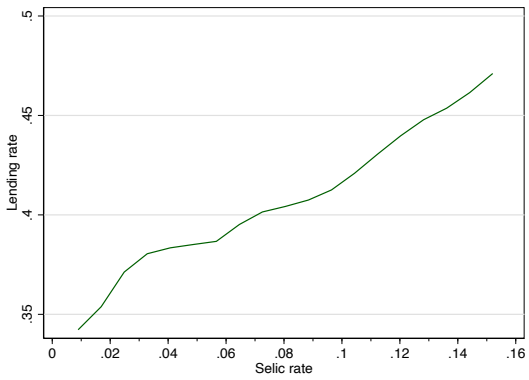
Panel B: Deposit rate



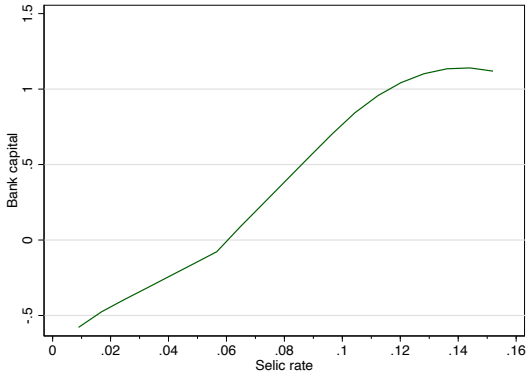
Panel C: Bank lending



Panel D: Loan rate



Panel E: Capital



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.

5.2 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.

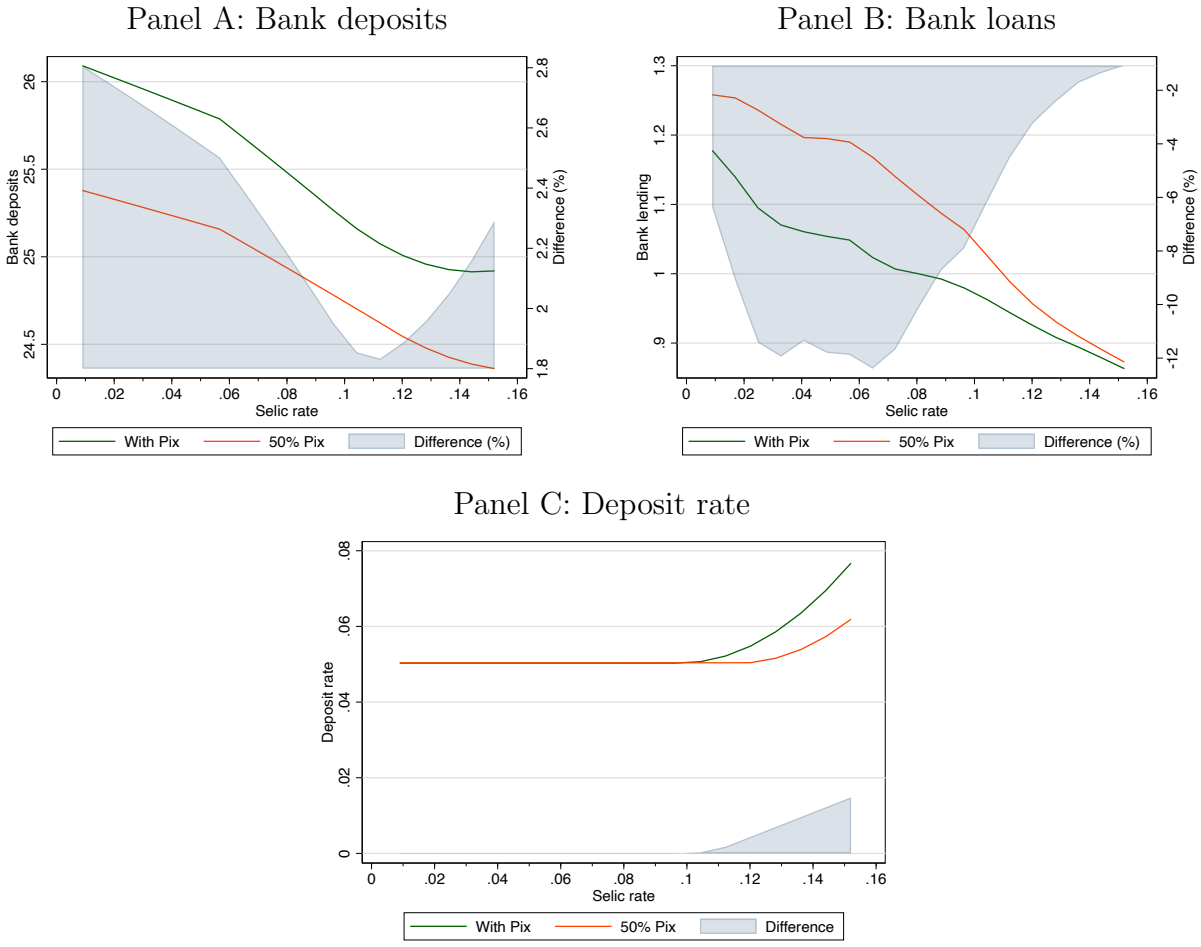
To analyze the counterfactual, we set the take-up of Pix to 50% of its original value by reducing β^d in households' utility function. The reduction of Pix changes the demand for deposits, so we plug the new demand into the bank problem and allow banks to re-optimize. We then compare deposit amounts and deposit rates in the baseline model with their counterfactual counterparts.

Figure 8 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 lower with less Pix because banks pay less competitive deposit rates. Finally, lending with Pix is lower. The estimation results are fully consistent with the empirical findings of the paper.

5.3 Counterfactual: FinTechs

An important channel through which Pix gained popularity is supply from non-bank financial intermediaries (NBFIs). Even though our sample of banks is close to 120 banks, the full list of Pix participants exceeds 900. Many of them do not offer banking services, and some of them became regulated banks following Pix. In this section, we augment the estimation sample to include large FinTechs that offer deposit products but do not appear in our sample, since they do not have branches. We then re-estimate the augmented model.

