Instant Payment Systems and Competition for Deposits*

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Abstract

I study how financial technology reshapes competition among banks. I exploit quasi-random variation in exposure to the introduction of Brazil's Pix, an instant payment system, and show that instant payments increase deposit competition. Small bank deposits rise relative to large banks because Pix allows small banks to offer payment convenience more similar to large banks. Since they become more competitive providing payment services, small banks reduce deposit rates relative to large banks. Finally, I estimate a deposit demand model and find that depositors' welfare increases with Pix. These findings suggest that universally available payment systems can foster banking competition.

Keywords: Deposit market competition, instant payment systems, banking, Pix

JEL Codes: E42, G21, G11, E58

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1 Introduction

The banking industry is highly concentrated, with large banks offering low deposit rates and holding significant market share (Drechsler et al. (2017)). The dominance of large banks is further influenced by payment services like credit cards and cashless apps. However, a relatively new type of payment service, instant payment systems (IPS), is emerging to replace traditional payment methods, enabling real-time money transfers. Major economies have developed their IPS (e.g., FedNOW in the United States, Swish in Sweden, UPI in India, and Pix in Brazil), many of which are becoming the preferred payment option.[1] When instant payment systems, unlike traditional services, have low entry costs for all banks, they are challenging the dominant role of large banks as payment service providers. In this paper, I investigate the impact of instant payment systems on the banking landscape, specifically deposit market competition.

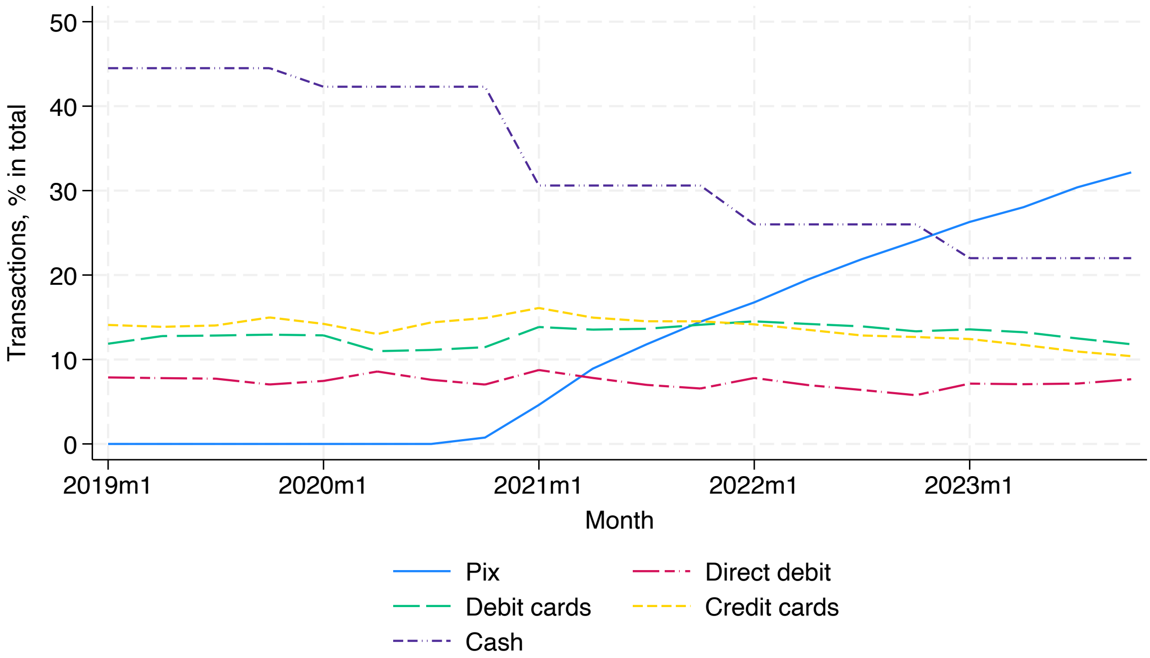
Leveraging the introduction of Pix in Brazil, I find that the adoption of instant payment systems increases deposit market competition by allowing small banks[2] to offer greater payment convenience to their depositors, making small banks' payment services more similar to large banks. Since small banks become more competitive, they are also able to reduce their deposit rates relative to large banks. Small banks no longer need to pay very high deposit rates to attract depositors. I find that they still pay more than large banks, but the gap between deposit rates narrows because the demand for deposits of small banks rises. I also argue that the introduction of Pix increases depositors' surplus by making an average depositor's interest rate more competitive because the average depositor moves from one of the large banks to a small bank.

To address the question, I utilize administrative data on the usage of Pix, an instant payment system introduced by the Central Bank of Brazil (CBB) in November 2020. Pix not only enables instant transfers but also boasts widespread acceptance as a merchant payment method due to its lower fees compared to credit cards. Since its launch, Pix

[1] See Ouyang (2021) and Dubey and Purnanandam (2023).

[2] Large banks are defined as banks with more than 50 million depositors as of November 2020. In Appendix D.7, I show that my results are robust to a variety of other definitions of large banks.

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



Note: Data is 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 percentage of the total number of transactions for the main means of payment in Brazil: cash, Pix (an instant payment system launched in November 2020), direct debit, debit cards, and credit cards.

has emerged as a preferred payment method by consumers, surpassing other prominent options such as *Boleto Bancário* (a slip to make fast cashless payments), *TED* (an express wire transfer service), direct debits, and even credit and debit cards (see Figure 1). As Figure 1 suggests, Pix mainly substitutes paper currency, with cash transactions steadily declining since Pix was introduced. By July 2024, Pix transactions reached almost R$ 2.5 trillion per month, equivalent to approximately $400 billion with more than 70% of Brazilians actively using it.

Although Pix surpasses traditional payment systems that rely on bank deposits,[3] it requires a bank account to be used. To ensure the service would be available to as many consumers as possible, the Central Bank of Brazil required large and medium-sized

[3]Pix even replaces some payment systems. The usage of cards, boleto, and direct debits declined in Brazil in percentage terms. See here for the Central Bank graphs.

banks to join Pix (banks with more than 500,000 depositors – a total of 38 banks). Entry costs for smaller banks were fairly low because the total service costs of Pix are shared among participating banks based on settled transactions to cover the costs of running the system.[4] Hence, more than 90% of commercial banks (a total of 790 intermediaries, including commercial banks, payment companies, credit unions, and FinTechs) joined Pix within the first two months. Such widespread and rapid adoption creates an excellent opportunity to study large-scale introductions of IPS more broadly. Brazil is also one of the largest economies in the world and the largest in Latin America.

In my analysis, I employ municipality-level monthly data on Pix transactions sourced from the Central Bank of Brazil and supplement it with branch-level banking and municipality-level demographic and economic data. Brazilian bank data has been widely used to study the impact of banks on the economy (Fonseca and Van Doornik (2022); Fonseca and Matray (2022)). Throughout the paper, I consider several measures of competition. First, I split the banks into large and small based on their number of depositors (banks with more than 50 million depositors are defined as large). Second, I use the local deposit HHI to measure how concentrated deposit markets in a given county are. Finally, I consider deposit betas and profitability in robustness tests.

Since Pix was introduced during the COVID-19 pandemic, and payment system development can be influenced by unobservables that also impact bank deposits, there are potential threats to the identification. To address these challenges, I utilize municipality-level survey data on the implementation and easing of COVID-19 restrictions in Brazil during the summer of 2020.[5] I assume that whether a municipality eased restrictions by *September 2020* only affects changes in deposit market competition *from October to November 2020* through its impact on Pix adoption.[6] First, the instrument is likely

[4]The annual costs of Pix are around 10 million BRL. With 790 participants in the system, the Central Bank only charges 0.01 BRL per 10 transactions per bank. See the report here and here.

[5]Made available by de Souza Santos et al. (2021).

[6]My preferred instrumental variable specification is the identification through heteroskedasticity in the simultaneous relation model (Rigobon and Sack (2003, 2004)), since it only requires assumptions on variances of regression shocks. In Appendix D.18, I use standard IV and show that my results are robust.

relevant since areas without COVID restrictions picked up Pix more due to increased economic activity. The evidence of the increased spending after COVID restrictions also exists for the US (Parker et al. (2022)). Second, the exclusion restriction only requires that the easing of COVID restrictions by September 2020 impacts changes to deposit market concentration in November 2020 only through Pix. Since my data is monthly, I am able to account for the changes in deposit market concentration between September and October – the time period when restrictions were already relaxed, but Pix did not yet exist. In other words, the initial effects of lifting the restrictions had already happened, and later differences in November are plausibly due to Pix take-up.

Using instrumental variables, I show that in areas with more use of Pix, deposits of small banks rise relative to large banks. The effects are especially strong for time deposits because those are the ones that pay interest in Brazil.[7] This results in a significant decline in local deposit market concentration measured as HHI. For instance, if residents of a hypothetical municipality with five banks of equal size increase their value of Pix transactions by R$ 1000 ($200), there will be six banks of equal size within five months in that municipality. As small banks raise more deposits, I show that they also increase their lending, but the effect on lending is limited because large banks have access to alternative sources of financing.

Based on these findings, I argue that the impact of Pix on deposit market concentration is mainly driven by leveling the playing field in terms of banks' ability to provide payment and transfer convenience. Large banks provide a number of benefits to their customers, which force many depositors to forgo higher deposit rates paid by small banks to open accounts at larger banks (D'Avernas et al. (2023)). Since Pix facilitates payments and transfers and is available to clients of both large and small banks, the costs of switching to higher-interest small banks decline. In other words, Pix reduces *the convenience gap* between large and small banks.

[7] Saving deposits also pay interest in Brazil, but the rate on those is regulated by the government, so banks have to pay the regulated rate. This is one of the reasons why I do not find a strong impact of Pix on saving deposits of small banks.

Since the comparison I focus on throughout the paper is between large and small banks, the way in which I define each category is critically important. In the main analysis, I define large banks as banks with more than 50 million depositors, which leaves me with the 2 largest (by depositor count)[8] banks in Brazil – Banco do Brasil and Caixa, who jointly own 41% of branches in Brazil. Both banks provide great convenience to their clients, especially since the government is a major shareholder in both. Those two banks also underwent branch expansion, making them very accessible to their clients (Fonseca and Matray (2022)). In the Appendix, I show that my main findings are robust to considering other definitions (more than 40 million depositors, top-4 banks, and top-5 banks), so the results about the effect of payment systems on competition for deposits are not driven by one particular approach to the classification of banks.

In support of payment and transfer convenience being the main channel, I show evidence that the increase in deposits is driven by an increase in *customers' demand* for bank deposits. I show that consistent with the rise in deposit demand, deposit rates of small banks decline by 14 b.p. relative to large banks after a doubling in Pix transaction value (approximately one s.d. increase in my sample), since small banks no longer need to pay high deposit rates to attract clients. Small bank deposit rates remain higher than large bank deposit rates because large banks still provide better non-payment services, such as direct deposits, credit cards, and better online banking apps, but the spread between deposit rates offered by small banks and large banks narrows.

I provide more evidence for the channel using rich Brazilian demographic data. Many financially constrained households prefer cash to bank cards due to their convenience and low costs (Carroll and Samwick (1998); Borzekowski et al. (2008)). The introduction of Pix makes deposits more convenient relative to cash and deposits in small banks more convenient relative to deposits in large banks. Consistent with this, I show that the increase in deposits of large banks is more prevalent in areas with more financially

[8]Note that my definition is based on the depositor count, not on total assets, because the paper focuses on the convenience for the depositors. In Appendix, I show that my results are robust to various definitions of large banks, including defining large banks as 3, 4, or 5 largest banks by assets. I also show that my results are robust if I exclude Banco do Brasil and Caixa.

constrained households. In addition, reallocation from large banks to small banks is more significant in areas with richer households who benefit more from high interest rates and are affected less by switching costs (Illanes (2017); Krishnamurthy and Li (2023)). Consistent with that, the most striking difference between rich and constrained households is the increase in time deposits, because time deposits require households to lock money for a fixed number of months.

I also examine whether the results are driven primarily by reallocation from large banks to small banks (intensive margin) or by new accounts opened by previously unbanked people (extensive margin). Specifically, I test if my results are stronger in areas with a larger share of the banked population. I find that in the areas with a larger share of the banked population, an increase in deposits of small banks relative to large banks is stronger. In contrast, an increase in deposits of large banks is more prevalent in areas with a larger share of unbanked people. Consistent with intensive margin explanation, Liang et al. (2024) find that the number of new bank accounts increases in areas with more Pix usage.

As a final step to show that Pix increases demand for deposits of small banks by increasing small banks' payment convenience, I construct and estimate a deposit demand model and explore counterfactual scenarios, following industrial organization literature (Berry et al. (1995); Nevo (2001); Egan et al. (2017); Wang et al. (2022)). The estimates of the demand sensitivity to deposit rates suggest, first, that a one s.d. increase in Pix usage leads to a 70 b.p. additional sensitivity of deposit demand to deposit rates. This implies that deposit rates become a more important determinant of deposit demand, consistent with increased competition due to the reduction in the payment convenience gap between banks. In other words, deposit demand becomes more elastic to deposit rate changes after Pix is introduced. I also study welfare increase in a counterfactual scenario and find that Pix increases the deposit-equivalent welfare of an average Brazilian by $380.

I conduct additional robustness tests to further support the interpretation of the results. For example, I consider an alternative measure of the deposit market power to address the concern that HHI does not fully capture deposit market power. I follow Drechsler et al. (2017) and construct deposit betas of banks in Brazil, i.e., sensitivities of deposits to the policy rate changes. When the policy rate increases, banks with higher market power raise deposit rates less and hence experience an outflow of deposits. I find that deposit flow betas decline in areas with more Pix transactions, consistent with an increased market power of small banks relative to large banks. Consistent with the increased market power of small banks, I find that the profitability of small banks increases relative to that of large banks.

This paper contributes to several strands of the literature. First, I provide causal evidence on the impact of instant payments on banking and add to the literature on technology and bank competition. Several empirical and theoretical studies document that the adoption of new technologies (such as ATMs and information technologies) gives a bigger advantage to large banks, thus decreasing the intensity of bank competition (Hannan and McDowell (1990); Hauswald and Marquez (2003); Massoud et al. (2006); Kwon et al. (2021); Haendler (2022)). Other papers show that adopting technologies intensifies competition by providing small banks and FinTechs with better information (Vives and Ye (2021); He et al. (2023); Ghosh et al. (2021)).[9] I add new evidence showing that instant payment systems, when universally accessible across banks, have a persistent positive impact on deposit market competition by increasing the convenience of small bank deposits relative to large banks.

My paper relates 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); Jack and Suri (2014); Suri and Jack (2016); Riley (2018); Duffie (2019); Howell et al. (2020); Ouyang (2021); Brunnermeier et al. (2019); Aker et al. (2020); Brunnermeier and Payne (2022); Haendler (2022); Garratt et al. (2022); Brunnermeier et al. (2023); Bian et al. (2023); Wang (2023); Koont et al. (2023); Erel et al. (2023); Liang et al. (2024); Ding et al. (2025)). More specifi-

[9]More broadly, new technologies and increased convenience can intensify competition among firms and lead to an increase in bank accounts (Dupas et al. (2018); Bachas et al. (2018, 2021); Higgins (2024)).

cally, fast payment systems impact welfare and consumption (Chodorow-Reich et al. (2020); Crouzet et al. (2023); Dubey and Purnanandam (2023)). 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); Yannelis and Zhang (2023)).[10] For example, Mariani et al. (2023) use the adoption of Pix to document a growth in FinTech lending. I add to this literature by showing that cashless payments are an important facet of banking concentration since they help banks to provide convenience to their depositors.

Finally, this paper adds to the literature on bank market power and the impact of central bank policy on banks. Commercial banks have significant 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); Blickle et al. (2023); Li et al. (2023)).[11] In addition, due to the costs of switching, clients of intermediaries often stay with them despite more profitable options (Petersen and Rajan (1994); Sharpe (1997); Kiser (2002); Ioannidou and Ongena (2010); Handel (2013); Illanes (2017); Lu et al. (2024)). I show that the central bank can promote deposit market competition by introducing fast, universal payment technology, thus increasing welfare and potentially clearing the way for a more efficient monetary policy.

The rest of the paper is organized as follows. Section 2 describes the institutional setting. Section 3 describes the main data sources. Section 4 shows how deposit markets evolved after the introduction of Pix. Section 5 discusses identification challenges in the analysis, and further uses COVID-19 restrictions to identify the impact of Pix on deposit

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

[11]Deposit market power is one of the channels of the monetary transmission. Monetary policy transmits to lending and investments through various banking channels, including reserves, capital, and deposits (Bernanke and Blinder (1988); Kashyap and Stein (2000); Bolton and Freixas (2000); Drechsler et al. (2017, 2021)). Central banks can also impact banks and hence, welfare through capital and leverage regulations (Begenau (2020); Elenev et al. (2021); Acharya et al. (2022)).

market concentration in Brazil. Section 6 discusses alternative measures of market power. Section 7 presents an estimation of the deposit demand model with further counterfactual and welfare analysis. Section 8 concludes.

2 Institutional setting

Instant payments have been developing worldwide to promote faster and more efficient payments. They effectively address several frictions existing in traditional banking payments. The first is a delay in transfers – senders' and receivers' banks have to verify details for security purposes, thus increasing wait times (e.g., it takes up to three business days to withdraw money from Venmo – a private payment platform operating in the US) and working only on business days. The second is accessibility. Most banking operations can be performed either within the same bank or a group of large banks, but they cannot be performed with banks outside of their systems, thus creating additional friction for transferring money to external bank accounts. Finally, P2B (person-to-business) payments are mostly dominated by credit and debit cards that require merchants to pay fees. As a result, many merchants charge higher prices to compensate for interchange fees or only accept cash, thus forcing their customers to either keep cash in advance or withdraw it from an ATM, incurring additional costs.

Brazil's payments are subject to frictions similar to those in the US. Credit and debit card markets are mainly dominated by Visa and MasterCard, who, together with issuing banks, collect interchange fees from merchants, which are estimated to be 1% for debit cards and 2.2% for credit cards (Duarte et al. (2022)). There are cashless payments in Brazil that do not have high fees and do not require carrying cash, but such payments are restricted to clients of larger banks in Brazil. For example, the payment slip Bancário is offered by only 114 banks, which creates challenges for clients of other intermediaries and FinTech companies. Finally, traditional interbank transfers are not instant since they must be verified for security reasons. For example, it can take two business days to make a transfer from an account at the Banco do Brasil (the largest bank in Brazil as of

November 2020).

Since traditional payments in pre-pandemic Brazil were subject to frictions and bank deposits were still the dominant payment and transfer instruments, banks that were able to offer better services dominated the deposit markets. Table 1 compares large banks and small banks in terms of the services they offer. I define large banks as banks that had more than 50 million depositors as of October 2020. The two largest Brazilian banks by depositor count fall under the definition – Banco do Brasil and Caixa Econômica Federal. Both banks provide great convenience to their clients, especially since the government is a major shareholder in both.[12] Those two banks also underwent the branch expansion, making them very accessible for their clients (Fonseca and Matray (2022)). This definition also leaves my samples of large and small banks relatively balanced, with large banks controlling 41% of branches in Brazil. In Appendix D.7, I show that my main results are robust to considering other definitions (top-3, top-4, top-5, no banks where the government is the largest shareholder).

The differences between large and small banks in Brazil are significant. First, an average large bank has forty times as many regional offices and fifteen times as many ATMs as an average small bank. Such stark differences imply that depositors with frequent demand for cash withdrawals and in-person banking services would prefer a large bank to a small bank. It also indicates that large banks have locations in most of Brazil, while most of the small banks are local. Second, online services are also more advanced for the average large bank – all large banks offer digital bank applications, compared to only 61% of small banks. Large banks are also more likely to have FGV (analog of FDIC) insurance on their deposits – all large banks are FGV members, while only 81% of small banks are FGV members. In Appendix D.21, I show that my results are robust to limiting the sample to insured banks.

One distinctive feature of the Brazilian banking system is salary accounts (direct

[12]A possible concern can be that the government-owned banks would behave differently due to the introduction of Pix. If anything, the government should be incentivized to help those banks, so the effects would be anti-competitive, contrary to my findings. However, Pix was introduced by the Central Bank, whose operations are independent from the government.

Table 1: Services Offered by Large and Small Banks in Brazil

	Average large bank	Average small bank
Regional offices	2,064	52
Number of ATMs	23,550	1,763
Direct deposits	100% of banks	5.2% of banks
Online banking app	100% of banks	61% of banks
Deposit insurance	100% of banks	81% of banks
Fee to open an account	0	30.3
Fee to maintain an account	51.1	73.6
Cross-bank transfer fee	10	11.5
Withdrawal fee	2.8	3
Deposit in outside branch fee	3.2	2.2
Package of services fee	12.8	29.6

Note: This table provides a comparison along several dimensions between services offered by large and small banks. Large banks are defined as banks that had more than 50 million depositors as of October 2020. Bank fees are in BRL. Data sources are the Central Bank of Brazil, ESTBAN, FGV, and Consumer Insights Global survey.

deposits). Many Brazilian employers require a salary account to pay their employees. This distinctive feature also affects large and small banks differently, as not all banks offer salary accounts. All large banks offer such accounts, but only 5.2% of small banks offer salary accounts. As such, if a Brazilian employee is required to have a salary account but is a depositor in a small bank, she might need to make a wire transfer from a salary account to her main bank account. The same problem applies to social help (such as pensions or COVID-19 stimuli), which are usually processed through government-owned large banks. As discussed above, money transfers in Brazil are costly and take time.

I also compare the fees that large and small banks charge in Brazil. It is generally cheaper to open and maintain bank accounts at large banks (opening is free) than at small banks. Consistent with this, I find in Section 5.3 that previously unbanked households prefer to open accounts at large banks. Cross-bank transfer and withdrawal fees are also higher at small banks. The only fee that is lower at small banks is the one for depositing funds in an outside branch. Large banks charge more for this service because they have a lot of their own branches in most states in Brazil. Finally, large banks allow flexibility in bundling services and charge less for them compared to small banks. For example, households can pay one fee for maintaining multiple accounts, withdrawing and transferring between them, and depositing money.