Figure 8: Counterfactual with Lower Pix Take-up

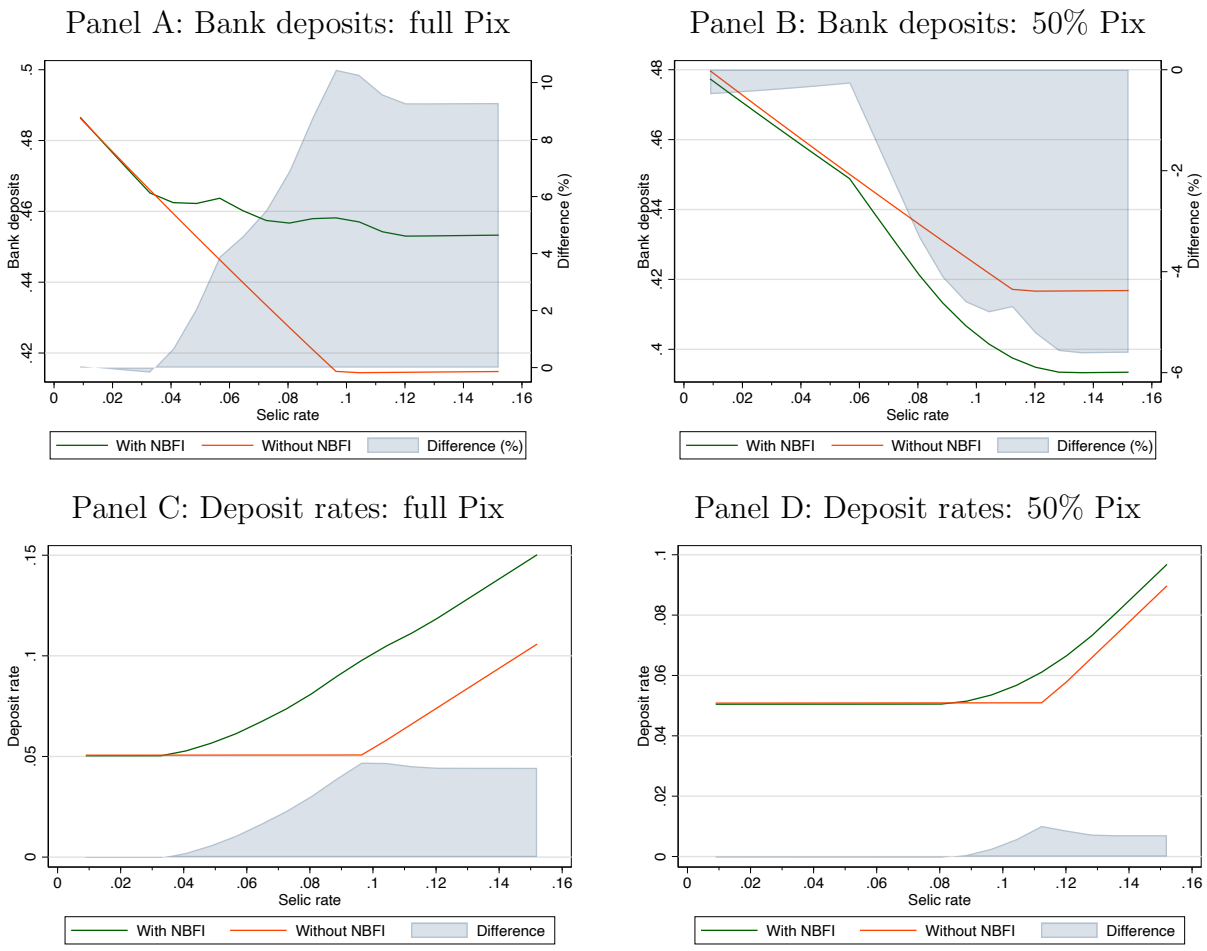


Note: This figure shows the counterfactual results with 50% of Pix take-up. The green lines correspond to the baseline solutions with Pix, whereas the orange lines correspond to the counterfactual solution where the take-up of Pix is reduced to 50% of the original value. The blue-shaded areas indicate 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 full results of the estimation are in Appendix D.15 of the paper. Overall, the effect of Pix on bank deposits, rates, and loans is stronger when non-banks are included. This is not surprising, given anecdotal evidence of Brazilians opening accounts at FinTech after Pix.

Using the results of the augmented model estimation, we consider a policy-relevant counterfactual – whether competition from FinTechs is considered or not. In other words, we compare the model with FinTechs to the model without them. We then show the results separately for the model with actual Pix take-up and for the counterfactual with

Figure 9: Counterfactual with and without FinTechs



Note: This figure shows the counterfactual results with and without FinTechs. Panels A and C show the results with full Pix take-up. Panels B and D show the results with a 50% Pix take-up. The green lines correspond to the solutions with FinTechs, whereas the orange lines correspond to the counterfactual without FinTechs. The blue-shaded areas indicate the difference between the baseline and counterfactual solutions. Bank deposits are scaled by steady-state bank loan amounts from the baseline model.

a 50% Pix take-up. We consider deposit rates and deposits, but not loans, given the special nature of FinTech lending.

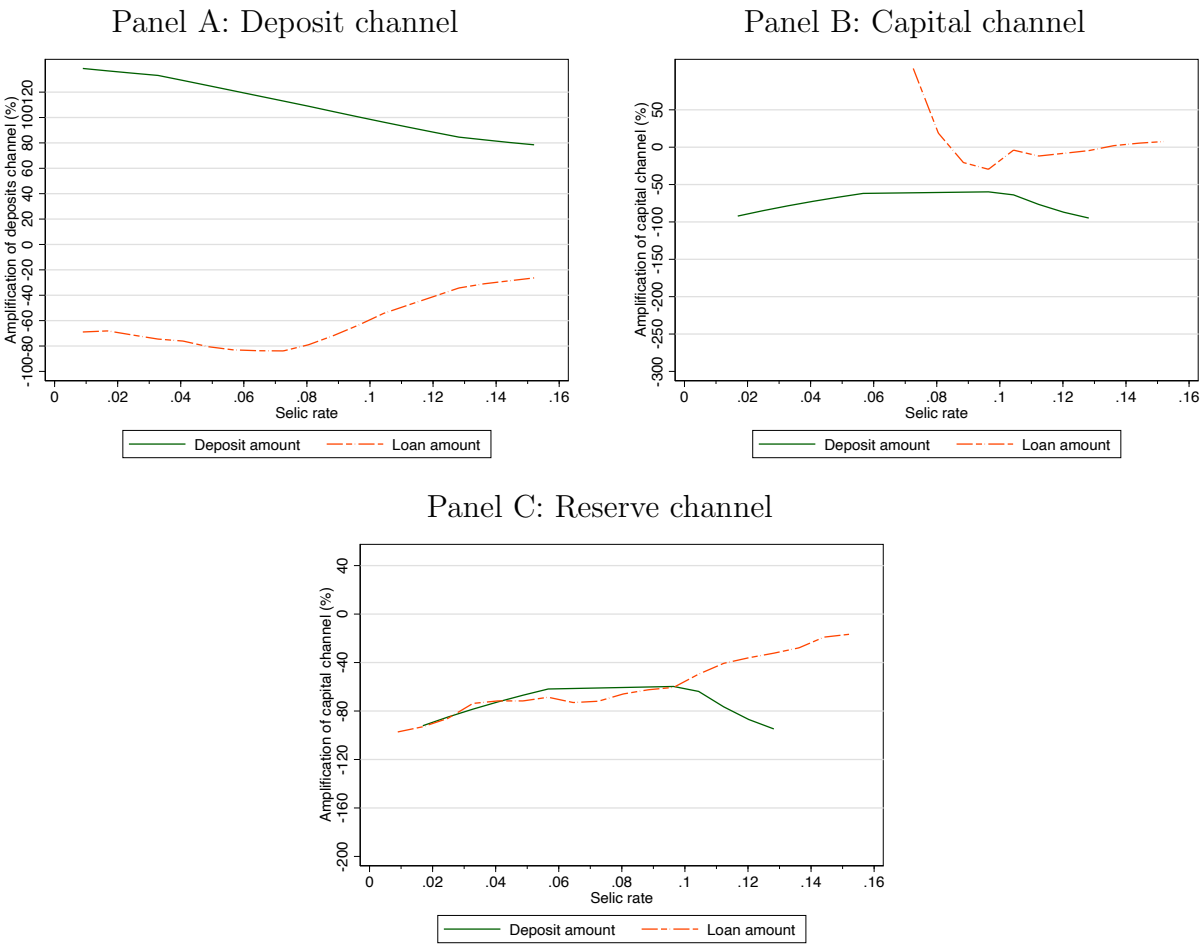
Figure 9 shows the results. Deposit rate differences between the cases with and without FinTechs are bigger if Pix is around, indicating an increased demand for deposits at FinTechs. Importantly, deposit rates are higher when FinTechs are included, because they move the average upwards. Bank deposits flow out less when FinTechs are included, but only in the model with a full Pix take-up. In other words, Pix incentivizes households to open more deposit accounts at FinTechs.

5.4 Counterfactual: Pix's effect through different channels

Now, we investigate the quantitative forces that shape the relationship between digital payment and monetary policy. We consider all three channels of monetary transmission that our model features. Specifically, we eliminate the effect of each channel in the model and check how deposits and loans 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 each channel in the monetary policy transmission. To eliminate the deposit channel, we assume no deposit market power, i.e., we assume that deposit rates simply follow policy rates. To eliminate the capital channel, we relax the equity constraint. Finally, we eliminate the reserve channel by assuming that there is no binding reserve requirement. Note that this type of analysis cannot be done without the structural model.

Figure 10 shows the results. The solid green line in Panel A 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. 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 80-130% on aggregate deposits. Similarly, the orange line plots the amplification effect of Pix on bank lending. Pix limits the deposit channel by 20-80% 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. The capital and reserve channels have a relatively more limited effect on total lending, but for low values of the Selic rate, the effects on total deposits are significant. On average, Pix impacts monetary transmission mostly through the deposit channel.

Figure 10: The Effect of Pix through Different Channels



Note: This figure shows Pix's effect on deposit and loan amounts through different channels of monetary transmission. Panel A plots the deposit channel, Panel B plots the capital channel, and Panel C plots the reserve channel. The solid green lines show how much Pix amplifies the channel effects 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 respective channels.