In the summer of 2019, the Central Bank of Brazil announced Pix.[13] It took slightly more than one year to officially launch it in November 2020. Large and medium-sized banks in Brazil (with more than 500,000 accounts) are required to offer Pix – there are 36 banks of such size in Brazil. However, most banks and FinTechs in Brazil joined Pix very soon after its launch – currently, there are more than 790 participants in Pix. Joining Pix means embedding the functionality within the mobile app or a digital platform. To use Pix, the sender needs to either click the Pix button in the bank app and then choose the recipient by phone number of ID, or scan a QR code that would directly prompt to the receiver. The latter method is used at points of sale. There is also no centralized app created by the Central Bank – intermediaries embed Pix in their own apps. However, there are third-party platforms (such as OpenPix) that allow users to use Pix by linking their bank accounts. This is useful, for example, for the banks that do not have a good mobile app.

It is also important to note that using Pix generates costs for banks, but the costs are quite small. According to the governor of the Central Bank, Roberto Campos Neto, the costs of Pix are estimated to be around 10 million USD per year.[14] This means that running the system is relatively inexpensive. The Central Bank covers around 40% of the

[13]The launch date was also announced then, so the development of Pix was not caused by the COVID-19 pandemic.
[14]See here.

cost, while the rest is covered by the banks. The fees also do not depend on the size of the bank, but they depend on a number of transactions.[15] The costs are 0.01 BRL for 10 transactions. If the bank settles a million transactions, the cost will be just 1000 BRL, which is very little for any bank, even a very small one. The costs are so low primarily because 790 participants cover just 6 million BRL annually. Since 36 banks were required to join, the per-bank fees were already quite low, and small banks faced low entry costs.

As of January 2024, more than 155 million Brazilians use Pix for transactions (nearly 70% of the population). The adoption was likely facilitated by the developing FinTech state in Brazil and an overall decline in usage of physical branches (Mariani et al. (2023)). Since then, Pix has dominated all retail payments in Brazil (see Figure 1). To transact money with Pix, users must have an active bank account. The settlement is fast because each user has a unique key regardless of the bank account. The procedure is quite similar to Venmo, except there is no intermediary between sender and receiver – funds become available at the receiver's bank account within seconds, even beyond business days. Pix is also more convenient than Boleto Bancário, which requires one to collect (either physically or electronically) a receipt and then scan the code in the mobile banking app and wait for verification. Merchants can also use Pix if their accounts are opened at the participating bank. Then, merchants offer their customers the option to scan a QR code to pay.

Another feature of the Brazilian markets is a huge underground economy, which is about 20% of the Brazilian GDP. Prior to Pix, the underground economy was heavily cash-dependent, mostly for tax evasion and technology access concerns. Pix is currently widely accepted by merchants in the underground economy, thus giving Brazilians more cashless options to make retail payments.

[15] See the report that discusses the fees.

3 Data

I use the adoption of Pix in Brazil as a setting to study how instant payments impact the banking landscape. I 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, and the number of users. I can then calculate per capita and per-user transactions for all 5,570 municipalities.[16] Pix data starts in November 2020 (the month Pix was launched). The Pix variable is only defined starting in November 2020. To include pre-period (and hence, controls at the time), I set the value of Pix to be equal to 0 before November 2020. This is then similar to running difference-in-differences where the independent variable varies over time. In Appendix D.28, I run more standard difference-in-differences where the Pix value is either fixed in November or averaged across several months.

I collect monthly balance sheet data for bank municipality offices operating in Brazil from ESTBAN.[17] The data covers 313 banks from August 1988 till November 2022 (119 banks from January 2020 till November 2022). The data includes bank identifiers (cnpj) and balance sheet data – deposits by type, loans, financing, cash positions, reserves, interbank loans, etc. I only include commercial banks in the sample and not credit unions, payment companies, or FinTechs because ESTBAN mostly covers commercial banks with physical branches, so information on credit unions, payment companies, and non-bank FinTechs is limited. Mariani et al. (2023) document a growth in FinTech lending after the launch of Pix. Data also contains municipalities where branches operate, which allows me to calculate deposit market concentrations (Herfindahl-Hirschman index or HHI) for municipality m at time t as follows using private deposits for each bank i in a

[16] An average municipality in Brazil has a population of just 37,738 as of 2019, so the unit is quite small. The largest municipality in Brazil is Sao Paolo with population of 11.45 million, while the smallest one is Serra da Saudade with 854 people.

[17] An example of an observation is Banco do Brasil had $R 2 million in Rio de Janeiro in January of 2014. ESTBAN also has branch-level data (municipalities usually have multiple branches of the same bank). Although my results are robust to using branch-level data, I choose to use the municipality office one because of the quality of branch-level data and misreporting (Fonseca and Matray (2022)).

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. In Appendix D.6, I show that the results are robust to measuring HHI using checking, saving, and time deposits separately. HHI might not fully reflect banks' market power. That is why I also test changes in the sensitivities of deposits to policy rate changes in robustness tests. I supplement the data with a bank-level series of interest rates from the Central Bank of Brazil. Specifically, I collect quarterly data on interest expenses to use them as proxies for deposit rates and monthly public and private payroll personal loan rates.

I collect data on capital investments and total savings from *O Instituto de Pesquisa Econômica Aplicada* (IPEA) – a source of economic data from Brazil. Data are annual and available at the municipality level from 1990 to the present. I collect annual data on the GDP of each municipality from *Instituto Brasileiro de Geografia e Estatística* (IBGE). Finally, I gather macroeconomic data on inflation, unemployment, economic growth, and exchange rates from the Central Bank of Brazil.

I supplement economic data with demographic data from the 2010 Census, maintained by IBGE. Specifically, for each municipality, I observe the population, percent of educated and unemployed, gender and race statistics, measures of the conservatism of the family, percent of banked population, and level of income. I also observe the status of the municipality, i.e., whether it is a capital or not. For example, the municipality of Curitiba is the capital of the state of Paraná. I provide a complete description of data definitions and sources in Appendix B.

Table 2 shows summary statistics. Panel A provides statistics for Pix usage depending on the status of the municipality. Pix is used significantly more in the capitals. However, the per-person value of transactions is only twice as large in the capitals as in the rest of the country. Panel C shows the main differences between municipalities. There is a striking difference in deposit market concentration across municipalities – deposit markets in peripheral areas are significantly more concentrated than in the capitals. Generally, deposit markets in Brazil are concentrated, with, on average, one to two banks per municipality. At the same time, GDP per capita does not vary considerably across types of municipalities.

Table 3 provides statistics on banks (aggregated from the branch-bank-level data) separately for large and small banks for two months before the Pix launch and after. I define large banks as intermediaries with more than 50 million depositors. Large banks own 35% of total assets in the economy and around 41% of branches. Checking, time, and saving deposits increase in both groups of banks, but the increase is relatively larger for smaller banks.[18] Note that neither small nor large banks change their deposit composition significantly, implying increases in all types of deposits. On the asset side, small banks increase their loans, whereas large banks increase loans but reduce financing (includes low-interest-bearing safe credit, such as agricultural and real estate loans).

I also plot deposits and assets of large and small banks in Figure 2, respectively. Total deposits of small banks increased relative to large banks after November 2020. The graphs alone do not allow for cross-sectional implications or to draw statements about the impact of Pix on deposit concentration, especially around the COVID-19 pandemic. For example, deposits of small banks were rising even before the introduction of Pix, so there are potential confounders.

4 Impact of instant payments on deposit markets

Instant payment systems facilitate transactions by mitigating payment and transfer frictions. Most banks also adopt them because entry costs are low. I thus hypothesize that adoption of Pix in Brazil changes the banking landscape – namely, deposit market concentration, deposits, interest rates, and loans. I test the hypotheses in this section.

[18] Small banks have, on average, more saving deposits than checking deposits in real value but less in percents of total deposits. This is because most small banks do not have any saving deposits but some of them have very large amounts of saving deposits, so the mean is skewed.

Table 2: Summary Statistics: Municipalities

	All municipalities		Capitals		Non-capitals	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Panel A: Pix data (Banco Central do Brasil)						
Total transaction value (mill. R$)	65	628	2,939	5,927	40	143
Total transactions (th.)	101	1,043	4,792	9,961	60	207
Value per person (th. R$)	0.62	0.95	1.39	1.01	0.61	0.95
Panel B: Investments and savings (IPEA)						
Capital investments (mill. R$)	66	346	1,919	3,114	51	119
Personal savings (mill. R$)	0.81	7.35	39	68	0.47	1.29
Panel C: Municipality characteristics (IBGE)						
Population (th.)	62	297	1,886	2,451	46	88
% under 40 y.o.	57	4.8	60	4.1	57	4.8
% females	50	1.5	52	1.2	50	1.5
% single responsible	71	8.1	66	3.2	71	8.1
% rural	28	20	1.9	2.6	28	20
% illiterate	14	9.5	5.1	2.5	14	9.5
GDP per capita (th. R$)	32	30	36	16	31	30
Deposit HHI	0.63	0.31	0.06	0.06	0.63	0.31
Panel D: Macro data (Banco Central do Brasil)						
Inflation (%)	6.63	1.91				
Unemployment (%)	14.3	0.52				
USD exchange rate (R$)	5.31	0.2				

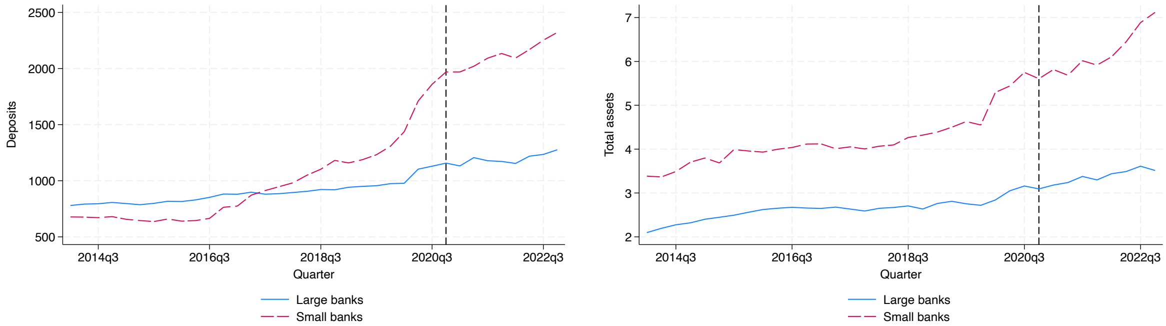
Note: This table provides descriptive statistics for the data used in the main analysis of the paper. Panel A shows statistics for Pix data. Panel B provides means and standard deviations for investments and savings. Panel C shows demographic and economic data for municipalities. Panel D provides macro data. Finally, Panel E contains branch characteristics. The table splits the sample of municipalities by their status – columns 3 and 4 contain statistics for the capitals, and columns 5 and 6 contain statistics for other municipalities.