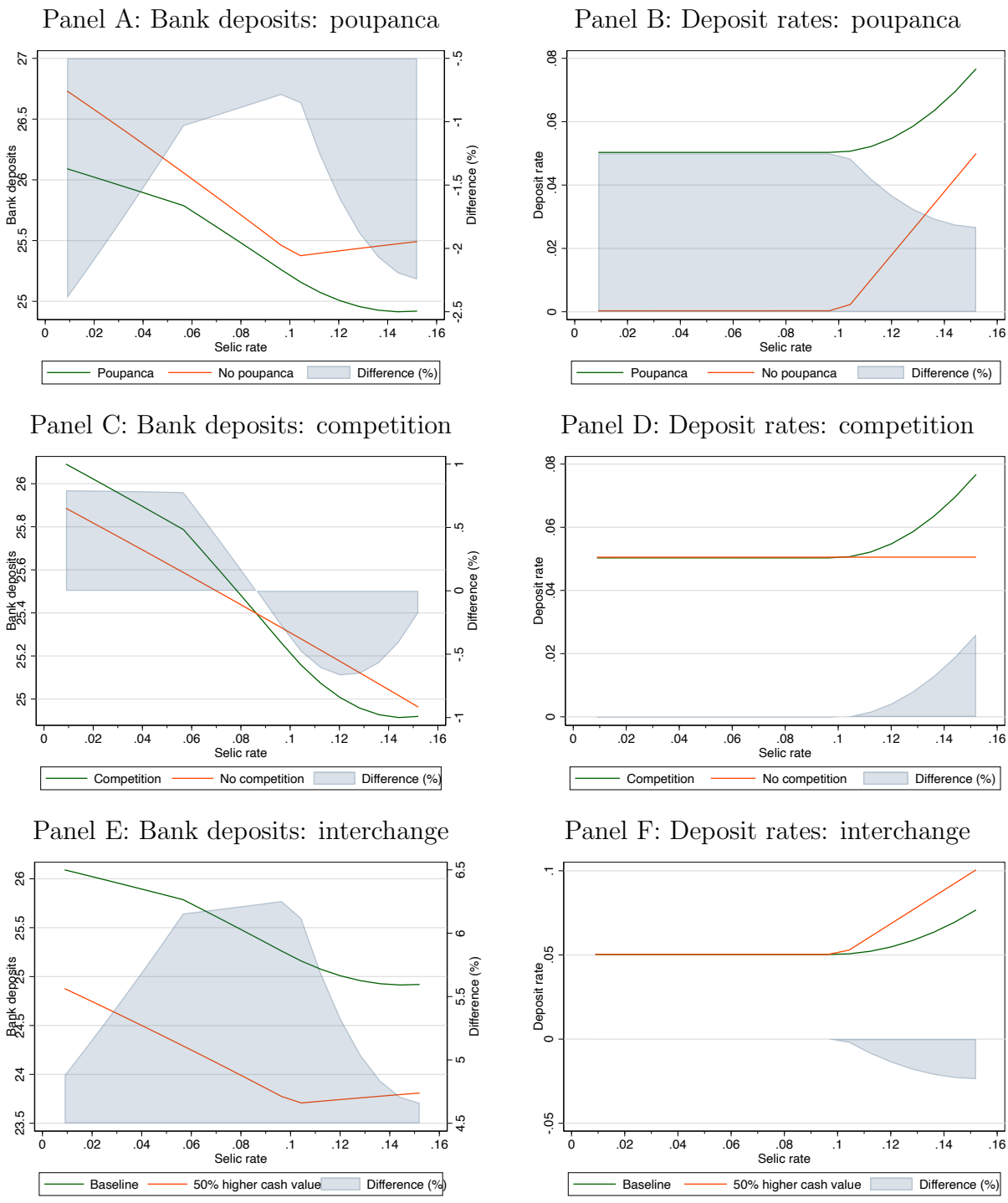
5.5 Counterfactual: other counterfactual

Finally, our model allows us to consider several other policy-relevant counterfactuals. First, Brazil has a regulated fixed rate on savings deposits, *poupança*, which naturally creates a benchmark for time deposits in Brazil. If time deposits pay much less than savings deposits, Brazilians would not hold money in time deposits. We consider a counterfactual scenario without savings deposits, i.e., when there is no lower bound to the deposit rates. Panel B of Figure 11 shows that the deposit rates would have been much lower in that case. As a result, banks would be willing to supply more deposits, as Panel A shows.

Next, we explore the competition effects from Pix. Since Pix levels the playing field in the market of payments and allows for cheaper and faster transfers, the semi-elasticity of the deposit demand increases. If Pix were created similarly to some private payment systems, it would likely dampen the competition or not change it at all. We consider the counterfactual scenario when the semi-elasticity of the deposit demand does not change. Panel D of Figure 11 shows that the deposit rates would have been lower and flat in that case, just high enough to exceed the poupança rate. Panel C shows that deposits would be lower as long as deposit rates are the same across the two scenarios, but then banks would be willing to issue more deposits, especially without the competitive pressure.

Finally, we explore the fees on Pix. Pix is free for banked households, and there is a small interchange fee, so consumers are usually charged in Pix as much as they would in cash. We do not model interchange fees directly, but our model estimates both the convenience value of deposits and the convenience value of cash. In the last counterfactual, we increase the convenience value of cash by 50% to resemble potential higher fees on Pix. As Panel F of Figure 11 shows, in that case, banks would have to pay a higher deposit rates to attract depositors. Households would also prefer cash more, so deposits would be smaller, as Panel E shows. In other words, the absence of fees for Pix helps banks attract depositors.

Figure 11: Other policy-relevant counterfactuals



Note: This figure shows three additional counterfactuals. Panels A, C, and E plot deposits, panels B, D, and F plot deposit rates. Panels A and B consider a counterfactual without the existence of poupança. Panels C and D consider a counterfactual without Pix increasing the semi-elasticity of the deposit demand. Panels E and F consider a counterfactual where the value of cash increases by 50%. The green lines correspond to the original model, whereas the orange lines correspond to the counterfactual scenarios. The blue-shaded areas indicate the difference between the baseline and counterfactual solutions. Bank deposits are scaled by steady-state bank loan amounts from the baseline model.

6 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 80% of the population, all of whom maintain deposit accounts with banks. Leveraging branch-level data and Pix transaction data, we empirically establish that Pix adoption mitigates banks' market power. Specifically, in regions with a higher volume of Pix transactions, hikes in policy rates result in more substantial rises in deposit rates and 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.

References

Abad, J., G. Nuño, and C. Thomas (2025). CBDC and the Operational Framework of Monetary Policy. *Journal of Monetary Economics 151*, 103762.

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

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

B. P. Gomes, D., F. Iachan, A. P. Ruhe, and C. Santos (2023). Monetary Policy and Labor Markets in a Developing Economy. *SSRN Electronic Journal*.

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

Bachas, P., P. Gertler, S. Higgins, and E. Seira (2021). How Debit Cards Enable the Poor to Save More. *The Journal of Finance 76*(4), 1913–1957.

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

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

Benmelech, E., J. Yang, and M. Zator (2023). Bank Branch Density and Bank Runs.

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

Berg, T., J. Keil, F. Martini, and M. Puri (2023). Payment Firms, Cryptocurrencies, and CBDCs. *SSRN Electronic Journal*.

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

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

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

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

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

Blickle, K., J. Li, X. Lu, and Y. Ma (2024). The Dynamics of Deposit Flightiness and its Impact on Financial Stability. *SSRN Electronic Journal*.

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

Brown, J. R., J. A. Cookson, and R. Z. Heimer (2019). Growing up without Finance. *Journal of Financial Economics 134*(3), 591–616.

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

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

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

Buchak, G., J. Hu, and S.-J. Wei (2024, 11). FinTech as a Financial Liberator.

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

Célerier, C. and A. Matray (2019). Bank-Branch Supply, Financial Inclusion, and Wealth Accumulation. *The Review of Financial Studies 32*(12), 4767–4809.

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

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

Corbae, D. and P. D'Erasmo (2014). Capital Requirements in a Quantitative Model of Banking Industry Dynamics. *SSRN Electronic Journal* (779).

Crouzet, N., P. Ghosh, A. Gupta, and F. Mezzanotti (2024). Demographics and Technology Diffusion: Evidence from Mobile Payments. *SSRN Electronic Journal*.

Crouzet, N., A. Gupta, and F. Mezzanotti (2023). Shocks and Technology Adoption: Evidence from Electronic Payment Systems. *Journal of Political Economy 131*, 3003–3065.

D'Avernas, A., A. Eisfeldt, C. Huang, R. Stanton, and N. Wallace (2023, 11). The Deposit Business at Large vs. Small Banks. Technical report, National Bureau of Economic Research, Cambridge, MA.

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

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

Ding, D., R. B. Gonzalez, Y. Ma, and Y. Zeng (2025). The Effect of Instant Payments on the Banking System: Liquidity Transformation and Risk-taking. *Banco Central do Brasil Working Paper Series*.