Table 3: Summary Statistics: Banks

	Large banks			Small banks		
	Mean	Median	Std. dev.	Mean	Median	Std. dev.
Panel A: Before Pix launch (ESTBAN)						
Checking deposits (bn. R$)	21.1	21	5.5	0.39	0.09	1
Saving deposits (bn. R$)	117.3	117.3	21.7	1.3	0	6
Time deposits (bn. R$)	35.1	34.4	7.6	3.4	1.1	8.1
Total loans (bn. R$)	58.5	58.7	11.6	2.2	0.6	4.3
Total financing (bn. R$)	5.5	5.5	5.1	0.8	0.08	2.3
Total assets (bn. R$)	537.6	536.9	144.6	8.9	0.85	32.2
Checking deposits (% in total)	12	12	3.3	23	8.1	33
Saving deposits (% in total)	67	67	9.2	6.2	0	18
Time deposits (% in total)	20	20	5.4	71	90	35
Branches		7,741			11,136	
Panel B: After Pix launch (ESTBAN)						
Checking deposits (bn. R$)	22.5	22.9	6.8	0.42	0.09	1.2
Saving deposits (bn. R$)	120.3	120.4	22.2	1.4	0	6.3
Time deposits (bn. R$)	35.9	36.2	9.5	3.6	1.1	8.7
Total loans (bn. R$)	61.5	61.8	11.5	2.5	0.7	4.5
Total financing (bn. R$)	5.5	5.5	5.1	0.8	0.06	2.3
Total assets (bn. R$)	574.1	559.2	175.5	9.2	0.85	33.8
Checking deposits (% in total)	13	13	3.2	23	7.2	32
Saving deposits (% in total)	67	67	10	6.2	0	18
Time deposits (% in total)	20	20	6	71	88	35
Branches		7,741			10,903	

Note: This table provides descriptive statistics for the bank data used in the main analysis of the paper. Panel A shows statistics for September and October of 2020. Panel B provides means, medians, and standard deviations for November and December 2020. The table splits the sample of banks into large and small. Large banks are defined as intermediaries with more than 50 million depositors. The numbers sum up across branches with available balance sheet data and do not include branches without available data. I provide bank-level summary statistics sourced from the bank-level IF data in Appendix D.1.

Figure 2: Deposits and Assets of Large and Small Banks in Brazil



(a) Deposits

(b) Assets

Note: Data is from the IF. The graph plots the deposits (panel (a)) and total assets (panel (b)) of Brazilian banks separately for large and small banks from March 2014 to December 2022. The vertical black line corresponds to November 2020, when Pix was launched. All values are in billion Brazilian Reals for deposits and in trillions for assets (the exchange rate as of January 2023 is 0.19 USD per 1 BRL).

4.1 Pix and bank deposits

Commercial banks have significant deposit market power, which allows them to set low rates, especially in counties where they do not face high competition (Drechsler et al. (2017)). However, location is not the only source of deposit market power – another determinant is the products and convenience that banks offer. For example, if JP Morgan Chase is the only bank in Philadelphia that offers online banking, it can afford to pay lower deposit rates than its competitors. That is why large banks set lower deposit rates than small banks – partly because they offer greater convenience (D'Avernas et al. (2023)).

The introduction of instant payment systems should impact deposit market concentration because it is a product delivered through banks, so it changes the convenience gap between large and small banks. Then, how participants are selected is important. If large banks create IPS, so small banks cannot deliver it, large banks will probably gain even more market share (I discuss this more in Appendices D.11 and D.13 where I analyze the impact of Boleto and Swish in Sweden on deposit markets). However, suppose a centralized agency designs IPS, and all banks in the economy have access to it. In that case, the convenience gap decreases, thus creating competition between large banks and smaller banks. It is also important to know whether joining IPS is a choice or mandatory. The Central Bank of Brazil required large and medium-sized banks to join the system and also set low entry costs for smaller banks. Then, most banks in Brazil joined the system from the launch date, so potential identification problems related to selection bias are mitigated.

Based on the above, I hypothesize that the launch of Pix reduced deposit market concentration in Brazil despite the fact that large banks usually adopt payment technologies faster than small banks and despite the fact that the deposit demand is very inelastic. In other words, I aim to show that Pix leads to a relative inflow of deposits of small banks.

Before showing the main identified results of the paper (Section 5), I provide evidence that the usage of Pix is associated with the rise in deposits of small banks. I limit the sample to start in September 2020 and end in December 2021.[19] I then construct a measure of deposit market power – HHI defined in equation (1). I normalize HHI and log of Pix value of transactions to use them in interaction terms. The regression specification is

$$\log D_{imt} = \delta \cdot \log Pix_{mt} \cdot S_i + \gamma X_{imt} + \theta_t + \alpha_i + \eta_{mt} + \varepsilon_{imt} \tag{2}$$

where D_{imt} are deposits of bank i in municipality m at time t, Pix_{mt} are the value of Pix transactions in municipality m at time t after November 2020 and 0 before November 2020, S_i is an indicator equal to 1 for small banks that I define as banks having less than 50 million depositors, X_{imt} is a vector of controls, θ_t and α_i are time and bank fixed effects, η_{mt} are municipality-time fixed effects. Control variables are: all relevant interaction terms, log of total assets (or log of loans to address a pre-trend concern described below), population, urban area share, share of males, share of young people (several thresholds), share of illiterate people, share of families with a single responsible person, income per capita (and municipality-level GDP per capita), inflation, unemployment, and number of

[19] In Appendix D.27, I show that my results are robust to using a longer sample period that starts in August 2020 and ends in January 2021.

Table 4: Impact of Pix on Bank Deposits

$$\log D_{imt} = \delta \cdot \log Pix_{mt} \cdot S_i + \gamma X_{imt} + \theta_t + \alpha_i + \eta_{mt} + \varepsilon_{imt}$$

	Dependent variable:		
	Checking deposits	Saving deposits	Time deposits
	(1)	(2)	(3)
Pix · Small	0.030***	0.032***	0.043***
	(0.005)	(0.005)	(0.006)
Bank FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Muni × Time FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	32,097	32,097	32,097
R^2	0.882	0.961	0.923

Note: This table provides results of estimation of equation (2). The first column corresponds to checking deposits. Column 2 shows results for saving deposits. Column 3 corresponds to time deposits. Standard errors are clustered at the municipality level and displayed in parentheses. Bank, time, and municipality-time fixed effects are included. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

accounts. I show robustness to excluding controls and fixed effects by running more than 25 thousand various specifications in Appendix D.25.

Column 1 of Table 4 shows the results. The increase in Pix usage is significantly associated with an increase in checking deposits of small banks relative to the deposits of large banks. Specifically, a one s.d. increase in the value of Pix transactions (roughly 100% rise) is associated with a 3% increase in deposits of small banks relative to large banks.

Checking deposits are directly impacted by Pix because to transact money with Pix, clients must use their checking accounts. I then check if Pix significantly impacts saving and time deposit composition by estimating (2) for saving and time deposits. Columns 2-3 of Table 4 contains the results. I find that a doubling (approximately one s.d. increase in Pix) of Pix transactions is associated with an increase in saving deposits of small banks by 3.2% more than in saving deposits of large banks. Time deposits of small banks increase by 4.3% more than time deposits of large banks.

The intuition behind an increase in time deposits is as follows. Time deposits of small banks pay higher interest rates than time deposits of large banks. However, depositors, on average, prefer accounts in large banks since they provide better payment convenience. When Pix is introduced, small banks' payment convenience increases, so having a time account at a small bank does not incur large convenience costs; hence, households increase their demand for time deposits. Saving deposits also pay interest rates in Brazil but they are regulated by the government, and banks are not allowed to pay saving rates that are different from the regulated one (called *poupança*). In other words, large and small banks pay the same rate on their saving deposits.

I discuss the mechanisms in the next section, but to briefly outline them, I argue that the results are driven by an increased convenience of small banks relative to large banks. Specifically, I show that the effects are mostly concentrated in highly-banked and high-income areas, which is consistent with households moving from large banks to small banks, rather than opening new accounts.

Importantly, an increase in deposits of small banks does not have to happen inside the municipality. Pix reduces barriers to opening accounts in different municipalities. This is relevant if, for example, a neighboring municipality has a bank with better interest rates. I show in Appendix D.12 that areas with more cross-border Pix usage had a growth in deposits of small banks. I argue that most of the movement happens in urban areas, and there are no effects for areas that had travel restrictions in place.

In Table 4, standard errors are clustered at the municipality level to account for potential correlation between the residuals within the same municipality (Petersen (2009); Abadie et al. (2022)). The correlation between the residuals across municipalities is also possible, and it would require clustering standard errors at the time level. Since my sample in the regressions includes only two months before and two months after the launch of Pix, clusterization can bias standard errors (Bertrand et al. (2004)). In Appendix D.22, I follow Bertrand et al. (2004) and bootstrap standard errors. I also include municipality-time fixed effects to account for regional unobservables.

The results in Table 4 include the sample of 119 banks during the analyzed period. Account holders at most of those banks can use Pix but not always through the banks' mobile app directly. 64 out of 119 banks allow to use Pix directly through their apps and they are listed as Pix participants on the Central Bank's website. Appendix D.31 shows that the main results hold in the sample of banks that directly participate in Pix.

4.2 Pix and deposit market concentration

Next, I test if Pix is correlated with my main measure of deposit concentration – Herfindahl-Hirschman index. To test this, I run the following regressions:

$$HHI_{m,t+s} = \theta PixPerCap_{mt} + \gamma X_{mt} + \varepsilon_{mt} \tag{3}$$