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

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

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

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

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

Egan, M., A. Hortaçsu, and G. Matvos (2017). Deposit Competition and Financial Fragility: Evidence from the US Banking Sector. *American Economic Review 107*(1), 169–216.

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

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

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

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

Fonseca, J. and A. Matray (2022). Financial Inclusion, Economic Development, and Inequality: Evidence from Brazil. Technical report, National Bureau of Economic Research, Cambridge, MA.

Fonseca, J. and B. Van Doornik (2022). Financial Development and Labor Market Outcomes: Evidence from Brazil. *Journal of Financial Economics 143*(1), 550–568.

Garratt, R., J. Yu, and H. Zhu (2022). How Central Bank Digital Currency Design Choices Impact Monetary Policy Pass-Through and Market Composition. *SSRN Electronic Journal*.

Gelman, M., I. Goldstein, and A. MacKinlay (2022). Bank Diversification and Lending Resiliency. *SSRN Electronic Journal*.

Gertler, M. and P. Karadi (2011). A Model of Unconventional Monetary Policy. *Journal of Monetary Economics 58*(1), 17–34.

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

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

Haendler, C. (2022). Keeping Up in the Digital Era: How Mobile Technology Is Reshaping the Banking Sector. *SSRN Electronic Journal*.

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

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

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

Higgins, S. (2024). Financial Technology Adoption: Network Externalities of Cashless Payments in Mexico. *American Economic Review 114*(11), 3469–3512.

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

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

Jiang, E. X., G. Y. Yu, and J. Zhang (2022). Bank Competition amid Digital Disruption: Implications for Financial Inclusion. *SSRN Electronic Journal*.

Jordà, (2005). Estimation and Inference of Impulse Responses by Local Projections. *American Economic Review 95*(1), 161–182.

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

Koont, N. (2023). The Digital Banking Revolution: Effects on Competition and Stability. *SSRN Electronic Journal*.

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

Kundu, S., T. Muir, and J. Zhang (2024). Diverging Banking Sector: New Facts and Macro Implications. *SSRN Electronic Journal*.

Li, L., E. Loutskina, and P. E. Strahan (2023). Deposit Market Power, Funding Stability and Long-Term Credit. *Journal of Monetary Economics 138*, 14–30.

Li, Y., Y. Li, S. Sarkisyan, and H. Sun (2021). Bank Credit and Money Creation on Payment Networks: A Structural Analysis of Externalities and Key Players. *SSRN Electronic Journal*.

Lu, X., Y. Song, and Y. Zeng (2024). The Making of an Alert Depositor: How Payment and Interest Drive Deposit Dynamics. *SSRN Electronic Journal*.

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

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

Nakamura, E. and J. Steinsson (2018). High-Frequency Identification of Monetary Non-Neutrality: The Information Effect. *The Quarterly Journal of Economics 133*(3), 1283–1330.

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

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

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

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

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

Paul, P. (2020). The Time-Varying Effect of Monetary Policy on Asset Prices. *Review of Economics & Statistics 102*(4), 690–704.

Philippon, T. (2019). On Fintech and Financial Inclusion. Technical report, National Bureau of Economic Research, Cambridge, MA.

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

Sampaio, M. and J. R. H. Ornelas (2024). Payment Technology Complementarities and their Consequences on the Banking Sector.

Sarkisyan, S. (2024). Instant Payment Systems and Competition for Deposits. *SSRN Electronic Journal*.

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

Van den Heuvel, S. (2008). The Welfare Cost of Bank Capital Requirements. *Journal of Monetary Economics 55*(2), 298–320.

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

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

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

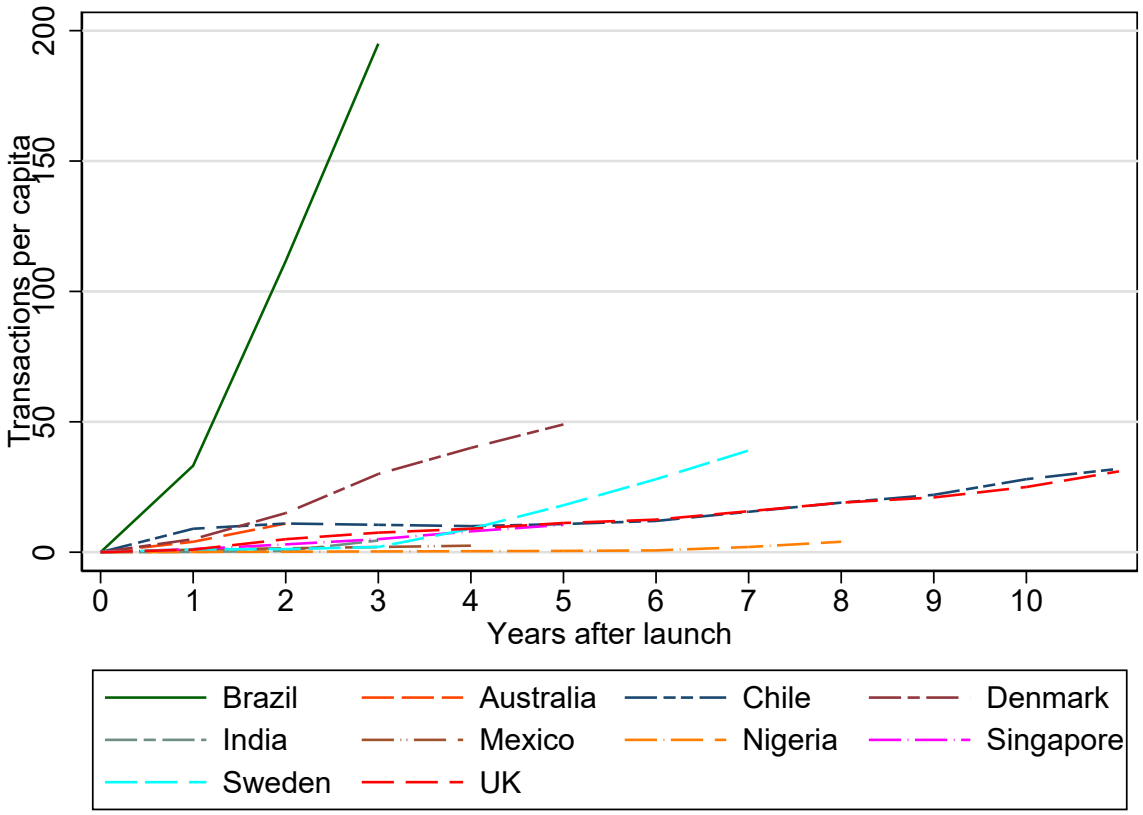
Xiao, K. (2020). Monetary Transmission through Shadow Banks. *The Review of Financial Studies 33*(6), 2379–2420.

Yannelis, C. and A. L. Zhang (2023). Competition and Selection in Credit Markets. *Journal of Financial Economics 150*(2), 103710.

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)).

C Simple model

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

C.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

$$v_-(\text{Bank } i) = r_i + u_i - t_d x_-, \tag{C.1}$$

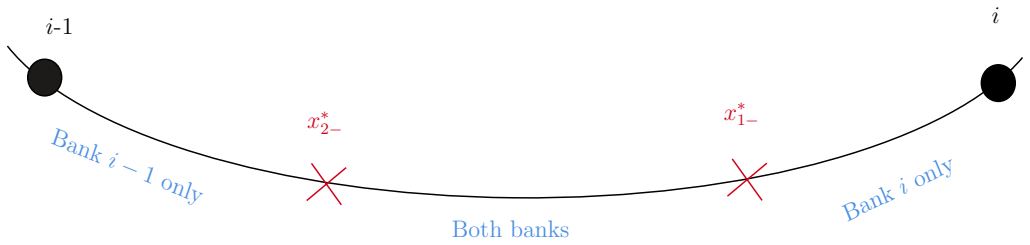
$$v_-(\text{Bank } i-1) = r_{i-1} + u_{i-1} - t_d(\frac{1}{n} - x_-), \tag{C.2}$$

$$v_{-}(\text{Mix}) = \alpha_{-} r_i + (1-\alpha_{-}) r_{i-1} + \underbrace{\frac{u_i + u_{i-1} + |u_i - u_{i-1}|}{2}}_{\max(u_i, u_{i-1})} - t_d \frac{1}{n}, \tag{C.3}$$

C.2 Household's deposit decision

Intuitively, the household's deposit decision depends on their location in the city. Figure C.1 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 C.1: Households' Deposit Decision