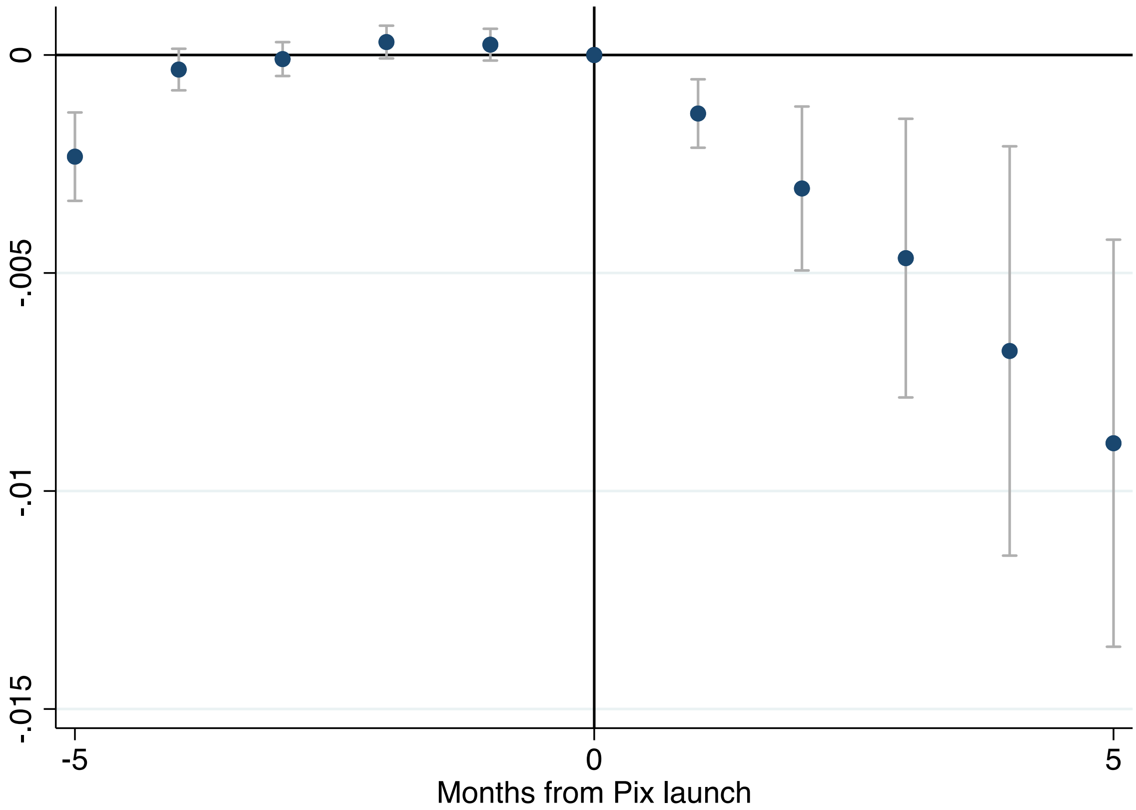
where I consider different values of s – from five months before to five months after t. $PixPerCap_{mt}$ is Pix transactions per person in municipality m at month t (equal to 0 before November 2020). Controls include economic and demographic variables. I use Pix per capita instead of the log value to have more comparable independent and dependent variables and for more intuitive interpretations. The main results are robust to using log Pix, Pix value per capita, or Pix quantity per capita, as I show in Appendix D.26.

Figure 3 presents the results and pre-trends. There is a significant and persistent decline in deposit market concentration in Brazil after the introduction of Pix. The drop is small in the first few months but becomes sizable afterward. The results are consistent with findings in Table 4 and suggest that deposit markets became more competitive after Pix was launched, possibly because households deposited relatively more at smaller banks than at larger banks. In Appendix D.5, I also show that the change in market concentration is associated with flows of deposits within the banking sector rather than with openings of new branches.

One concern is that HHI does not fully capture sources of banks' market power. For example, payment convenience, online banking, and other factors can provide large banks

Figure 3: Impact of Pix on Deposit Market Concentration

$$HHI_{m,t+s} = \theta PixPerCap_{mt} + \delta HHI_{m,t-1} + \gamma X_{mt} + \varepsilon_{mt}$$



Note: This figure plots results of estimation of equation (3). The vertical axis corresponds to θ – sensitivity of future deposit market concentration to per capita Pix transactions. The horizontal axis corresponds to months since t. t moves from November to December. In Appendix D.28, I fix Pix per capita to either its November value or the average between November and December. Blue dots are coefficients, whereas grey lines are 95% confidence intervals constructed by clusterization on the municipality level.

with market power even in non-concentrated markets (Drechsler et al. (2017)). In Section 6, I use deposit flow betas as a measure of market power and show that my main results hold – small banks gain significant deposit market power relative to large banks in areas with more Pix usage. In Appendix D.4, I also document an increase in profitability of small banks relative to large banks, consistent with an increased market power of small banks.

4.3 Pix and interest rates

To better address how banks choose their rates after the Pix launch, I check how deposit rates changed. Large banks in Brazil generally pay lower deposit rates since they can attract deposits through payment or service convenience.[20] Small banks, in contrast, have to pay higher deposit rates to attract clients. I collect data on interest expense from the Central Bank of Brazil and compute proxies for deposit rates in two ways. First, I divide interest expense by total deposits to capture how much banks spend on interest payments per dollar of deposits. Second, I use time deposits as a denominator, because banks are generally not allowed to pay interest above or below the regulated rate on saving and checking accounts; hence, most of the cross-sectional variation in interest rate expense comes from time deposits. The Central Bank does not provide deposit rates for each municipality office, but conversations with bankers in Brazil confirm that, unlike in the US, banks in Brazil do not base their time deposit rates on the location. In other words, they follow a uniform pricing. Hence, I follow D'Avernas et al. (2023) and run municipality-level regressions by assuming that the deposit rates of bank i and time t are the same in all areas. In Appendix D.8, I aggregate the Pix variable to the bank level and show that bank-level regressions yield similar (even larger) results. I estimate the following regression:

$$r_{imt} = \delta \cdot \log Pix_{mt} \cdot S_i + \gamma X_{imt} + \theta_t + \alpha_i + o_{imt} \tag{4}$$

[20]Figure A.4 in Appendix shows that the net interest margin in Brazil has been stable, also indicating significant deposit franchise value of Brazilian banks.

where r_{imt} is a deposit rate of bank i at time t in municipality m.

Table 5 shows the results. Following the introduction of Pix, small banks reduce their deposit rates relative to large banks. Specifically, a one standard deviation increase in the value of Pix transaction is associated with a 14 b.p. decline in deposit rates of small banks relative to large banks. The finding is consistent with the hypothesis that the deposit markets in Brazil became more competitive after Pix – small banks can afford to pay lower rates to attract depositors. Columns 3 and 4 consider two types of personal loans in Brazil – public and private payroll loans. I show that loan rates of small banks also decline relative to large banks. One of the channels driving a reduction in loan rates of small banks can be changes to the funding costs – small banks' costs of financing loans (time deposits) decline. In Appendix D.4, I also document that small banks become more profitable relative to large banks. In Appendix D.8, I run bank-level regressions by averaging Pix across banks and show that the results are robust.

4.4 Pix and bank lending

Pix adoption is associated with an increase in bank deposits, especially for smaller banks. In Brazil, deposits are the main funding source for banks to lend to companies and households. Banks in Brazil can originate two types of loans – traditional loans and financing. Traditional loans pay higher interest and originate without a specific purpose, whereas financing is usually provided for a predetermined purpose, and its interest rate is lower. In other words, financing is generally safer but less profitable, so banks make their profits mainly on loans while incurring risks.

Since Pix adoption is associated with an inflow of deposits (especially time deposits), it should also correlate with lending and financing. Although ESTBAN contains data at municipality-level lending by banks (depending on the place of origination), raised deposits are fungible across banks' internal capital markets (Drechsler et al. (2017)), so lending decisions tend to be jointly optimized at the bank-level. I thus follow Drechsler et al. (2017) and construct bank-level versions of municipality-level variables (Pix, HHI, and

Table 5: Impact of Pix on Deposit and Loan Rates

$$IntRate_{imt} = \delta \cdot \log Pix_{mt} \cdot S_i + \gamma X_{imt} + \theta_t + \alpha_i + o_{imt}$$

	Dependent variable:			
	Deposit rates		Public loans	Private loans
	(1)	(2)	(3)	(4)
Pix	−0.289	−0.352	0.021***	−0.000
	(0.188)	(0.267)	(0.003)	(0.005)
Pix · Small	−0.137***	−0.137***	−0.047***	−0.016***
	(0.010)	(0.017)	(0.000)	(0.001)
Denominator	All deposits	Time deposits	–	–
Bank FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	18,247	18,196	35,256	34,805
R^2	0.122	0.963	0.932	0.974

Note: This table provides results of estimation of the effect of Pix on deposit rates and personal loan rates – equation (4). Column 1 shows results for deposit rates computed as an interest expense divided by total deposits, while Column 2 uses time deposits as a denominator. Column 3 corresponds to public payroll loans. Column 4 represents private payroll loans. Standard errors are clustered at the municipality level and displayed in parentheses. Bank and time fixed effects are included. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

instruments that I use in Section 5) by taking weighted averages across bank branches.[21] I use time deposits as weights. I run the following bank-level regressions:

$$\log Y_{it} = \delta \cdot \log Pix_{it} \cdot S_i + \gamma X_{it} + \theta_t + \alpha_i + o_{it} \tag{5}$$

where Y_{it} are either loans or financing of bank i at month t and Pix_{it} is a bank-level measure of Pix transactions (equal to 0 before November 2020). I source bank-level loans from the IF – quarterly bank reports. Control variables include deposits and fixed effects.

Columns 1 and 2 of Table 6 present the results. Surprisingly, large banks do not lend less than small banks[22] but originate less financing due to several potential reasons. First,

[21] I show branch-level results in Appendix D.10.

[22] Identified results in Section 5 show that small banks increase loans relative to large banks, but the increase does not fully capture inflows of deposits.

Table 6: Impact of Pix on Loans, Financing, and Alternative Funds

$$\log Y_{it} = \delta \cdot \log Pix_{it} \cdot S_i + \gamma X_{it} + \theta_t + \alpha_i + o_{it}$$

	Dependent variable:		
	Loans	Financing	Alternative funding
	(1)	(2)	(3)
Pix	−0.456	−1.074	0.533
	(0.450)	(0.685)	(0.692)
Pix · Small	0.057	0.102**	−0.164
	(0.039)	(0.0504)	(0.139)
Bank FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	176	534	176
R^2	0.989	0.992	0.990

Note: This table provides results of estimation of equation (5). The regressions are bank-level, so all municipality-level variables are aggregated using time deposits as weights. Column 1 shows results for traditional loans. Column 2 shows results for financing. Column 3 presents results for reserves. Loans and alternative funds are sourced from the quarterly bank-level data, so the number of observations is smaller. Standard errors are clustered at the bank level and displayed in parentheses. Bank and time fixed effects are included. *,**, and *** correspond to 10-, 5-, and 1% significance level, respectively.

large banks have more stable lending relationships and access to secondary markets, which allows them to lend more in general if they have additional funds. Second, they switch from financing to loans to increase their interest gains. Finally, large banks can change the composition of funds used for lending. Retail deposits are insured, which makes them the safest and most reliable source of financing (Whited et al. (2022)). Although large banks lose retail deposits relative to smaller banks, they still do not cut relative lending. Therefore, it is possible that they increase alternative sources of financing.

Column 3 of Table 6 presents the result of the estimation of the effect of Pix on alternative sources of financing. Alternative sources of financing include net interbank borrowing, payment orders, checks, net foreign positions, etc. Naturally, large banks have better access to such funds and use them to finance loans. The results reveal that, indeed, large banks increase alternative funding after the introduction of Pix (the coefficient is not statistically significant, but it is large). The evidence suggests that larger banks are still able to finance their loans as before because they switch financing. However, retail deposit financing is the safest since deposits are insured. In other words, large banks choose riskier and less stable funding after the Pix launch, consistent with seemingly riskier loan portfolios (i.e., more loans and less financing). Appendix D.3 shows that stock returns of large banks drop in the one-month window around Pix introduction, potentially reflecting that large banks became more prone to runs.

Evidence in this section shows that the launch of Pix potentially affects small and large banks differently: it is associated with an increase in checking, saving, and time deposits of smaller banks relative to larger banks. Moreover, deposit market concentration declines steadily over the next five months following the launch of Pix. Since deposit markets become more competitive, I also find a reduction in deposit rates of small banks relative to large banks. The results so far are subject to identification concerns. In the next section, I argue that the positive effect of Pix on deposit market competition is causal.