We derive the expression for the two thresholds x^*_{1-} and x^*_{2-} using the utilities from (C.1)-(C.3). 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

$$x^*_{1-} = \frac{1-\alpha_{-}}{t_d}(r_i - r_{i-1}) + \frac{1}{2t_d}(u_i - u_{i-1}) - \frac{1}{2t_d}|u_i - u_{i-1}| + \frac{1}{n}, \tag{C.4}$$

$$x^*_{2-} = \frac{\alpha_{-}}{t_d}(r_i - r_{i-1}) + \frac{1}{2t_d}(u_i - u_{i-1}) + \frac{1}{2t_d}|u_i - u_{i-1}|. \tag{C.5}$$

The share of households that will deposit with both banks is

$$x^*_{2-} - x^*_{1-} = \frac{2\alpha_{-} - 1}{t_d}(r_i - r_{i-1}) + \frac{1}{t_d}|u_i - u_{i-1}| - \frac{1}{n}. \tag{C.6}$$

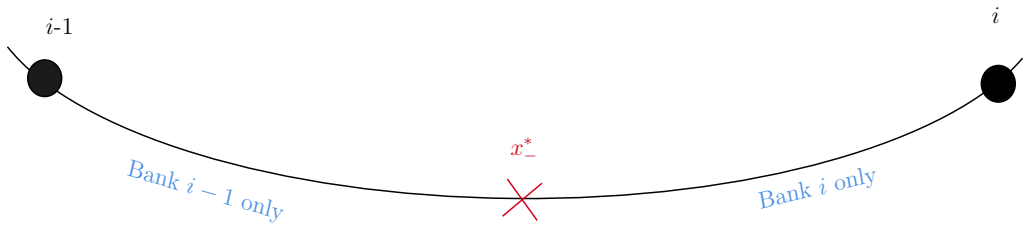
Of course, if the travel cost is large relative to the additional benefits gained from having another bank account, the middle region will shrink until it reaches zero. Figure C.2

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,

$$x^*_- = \frac{1}{2t_d}(r_i - r_{i-1}) + \frac{1}{2t_d}(u_i - u_{i-1}) + \frac{1}{2n}. \tag{C.7}$$

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

Figure C.2: 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

$$\frac{1}{n}t_d \geq (2\alpha_- - 1)(r_i - r_{i-1}) + |u_i - u_{i-1}|. \tag{C.8}$$

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

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

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

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

C.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 4. 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

$$DepShare_{i-} = \begin{cases} \overbrace{\frac{1}{t_d}[(2\alpha_-^2 - 2\alpha_- + 1)(r_i - r_{i-1}) + \frac{1}{2}(u_i - u_{i-1}) + (\alpha_- - \frac{1}{2})|u_i - u_{i-1}|]}^{\text{Competitiveness}} + \overbrace{\frac{1-\alpha_-}{n}}^{\text{Market concentration}}, & \text{Mix region exists} \\ \underbrace{\frac{1}{t_d}[\frac{1}{2}(r_i - r_{i-1}) + \frac{1}{2}(u_i - u_{i-1})]}_{\text{Competitiveness}} + \underbrace{\frac{1}{2n}}_{\text{Market concentration}}, & \text{No mix region} \end{cases} \tag{C.12}$$

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

$$DepShare_{i+} = \begin{cases} \overbrace{\frac{1}{t_d}[(2\alpha_+^2 - 2\alpha_+ + 1)(r_i - r_{i+1}) + \frac{1}{2}(u_i - u_{i+1}) + (\alpha_+ - \frac{1}{2})|u_i - u_{i+1}|]}^{\text{Competitiveness}} + \overbrace{\frac{1-\alpha_+}{n}}^{\text{Market concentration}}, & \text{Mix region exists} \\ \underbrace{\frac{1}{t_d}[\frac{1}{2}(r_i - r_{i+1}) + \frac{1}{2}(u_i - u_{i+1})]}_{\text{Competitiveness}} + \underbrace{\frac{1}{2n}}_{\text{Market concentration}}, & \text{No mix region} \end{cases} \tag{C.13}$$

The total deposit share of bank i is

$$DepShare_i = DepShare_{i-} + DepShare_{i+}. \tag{C.14}$$

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

$$\begin{aligned} MixDepositors_i &= (x^*_{2-} - x^*_{1-}) + (x^*_{2+} - x^*_{1+}) \\ &= \frac{1}{t_d} \underbrace{\Big((2\alpha_- - 1)(r_i - r_{i-1}) + (2\alpha_+ - 1)(r_i - r_{i+1}) + |u_i - u_{i-1}| + |u_i - u_{i+1}| \Big)}_{\geq 0 \text{ by assumption}} - \frac{2}{n}. \end{aligned} \tag{C.15}$$

C.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 (C.12) and (C.13) 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 (C.8), as well as

the share of mixed strategy depositors from (C.15).

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 (C.12), 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 (C.15),

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

Secondly, the demand for deposits of bank i generally decreases. We see this from the derivative of (C.12) and (C.13), 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.

D Additional results

D.1 Changes in spread betas: accounting for income

In Section 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 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:

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

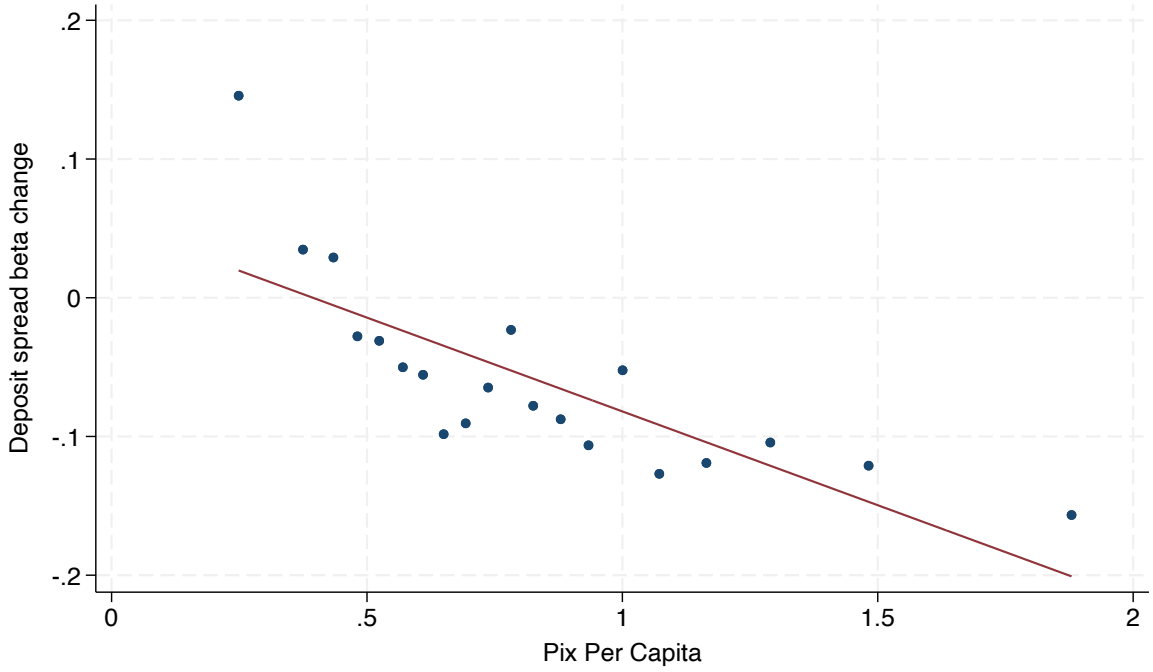
where $IncomePC_m$ is income per capita in municipality m. We do not observe this value across years, but we do observe a municipality-level cross-section from the 2010 Census. The estimation results are shown in Figure D.1 – our results are robust to accounting for income.

Even though controlling for income leaves our deposit spread graph unchanged, there 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 D.2 shows that deposit spread betas decline in areas with a larger number of Pix transactions.

D.2 Results without FinTechs

In this section, we exclude FinTechs and repeat the analysis from Table 2. Table D.1 shows that the results are robust.

Figure D.1: 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 value 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.

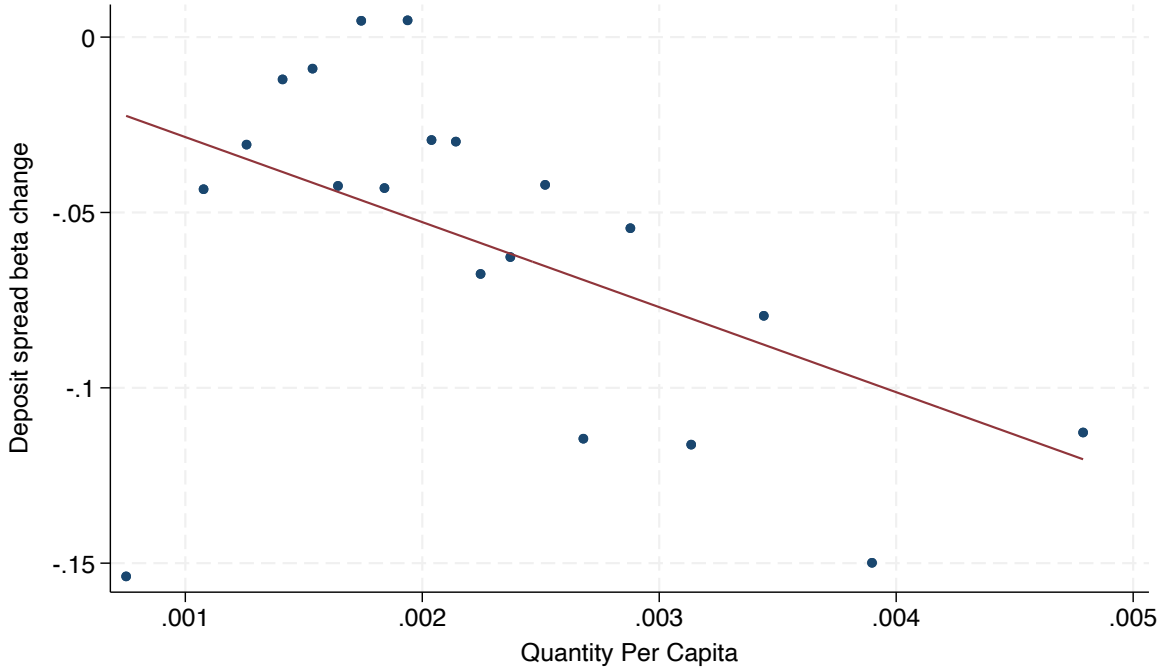
D.3 Results using payment shares for FinTechs

In this section, we repeat the analysis from Table 2 but add another layer of shares to the definition of branch variables for FinTechs. We use administrative data on the share of Pix payments that are received by FinTech banks in each state, in addition to the municipality-level share of Pix transactions. Table D.2 shows that the results are robust.

D.4 OLS results

In this section, we show the results without instrumenting. Table D.3 shows that the results are robust.

Figure D.2: 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.

D.5 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)).[20] The surprises are constructed using changes 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 D.4 shows that our results are robust to using high-frequency monetary shocks as a measure of monetary policy.

[20]We thank the authors of B. P. Gomes et al. (2023) for sharing their monetary shock data up to September 2022 with us.

Table D.1: Impact of Pix on Deposit Spreads, Loan Flows, and Deposit Flows: No FinTechs

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

	Deposit spread change		Loan flows		Deposit flows	
	(1)	(2)	(3)	(4)	(5)	(6)
Pix Per Capita × MS	−0.320***	−0.320***	−1.434***	−1.426***	0.571***	0.562***
	(0.009)	(0.009)	(0.053)	(0.053)	(0.101)	(0.101)
Pix Per Capita	−0.039***	−0.039***	−0.546***	−0.607***	0.251***	0.211***
	(0.002)	(0.002)	(0.014)	(0.015)	(0.029)	(0.030)
MS	0.947***	0.945***	2.813***	2.776***	−1.504***	−1.489***
	(0.009)	(0.008)	(0.071)	(0.071)	(0.146)	(0.145)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Branch FE	No	Yes	No	Yes	No	Yes
Obs.	152,924	152,863	523,752	523,730	524,179	524,158
R^2	0.066	0.070	0.004	0.006	0.000	0.000

Note: This table provides results of the second-stage within-bank estimation of the effect of Pix on loan flows, deposit flows, and deposit spreads – equation (3). FinTech banks are excluded. 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. Z-scored Pix per capita is instrumented with the interaction of the time dummy for the introduction of Pix Saque and municipality-level concentration of MEIs. Interaction terms are also instrumented. 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.

D.6 Different measure of Pix

Tables D.5 and D.6 replicate the main analysis but use Pix users per capita as a definition of Pix. The results are fully robust.

D.7 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 D.7 shows that our results are robust.

Table D.2: Impact of Pix on Deposit Spreads, Loan Flows, and Deposit Flows: Payment Shares

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

	Deposit spread change		Loan flows		Deposit flows	
	(1)	(2)	(3)	(4)	(5)	(6)
Pix Per Capita × MS	−0.034***	−0.034***	−2.829***	−2.824***	0.522***	0.522***
	(0.005)	(0.005)	(0.051)	(0.051)	(0.067)	(0.067)
Pix Per Capita	−0.065***	−0.064***	−0.720***	−0.764***	−0.852***	−0.900***
	(0.001)	(0.001)	(0.010)	(0.010)	(0.022)	(0.023)
MS	1.025***	1.026***	3.795***	3.766***	−3.068***	−3.088***
	(0.005)	(0.005)	(0.046)	(0.046)	(0.084)	(0.084)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Branch FE	No	Yes	No	Yes	No	Yes
Obs.	269,313	269,252	867,388	867,366	867,815	867,794
R^2	0.245	0.246	0.009	0.012	0.006	0.006

Note: This table provides results of the second-stage within-bank estimation of the effect of Pix on loan flows, deposit flows, and deposit spreads – equation (3). The FinTech sample is constructed by using state-level shares of Pix payments received by FinTech banks. 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. Z-scored Pix per capita is instrumented with the interaction of the time dummy for the introduction of Pix Saque and municipality-level concentration of MEIs. Interaction terms are also instrumented. 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.

D.8 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 monetary shocks over time. In other words, we plot impulse response functions of bank lending to the monetary policy shocks.

Figure D.3 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

Table D.3: Impact of Pix on Deposit Spreads, Loan Flows, and Deposit Flows: OLS

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

	Deposit spread change		Loan flows		Deposit flows	
	(1)	(2)	(3)	(4)	(5)	(6)
Pix Per Capita × MS	0.000	−0.017***	−0.332***	−0.431***	1.284***	1.228***
	(0.004)	(0.004)	(0.022)	(0.023)	(0.040)	(0.042)
Pix Per Capita	−0.058***	−0.069***	−0.325***	−0.441***	−0.448***	−0.528***
	(0.001)	(0.001)	(0.009)	(0.010)	(0.014)	(0.017)
MS	0.992***	1.013***	0.768***	0.857***	−3.953***	−3.903***
	(0.004)	(0.005)	(0.027)	(0.027)	(0.057)	(0.059)
Branch FE	Yes	No	Yes	No	Yes	No
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	269,437	269,376	895,888	895,867	868,229	868,208
R^2	0.260	0.261	0.039	0.061	0.024	0.030

Note: This table provides results of the within-bank estimation of the effect of Pix on loan flows, deposit 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. 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.

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.

D.9 Placebo test with lagged effects

In this section, we test if deposit flows, loan flows, and deposit spreads respond similarly to the main analysis in areas with more Pix transactions following a contractionary monetary policy change, even before Pix was introduced.[21] This test serves to show that high-Pix and low-Pix areas were not different before the introduction of Pix, even without instrumenting. Table D.8 shows that deposit spreads were the same across areas with more or less Pix usage. Deposit flows and loan flows also do not behave the way they did with contemporaneous effect – if anything, there is a decline in deposit flows and an increase in loan flows. The evidence is consistent with Pix driving changes in

[21] We hence restrict the sample to the end of 2021.

Table D.4: Impact of Pix on Deposit Flows, Loan Flows, and Deposit Spreads: Identified Monetary Shocks

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

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

	Deposit spread change		Loan flows		Deposit flows	
	(1)	(2)	(3)	(4)	(5)	(6)
Pix Per Capita × MS	−0.204***	−0.238***	−1.031***	−1.104***	0.998***	0.990***
	(0.025)	(0.026)	(0.090)	(0.096)	(0.180)	(0.198)
Pix Per Capita	0.117***	0.135***	0.051	−0.133***	−0.436***	−0.588***
	(0.021)	(0.021)	(0.041)	(0.045)	(0.063)	(0.065)
MS	0.719***	0.719***	1.720***	1.786***	−1.492***	−1.461***
	(0.010)	(0.010)	(0.115)	(0.124)	(0.239)	(0.263)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Branch FE	No	Yes	No	Yes	No	Yes
Obs.	126,697	126,672	387,487	387,465	367,398	367,375
R^2	0.092	0.091	0.002	0.003	0.000	0.001

Note: This table provides results of within-bank estimation of the effect of Pix on deposit and loan flows and spread betas – equation (3). We use high-frequency identified monetary surprises sourced from B. P. Gomes et al. (2023) to instrument for the change in Selic rate. We run a 2SLS regression, instrumenting both the standalone term and the interaction term. 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. FinTech banks are not included. 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.

deposit spreads, deposit flows, and loan flows.