5 Identification using COVID-19 restrictions

The OLS results suggest that the introduction of Pix is associated with a positive and lasting increase in deposit market competition. However, there are identification concerns that prevent us from treating the results in the previous section as causal. In this section, I use instrumental variables to estimate the effect of Pix on deposits and local deposit market concentration.

5.1 Identification challenge

I first set up the problem through the lens of a simultaneous equation problem following Rigobon and Sack (2004). For notational simplicity, I drop control variables and fixed effects from equations in the text, but I include them in empirical tests. I describe the equations and identification strategy for HHI, but the same sets of equations apply to deposits. The model is

$$Pix_{mt} = \delta HHI_{mt} + \gamma_P F_{mt} + u_{mt} \tag{6}$$

$$HHI_{mt} = \alpha Pix_{mt} + \gamma F_{mt} + \varepsilon_{mt} \tag{7}$$

where F_{mt} is an unobservable single factor that moves both Pix and HHI. u_{mt} and ε_{mt} are uncorrelated shocks to Pix and HHI, respectively.

I have already shown (see Figure 3) that Pix usage is associated with changes to HHI. In other words, α in (7) is significant. However, δ in (6) can also be significant due to the reverse causality concerns. For example, rolling out Pix in areas with many banks can be easier.

The second source of bias is illustrated by the equations (6)-(7) themselves. They include an unobserved factor F_{mt}, thus creating an omitted variable bias. For example, a more reliable business environment in the municipality can promote more banking competition and, at the same time, more spending. Since Pix dominates retail payment markets in Brazil, Pix transactions should be larger in such municipalities. Another example is the effect of the COVID-19 pandemic – the development of Pix took place during the active phase of the pandemic, when regional banks also provided loans to local businesses, thus creating a bias.

5.2 Identification strategy

I exploit an instrumental variable approach to estimate the causal effect of Pix on bank deposits and market power. Specifically, I use municipality-level data on COVID-19 restrictions in Brazil that are constructed by de Souza Santos et al. (2021) in collaboration with the Brazilian Confederation of Municipalities. After the first wave of COVID, during the summer of 2020, many municipalities in Brazil decided to lift COVID restrictions. To understand which municipalities relaxed COVID restrictions, the Brazilian government conducted a survey in September, asking each mayor if the restrictions in their municipality were relaxed. The second wave of COVID started in October 2020, so the state of severe COVID restrictions likely stayed the same as in September until the second wave of COVID was over.

The authors surveyed mayors of most Brazilian municipalities and collected information about types of restrictions and their easing. I use the easing of COVID-19 restrictions prior to the introduction of Pix to instrument for Pix usage in the analysis.[23] I denote municipalities that eased COVID restrictions by September 2020 as *treated* and those that did not as *control*. I show summary statistics separately for the two groups of municipalities in Appendix D.14. Demographic and economic indicators are fairly similar across the two groups, but there can still be differences in unobservables. For example, the treatment group might have more conservative political views, lower mortality, or younger people.[24] Such differences do not violate the identifying assumptions as long as they do not impact the demand for deposits of small banks in November 2020, when Pix was launched. Note that simply the fact that unobservables make deposits in treated areas larger does not violate identifying assumptions – if unobservables move deposits exactly when Pix is rising (November 2020), then there is a violation of identifying assumptions.

The key identifying assumption is that shocks u_{mt} in (6) are easings of COVID restrictions. In other words, two conditions must be satisfied to make causal statements – relevance condition, i.e., easing of COVID-19 restrictions should increase usage of Pix, and exclusion restriction, i.e., easing COVID restrictions can affect deposits of small banks relative to large banks only through their impact on Pix. The relevance condition is likely satisfied because Pix dominates the retail payment market, and the easing of COVID restrictions allows households to spend more (for example, they can freely go to restaurants), and hence, they should increase Pix transactions. Another argument in favor of the relevance condition is that Pix is used most for in-person payments, where

[23] To remove municipalities that never imposed COVID restrictions, I drop municipalities without mask mandates in place as of May 2020. Such municipalities comprise less than 5% of the sample.

[24] I shoc in Appendix D.30 that political views, mortality and age did not drive the easing of COVID restrictions and did not impact the usage of Pix.

merchants are likely to give discounts for Pix payments and for transfers. Both types of transactions are more prevalent when COVID restrictions are relaxed. My first-stage specification is

$$\log Pix_{mt} = \alpha Eased_m + \theta Pix_t + \gamma Eased_m Pix_t + \theta X_{mt} + \theta_t + v_m + \varepsilon_{mt} \tag{8}$$

where the vector of controls is the same as in OLS regressions (defined above)[25]

Table 7 provides the results of the first-stage regression estimation. Note that for the specification where I interact with the small bank dummy, I instrument both the Pix variable and an interaction of Pix with the dummy. The easing of COVID-19 restrictions by September 2020 has a strong positive impact on the use of Pix after its introduction. Specifically, in the areas without COVID restrictions the use of Pix is higher by 35.7%, which is both statistically and economically significant, suggesting that the instrument is relevant. Note that the regression coefficients are similar across specifications, and R^2s are very high even without fixed effects. This is because the *Post* variable has high predictability, as Pix equals 0 when $Post = 0$. It is important to note that the relevance is impacted by the timing – Pix was introduced two months after the initial restrictions were relaxed. I do not find strong increase in the use of Pix after most of the rest of the municipalities relax COVID restrictions in Spring of 2021 following the launch of the vaccine, as I show in Appendix D.17.

The exclusion restriction implies that COVID restrictions can affect deposit market concentration changes from October 2020 to November 2020 only through their impact on Pix usage. COVID restrictions are eased by September 2020, and hence, the exclusion restriction can be violated if the treatment has a two-month delayed impact on deposit market concentration. One concern might be the COVID stimulus; however, it was paid mainly through two large banks in Brazil – Caixa Economica and Banco do Brasil –

[25]When I include a small bank dummy in the regressions, I also interact variables in (8) with the dummy for a small bank to include municipality-time fixed effects. In Appendix D.20, I show the results without municipality-time fixed effects, where the variables in the first stage are not interacted with a small bank dummy.

Table 7: Impact of the Easing of COVID-19 Restrictions on Pix

$$\log Pix_{mt} = \alpha Eased_m + \theta Pix_t + \gamma Eased_m Pix_t + \theta X_{mt} + \theta_t + v_m + \varepsilon_{mt}$$

	Dependent variable:			
	Pix			
	(1)	(2)	(3)	(4)
Eased	-0.131^{***}	-0.131^{***}		
	(0.027)	(0.027)		
Post Pix	13.750^{***}		13.750^{***}	
	(0.037)		(0.041)	
Eased · Post Pix	0.357^{***}	0.357^{***}	0.357^{***}	0.357^{***}
	(0.045)	(0.045)	(0.050)	(0.050)
Municipality FE	No	No	Yes	Yes
Time FE	No	Yes	No	Yes
Controls	Yes	Yes	Yes	Yes
Observations	7,124	7,124	7,122	7,122
R^2	0.984	0.984	0.986	0.986

Note: This table provides results of the first stage in the IV estimation. $Eased_m = 1$ for municipalities that eased COVID-19 restrictions by September 2020. $Pix_t = 1$ for November 2020. Columns 2-3 include time and/or municipality fixed effects. Robust standard errors are displayed in parentheses. *,**, and *** correspond to 10-, 5-, and 1% significance level, respectively. Regression coefficients are similar across specifications and R^2s are very high even without fixed effects, because the Post variable has high predictability, since Pix is equal to 0 for $Post = 0$.

which are both in the sample of large banks (hence, if anything, the COVID stimulus would understate my results).[26] In Appendix D.19, I run an event study around COVID stimulus payments to show that there was no significant increase in deposits of small banks in high-Pix areas. The limitation of the approach is an implicit assumption that COVID restrictions did not change from September to November, but since COVID cases were rising at the time, municipalities likely imposed more restrictions, which should understate my findings. I conduct several tests to demonstrate that initial COVID-19 restrictions did not have a significant impact on deposits in the Appendix. I also show in Appendix D.14 that two groups of municipalities are not very different in observables.

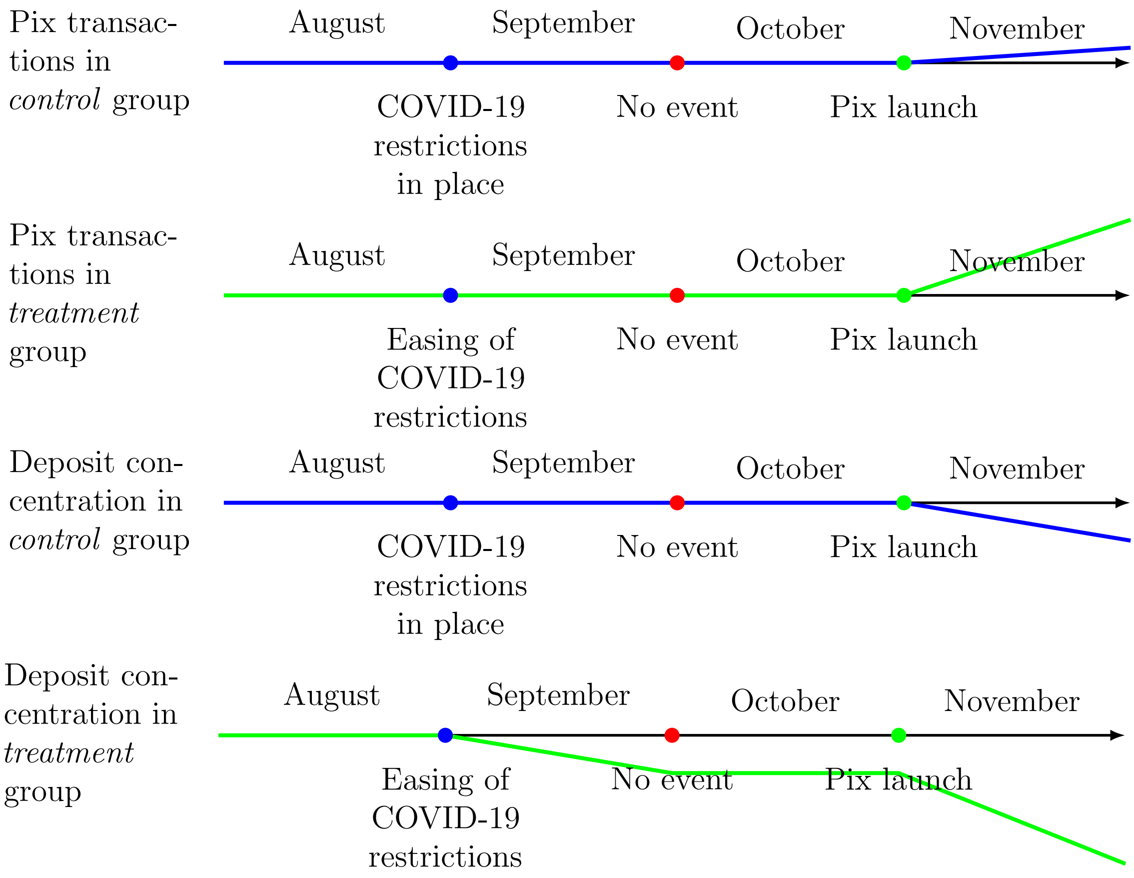
[26]Both banks were also involved in a credit expansion program in 2011 (Garber et al. (2024)), but the program was shut down shortly after 2014.

To better illustrate the timing of the events, I plot the timeline of the easing of COVID-19 restrictions and the subsequent introduction of Pix. Blue lines correspond to the control group – the group of municipalities that did not ease COVID-19 restrictions by September 2020 (the month of the survey). Green lines correspond to the treatment group – the group of municipalities that eased COVID-19 restrictions by September 2020. The first two lines plot Pix transactions, and the other two lines – deposit concentration. The relevance condition graph shows that Pix did not exist before November 2020, so the easing of COVID-19 restrictions had an effect on Pix only in November – the month when Pix was introduced. The effect is larger for the treatment group. The exclusion restriction shows that the easing of COVID-19 restrictions can impact deposit concentration directly without violating the identifying assumption as long as the effect is *immediate*, i.e., happens in September 2020. If there is no delayed impact of the easing of COVID-19 restrictions on deposit market concentration, the trends in October are parallel, and the only way the easing of COVID-19 restrictions can impact deposit concentration is the introduction of Pix.

A possible identification concern is that the areas that decided to relax COVID restrictions are fundamentally different from the areas that kept the restrictions in place. I address the concern in several ways. First, I include municipality-time fixed effects to account for confounders such as an increase in unobserved lending demand or local income. Second, a time difference between the easing of restrictions and the launch of Pix helps – for the differences between municipalities to violate the exclusion restriction, they need to increase the demand for deposits of small banks exactly in November 2020. Given that the municipalities relaxed COVID restrictions at various times during June-September 2020, but the first time there was a significant effect in November 2020, it helps to address the concern that omitted variables drive the results.

Another identification concern is that the standard IV approach may seem too restrictive since it assumes that the variance of Pix shocks is not affected by the easing of COVID-19 restrictions. For example, lifted restrictions allow travel, but not all

Figure 4: Illustration of the Relevance Condition and Exclusion Restriction



Note: This figure illustrates the relevance condition and exclusion restriction for using the easing of COVID-19 restrictions in Brazil as an instrument. Blue lines correspond to the control group – the group of municipalities that did not ease COVID-19 restrictions by September 2020 (the month of the survey). Green lines correspond to the treatment group – the group of municipalities that eased COVID-19 restrictions by September 2020. The first two lines plot Pix transactions, and the other two lines – deposit concentration. The lines are for illustrative purposes, and although they are consistent with the causal estimates, they are not plotted precisely.

households are comfortable spending money on travel, especially when COVID-19 is still spreading. Therefore, my preferred specification uses a heteroskedasticity-based identification strategy (Rigobon and Sack (2003, 2004)).[27] Specifically, the identifying assumption does not require the complete absence of common and idiosyncratic shocks during the easing of COVID restrictions. Instead, I assume that the variance of F_{mt} and ε_{mt} are the same in municipalities that eased COVID restrictions and in ones that did not, whereas the variance of u_{mt} is higher in municipalities that eased COVID restrictions. In other words, the assumption requires the variance of shocks to Pix to change due to eased COVID restrictions, but the variance of shocks to deposits and HHI to stay unchanged.

The first assumption regarding the variance of shocks to Pix only requires that the variance of Pix in affected municipalities is larger than in other municipalities in November 2020, since the variance of Pix in October 2020 is zero. The second assumption is an analog of the exclusion restriction and implies that all changes that are different for affected municipalities occurred before October 2020. The details for the heteroskedasticity-based identification strategy are contained in Appendix C.

The details of the estimation can be found in Rigobon and Sack (2004). The second-stage regression is

$$\log D_{imt} = \delta \cdot \log \widehat{Pix}_{mt} \cdot S_i + \gamma X_{imt} + \eta_{mt} + \varepsilon_{imt} \tag{9}$$

where i refers to the group of banks (small or large).[28] The vector of controls is analogous to the one in OLS regressions. Table 8 shows the results. As in the OLS estimates, an increase in the value of Pix transactions boosts checking and time deposits of small banks relative to large banks.[29] In contrast to the OLS results, I find that loans of small banks also increase relative to large banks, indicating possible downward bias in the OLS results. I also test if the introduction of Pix causes a decrease in deposit market concentration.

[27] In Appendix D.18, I show that my results are robust to using standard IV.
[28] The aggregation is required by the heteroskedasticity-based identification.
[29] I show that the results are robust to only keeping the banks that are insurced by FGV (analog of FDIC) in Appendix D.21.

Table 8: Impact of Pix on Deposits and Loans of Small Banks: IV with Easing of COVID Restrictions

$$\log D_{imt} = \delta \cdot \log \widehat{Pix}_{mt} \cdot S_i + \gamma X_{imt} + \eta_{mt} + \varepsilon_{imt}$$

	Dependent variable:			
	Checking deposits	Saving deposits	Time deposits	Total loans
	(1)	(2)	(3)	(4)
Pix · Small	0.019***	−0.008	0.174***	0.046***
	(0.007)	(0.006)	(0.021)	(0.008)
Muni × Time FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	7,123	7,123	7,123	7,123
R^2	0.636	0.545	0.072	0.289

Note: This table provides results of the second stage in the IV estimation of equation (10), including interactions with the small bank dummy. The easing of COVID-19 restrictions in Brazil is used as an instrument for Pix usage. The specification uses a heteroskedasticity-based IV approach. Column 1 presents results for checking deposits. Column 2 presents results for saving deposits. Column 3 shows results for time deposits. Column 4 corresponds to total loans. Municipality-time fixed effects are included. Standard errors are clustered at the municipality level and displayed in parentheses. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

Specifically, I run the following second-stage regression:

$$HHI_{m,t+s} = \theta Pix\widehat{PerCap}_{mt} + \delta HHI_{m,t} + \gamma X_{mt} + \eta_{mt} \tag{10}$$

where t is November 2020.

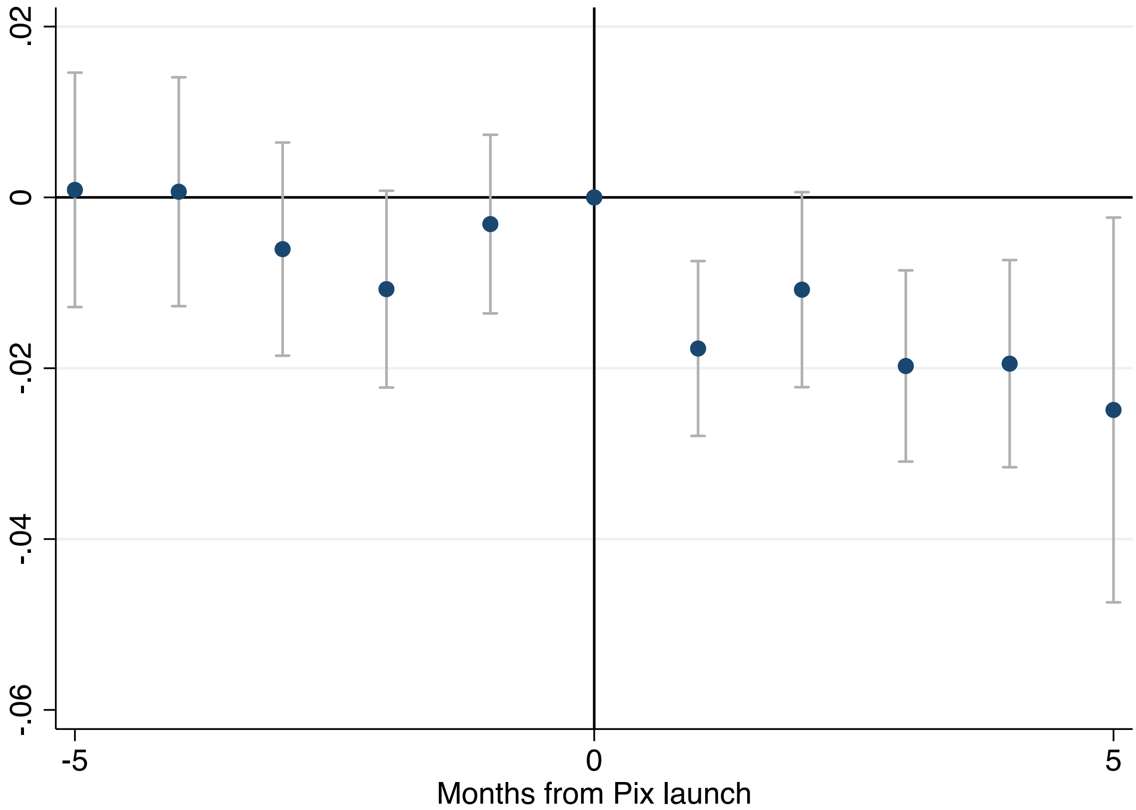
I analyze the next five months after the Pix launch and also plot pre-trends. Figure 5 plots the estimation results along with the 95% confidence intervals. I find that the introduction of Pix significantly negatively affected deposit market concentration. The local deposit market HHI declines steadily over at least five months after the launch of Pix. Hence, I argue that Pix has a causal impact on the local deposit market concentration.[30] To further mitigate the threat of pre-trends due to anticipation, I

[30]In Appendix D.9, I show that the results are unlikely to be driven by seasonality. Specifically, I repeat the analysis that produces Figure 5, but instead of using 2020 data, I exploit the 2018, 2019, and 2021 series.

conduct a Freyaldenhoven et al. (2019) test and reject the hypothesis that there are pre-trends.