D.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 section, we analyze how return on assets and interest return on assets (net interest income divided by assets) change. Table D.9 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.

Table D.5: Impact of Pix on Deposit Spreads, Loan Flows, and Deposit Flows: Pix Users

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

	Deposit spread change		Loan flows		Deposit flows	
	(1)	(2)	(3)	(4)	(5)	(6)
Pix User × MS	−0.318***	−0.333***	−20.602***	−20.828***	3.855***	3.704***
	(0.036)	(0.037)	(0.315)	(0.309)	(0.504)	(0.505)
Pix User	−0.495***	−0.495***	−5.283***	−5.676***	−6.240***	−6.645***
	(0.008)	(0.008)	(0.067)	(0.066)	(0.157)	(0.161)
MS	1.090***	1.094***	6.125***	6.182***	−3.132***	−3.094***
	(0.008)	(0.008)	(0.075)	(0.073)	(0.136)	(0.136)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Branch FE	No	Yes	No	Yes	No	Yes
Obs.	270,170	270,108	870,357	870,335	870,784	870,763
R^2	0.245	0.245	0.019	0.020	0.007	0.007

Note: This table provides results of the second-stage within-bank estimation of the effect of Pix on loan flows, deposit 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. Columns 5 and 6 correspond to changes in deposit flows. Z-scored Pix users per capita is instrumented with the interaction of the time dummy for the introduction of Pix Saque and municipality-level concentration of MEIs. Interaction terms are also instrumented. 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.

D.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 D.10. As in our main specifications, deposit demand becomes more elastic after the launch of Pix.

D.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 state-

Table D.6: Impact of Pix on Deposit Spreads, Loan Flows, and Deposit Flows: Pix Users, OLS

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

	Deposit spread change		Loan flows		Deposit flows	
	(1)	(2)	(3)	(4)	(5)	(6)
Pix User × MS	0.020	−0.075**	−5.823***	−6.297***	11.209***	11.078***
	(0.026)	(0.030)	(0.182)	(0.190)	(0.291)	(0.306)
Pix User	−0.421***	−0.466***	−1.902***	−2.492***	−4.518***	−4.978***
	(0.007)	(0.007)	(0.058)	(0.059)	(0.112)	(0.125)
MS	1.008***	1.035***	2.162***	2.296***	−5.106***	−5.068***
	(0.006)	(0.007)	(0.049)	(0.050)	(0.083)	(0.087)
depflow			0.074***	0.072***		
			(0.004)	(0.003)		
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Branch FE	No	Yes	No	Yes	No	Yes
Obs.	270,318	270,256	870,853	870,831	871,280	871,259
R^2	0.259	0.260	0.078	0.098	0.025	0.031

Note: This table provides results of the within-bank estimation of the effect of Pix on loan flows, deposit 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. Columns 5 and 6 correspond to changes in deposit flows. We use Pix users per capita. 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.

ments. The results of the demand estimation using BLP are presented in Table D.11. As in our main specifications, deposit demand becomes more elastic after the launch of Pix.

D.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 D.12 shows that the demand estimation produces qualitatively similar and economically larger results.

Table D.7: 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.

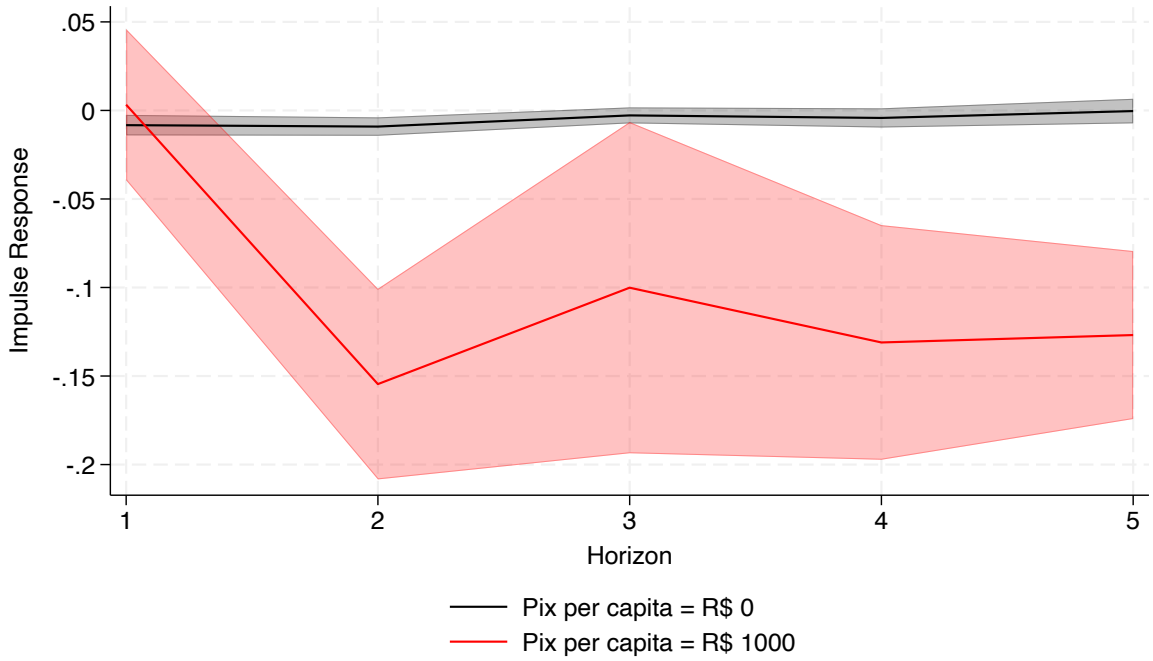
D.14 Higher discount rates

In this section, we increase the value for the discount factor, $1-\gamma$, to 0.96. Deposit rates respond more to policy rates, deposits increase, and lending decreases after Pix, at least for policy rates as high as Brazil has had for the duration of our sample.

D.15 Structural model with NBFIs

Table D.13 shows the estimates from the model augmented with NBFIs. Figure D.5 shows counterfactuals. The results with NBFIs exhibit stronger Pix effects because NBFIs create competition for large banks.

Figure D.3: 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.

Table D.8: Impact of Pix on Lagged Deposit Flows, Loan Flows, and Deposit Spreads

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

	Deposit spread change		Loan flows		Deposit flows	
	(1)	(2)	(3)	(4)	(5)	(6)
Pix Per Capita × MS	0.120	0.181	1.473***	1.450***	−1.420***	−1.584***
	(0.217)	(0.222)	(0.216)	(0.206)	(0.302)	(0.307)
Pix Per Capita	0.389**	0.473***	0.709***	0.448***	1.303***	1.186***
	(0.162)	(0.168)	(0.099)	(0.099)	(0.105)	(0.102)
MS	1.264***	1.320***	2.159***	2.212***	−0.968***	−0.787***
	(0.080)	(0.085)	(0.094)	(0.093)	(0.209)	(0.210)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Branch FE	No	Yes	No	Yes	No	Yes
Obs.	90,933	90,904	281,432	281,408	266,340	266,316
R^2	0.079	0.085	0.017	0.091	0.009	0.030

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. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

Table D.9: 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 D.10: 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 D.11: 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	

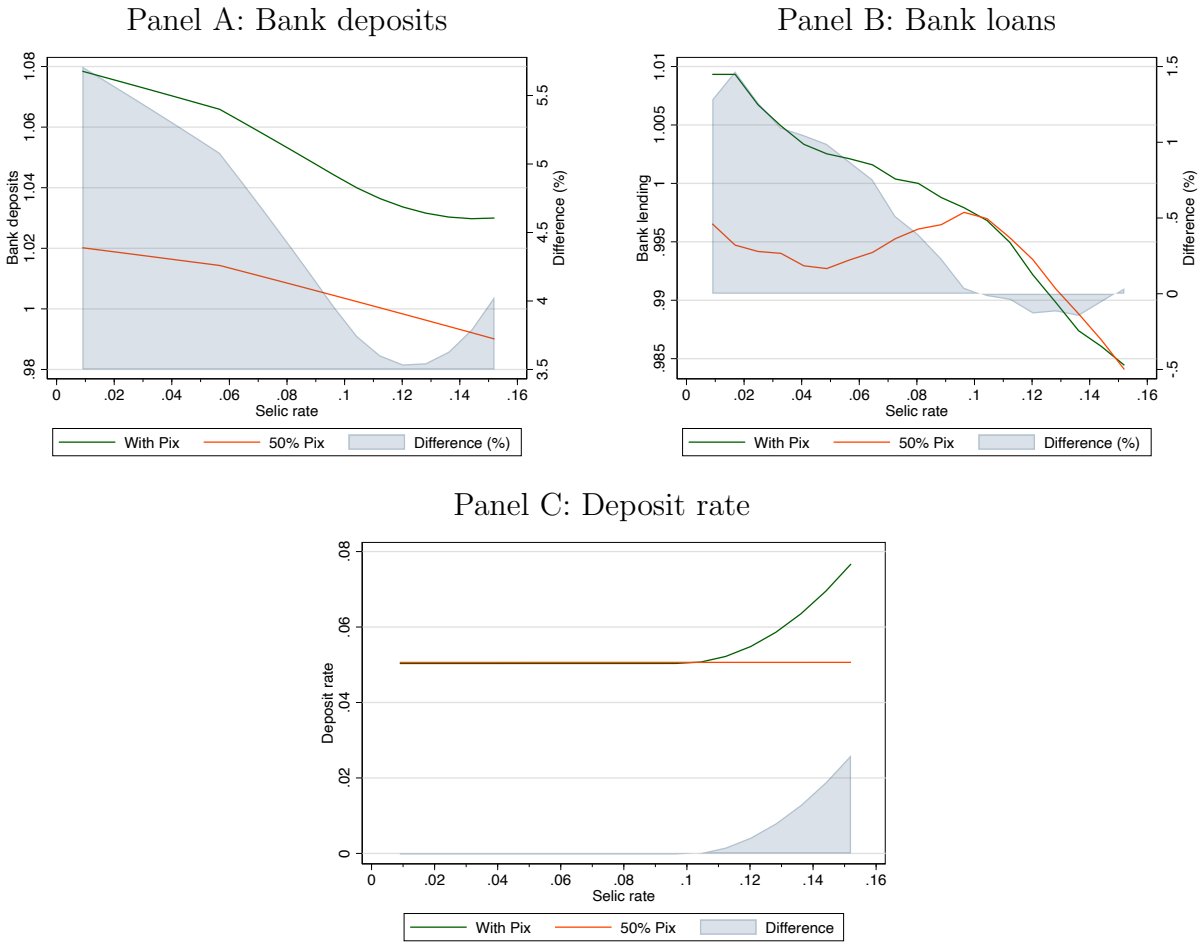
Note: This table provides results of the estimation of the deposit demand. The method used is GMM following the random coefficient logit procedure described in Berry et al. (1995). The estimated time period is from January 2015 to December 2021. Bank and time fixed effects are included. Deposit rates 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 D.12: 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.

Figure D.4: Counterfactual with Lower Pix Take-up: Higher Discount Factor



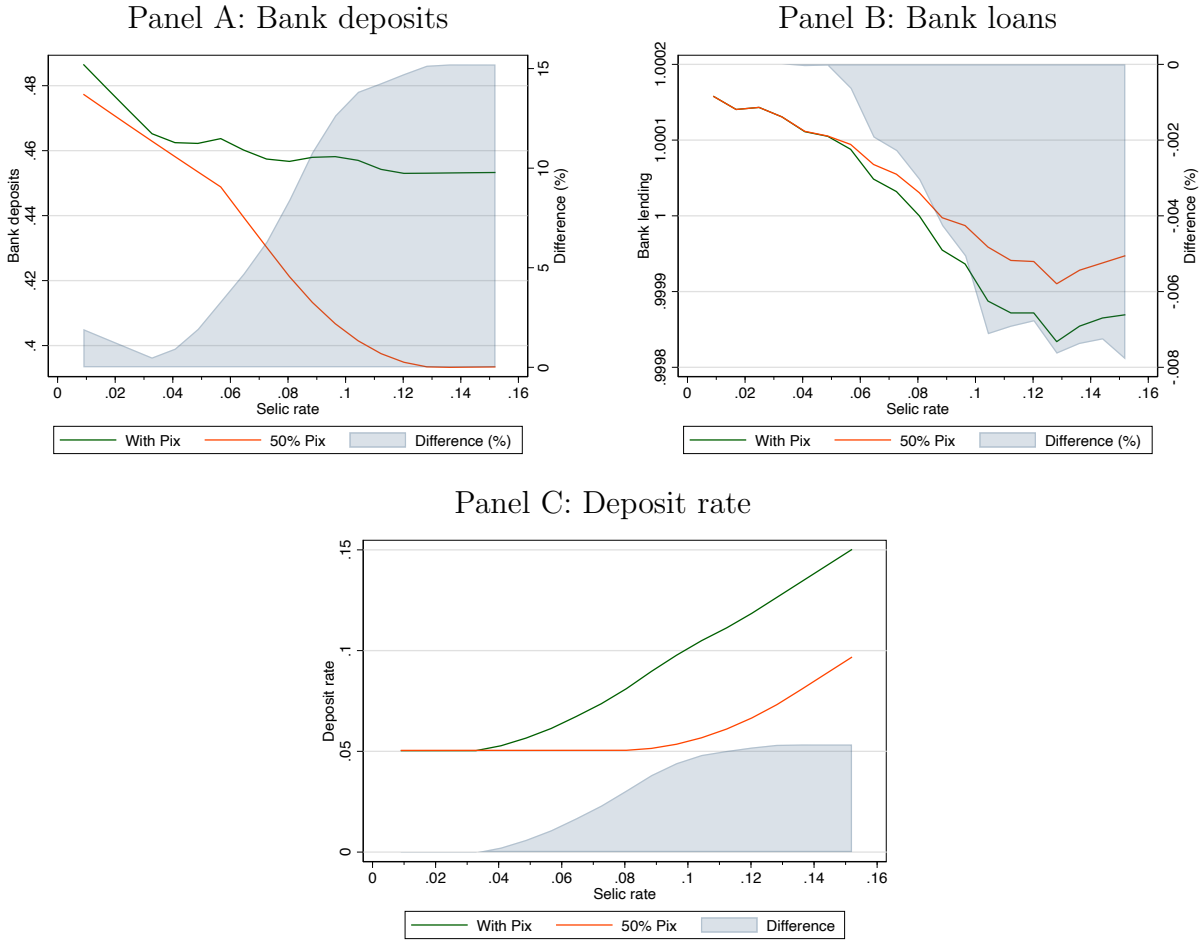
Note: This figure shows the counterfactual results with 50% of Pix take-up. The discount factor, $1-\gamma$, is calibrated to 0.96. The green lines correspond to the baseline solutions with Pix, whereas the orange lines correspond to the counterfactual solution where the take-up of Pix is reduced to 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.

Table D.13: Parameter Estimates in the Model with NBFIs

	Panel A: Parameters estimated from BLP		
α^d	Depositors' uniform sensitivity to deposit rates	0.018	[0.002]
β^d	Additional sensitivity to deposit rate from Pix	0.012	[0.001]
α^ℓ	Borrowers' sensitivity to loan rates	−0.032	[0.021]
	Panel B: Parameters estimated from SMD		
W/K	Relative deposit market size	1.7614	[0.123]
q_n^ℓ	Value of firms' outside option	−10.4685	[0.157]
ϕ^N	Quadratic cost of non-reservable borrowing	0.3046	[0.0128]
ϕ^d	Deposit preference shifter	−0.0031	[0.000]
ϕ^ℓ	Loan preference shifter	−0.0698	[0.4286]
ψ	Net fixed operating cost	−0.0004	[0.0011]

Note: This table presents the list of parameters calibrated or estimated in the model augmented by NBFIs. In Panel D, standard errors are reported in brackets for parameters estimated via SMD.

Figure D.5: Counterfactual with Lower Pix Take-up: Model with NBFIs



Note: This figure shows the counterfactual results with 50% of Pix take-up in the model with NBFIs. 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.