Figure 5: Impact of Pix on Deposit Market Concentration: IV with Easing of COVID Restrictions

$$HHI_{m,t+s} = \theta Pix\widehat{PerCap}_{mt} + \delta HHI_{m,t} + \gamma X_{mt} + \eta_{mt}$$

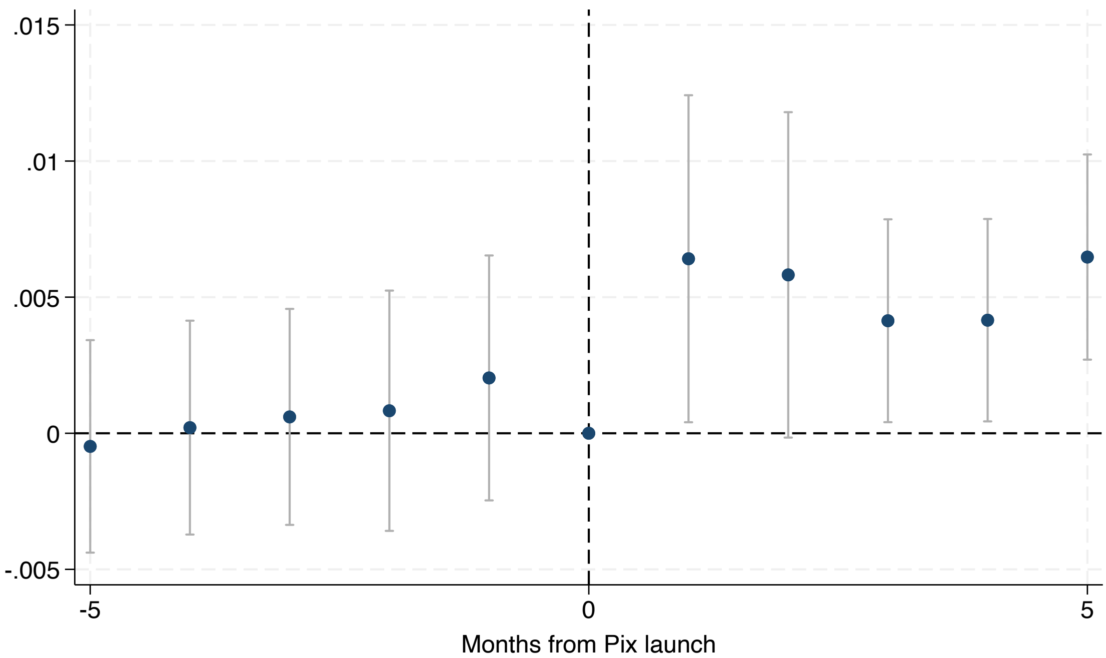


Note: This figure plots the results of the second stage in the IV estimation of equation (10). The vertical axis corresponds to θ – sensitivity of future deposit market concentration to per capita Pix transactions predicted by the COVID-19 restrictions easing using heteroskedasticity-based estimation. The horizontal axis corresponds to months since the Pix launch. t is November 2020. Blue dots are coefficients, whereas grey lines are 95% confidence intervals constructed by clusterization on the municipality level. The Freyaldenhoven et al. (2019) test rejects pre-trends with a P-value of 0.8915.

In addition to showing that there are no pre-trends in HHIs, I plot a similar figure for deposits. I regress total deposits on per capita Pix transactions for 5 months before and 5 months after the launch of Pix. Figure 6 shows that there are no statistically significant pre-trends in deposits of small banks prior to the launch of Pix. On the other hand,

Figure 6: Pre-Trends and Post-Trends for Total Deposits of Small Banks

$$\log D_{im,t+s} = \delta \cdot \widehat{\log Pix}_{mt} \cdot S_i + \gamma X_{imt} + \eta_{mt} + \varepsilon_{imt}$$



Note: This figure plots the results of the second stage in the IV estimation of equation (10) where the dependent variable is log of total deposits, and the independent variable is interaction between log Pix and a dummy for small bank. The vertical axis corresponds to θ – sensitivity of deposits or deposit rates to per capita Pix transactions, interacted with a dummy for small banks, predicted by the COVID-19 restrictions easing using heteroskedasticity-based estimation. The horizontal axis corresponds to months since the Pix launch. Blue dots are coefficients, whereas grey lines are 95% confidence intervals constructed by clusterization on the municipality level.

there is a significant and persistent rise in deposits of small banks after the launch of Pix. The evidence is in favor of the assumption that, absent Pix, municipalities with relaxed COVID restrictions would behave similarly to other municipalities.

In Appendix D.24, I add more evidence to mitigate the concerns regarding the parallel trend assumption. I follow Altonji et al. (2005) and run 2053 specifications with various controls to show that the coefficient in the regression is very stable. I hence assume that the part of deposits of small banks explained by observables is related to Pix the same way as the part explained by unobservables. In fact, the shift in the distribution of unobservables must be 3.94 times as large as the shift in observables to explain away the results.[31] I also follow Rambachan and Roth (2023) and allow for several violations of the parallel trend assumption to show that the estimate would still be significant for reasonable parameter values. Finally, I follow Roth (2022) and show statistics consistent with the parallel trend assumption.

To add more evidence that COVID restrictions are a relevant instrument, I explore heterogeneity in COVID restriction severity in Appendix D.16. I show that if I restrict the sample to municipalities that had gathering restrictions in place in addition to mask mandates, the results are stronger. If I further restrict the sample to municipalities that had isolation mandates, the results get even bigger – a greater increase in checking and time deposits, as well as loans, of small banks relative to large banks. I also address the concern that some municipalities do not follow health mandates by restricting the sample to municipalities with above median coverage of the hepatitis B vaccine (collected from the Ministry of Health). I find that the results are significant and even stronger in most specifications (see Table D.16).

Finally, Pix does not only make small bank deposits more convenient relative to large banks – it also makes deposits more convenient relative to cash. I next estimate IV regressions to test how Pix impacts deposits overall. Table 9 shows the results for deposits and total loans. As can be seen, all types of deposits increased due to the introduction of Pix. Specifically, a doubling of Pix increases checking deposits by 3.7%, saving deposits by 1.4%, and time deposits by 4%. All numbers are larger than the ones in OLS regressions, confirming a potential bias in simple regressions. Total loans also increase in municipalities with more Pix usage, indicating a rise in aggregate lending caused by the introduction of the instant payment system. The income increase is unlikely to drive the results due to relaxed COVID restrictions. Appendix D.23 shows that Pix usage does not predict an increase in municipality-level GDP per capita. In the same Appendix, I also run an event study and find an increase in investments with a short lag after the easing of COVID restrictions, but the effect was not persistent.

[31] The derivations of the statistic are described in Altonji et al. (2005).

Table 9: Impact of Pix on Deposits and Loans: IV with Easing of COVID Restrictions

$$\log D_{mt} = \delta \log \widehat{Pix}_{mt} + \theta X_{mt} + o_{mt}$$

	Dependent variable:			
	Checking deposits	Saving deposits	Time deposits	Total loans
	(1)	(2)	(3)	(4)
Pix	0.027***	0.007***	0.006	0.016***
	(0.003)	(0.001)	(0.005)	(0.001)
Controls	Yes	Yes	Yes	Yes
Observations	4,488	4,488	4,488	4,488
R^2	0.729	0.662	0.220	0.154

Note: This table provides results of the second stage in the IV estimation of equation (10). The easing of COVID-19 restrictions in Brazil is used as an instrument for Pix adoption. The specification uses a heteroskedasticity-based identification strategy conditional on the information in October 2020. Column 1 presents results for checking deposits. Column 2 presents results for saving deposits. Column 3 shows results for time deposits. Column 4 corresponds to total loans. Standard errors are clustered at the municipality level and displayed in parentheses. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

A standard concern with cross-sectional regressions is the missing intercept problem. The analysis in Section 4 allowed me to compare deposits between large and small banks only, so I could not imply how Pix impacted aggregate deposits. In this section, I directly tested the impact of Pix on deposits for all banks and showed that Pix leads to an increase in checking, saving, and time deposits. However, the cross-sectional analysis compares regions to one another – hence, it is not clear if Pix generally leads to an increase in deposits. Although this is a limitation of the cross-sectional analysis, I provide two arguments for why it is unlikely that total deposits declined. First, Pix has several advantages relative to cash, and aggregate data shows that Pix has become a dominant means of retail payments in Brazil. Second, Figure A.3 in the Appendix shows that all three types of deposits increased after November 2020 despite COVID-19 shocks (which, if anything, harmed deposits in Brazil according to the results in Appendix D.15). Taken together, the two arguments above suggest that a cross-sectional missing intercept bias is negative.

One may argue that COVID-19 restrictions are instruments for the **usage** of Pix, but the proposed channel of the impact of instant payments on deposit market concentration goes through the **access** to Pix. However, COVID restrictions preclude certain types of spending for which Brazilians use Pix, such as retail payments or plane tickets. During COVID restrictions, households tend to spend money on online platforms where there is generally uniform pricing and high credit card benefits. That is why Pix is used more in areas that eased COVID-19 restrictions. To provide another piece of evidence, in Appendix D.29, I try a different instrument – access to high-speed internet, which naturally implies access to cashless payment applications. I document economically and statistically comparable results.

5.3 Channel: payment and transfer convenience

The findings suggest that small banks gained market power because of the introduction of Pix. Specifically, they increase deposits and reduce deposit rates, thus intensifying competition. In this section, I provide evidence consistent with the hypothesis that payment and transfer convenience drive the results. I do not argue that there are no other channels impacting the findings of the paper, but instead hypothesize that payment and transfer convenience is one of the main drivers of the results.

Table 1 shows that large banks provide a number of benefits to their customers that small banks are not able to. For example, large banks offer salary accounts, so if an employee does not have a salary account, she will need to transfer money to her bank. Transfers became free after the introduction of Pix, thus reducing incentives to stick to a bank with salary accounts. Another inefficiency of the Brazilian economy is a huge underground economy, where, as of October 2020, credit cards were not accepted; thus, consumers in the underground economy had to use cash. After Pix, many merchants in the underground economy started accepting Pix for payments. Usage of Pix requires having a bank account and, at the same time, levels the field between small and large banks. I thus hypothesize that payment and transfer convenience is an important driver of the main results of the paper.

The underground economy's switch to digital payments incentivized many Brazilians to open bank accounts. Also, reduced transfer fees and the lack of credit card approval attract previously unbanked depositors or those with low credit scores. Such depositors tend to be financially constrained (Balyuk and Williams (2021)), and for them, the marginal impact of Pix on deposits can be stronger.

At the same time, deciding to open a new bank account at a smaller bank can be costly. First, there are switching costs associated with such a decision (Illanes (2017)). Second, using accounts of small banks is more expensive – it requires annual payments, and it has less flexibility in terms of access to physical branches and ATMs. Small banks' main advantage is that they pay higher deposit rates, but this is only relevant for the households who have savings. Hence, the convenience of having an account at a large bank can be different in poorer areas – more constrained households might still prefer large banks because it is cheaper to have accounts there, and deposit rates do not influence constrained households' demand too much.

I test the hypotheses above by interacting the explanatory variables with the income per capita variable collected from IBGE. I run the following regression:

$$\log D_{imt} = \alpha \cdot \log \widehat{Pix}_{mt} + \delta \cdot \log \widehat{Pix}_{mt} \cdot S_i + \beta \cdot \log \widehat{Pix}_{mt} \cdot I_m + \theta \cdot \log \widehat{Pix}_{mt} \cdot S_i \cdot I_m + \gamma X_{imt} + \varepsilon_{imt} \tag{11}$$

where I_m is income per capita in municipality m as of the last Census (2010). Controls include all interactions in addition to the same variables included in the regressions above.

Table 10 shows the results. The first row documents how much more Pix impacts deposits for wealthier households. Negative values imply that an increase in saving and time deposits in large banks is more relevant for financially constrained households, as the hypotheses suggest. The second row shows that the reallocation of deposits from large banks to small banks is more relevant for richer households, consistent with the high switching costs of the move. Note that the biggest difference is for time deposits because time deposits require locking money in the deposits for a fixed time. Such investments are not an option for many financially constrained households, and richer households

Table 10: Impact of Pix on Deposits and Loans: Interactions with Income

$$\log D_{imt} = \alpha \cdot \log \widehat{Pix}_{mt} + \delta \cdot \log \widehat{Pix}_{mt} \cdot S_i + \beta \cdot \log \widehat{Pix}_{mt} \cdot I_m + \theta \cdot \log \widehat{Pix}_{mt} \cdot S_i \cdot I_m + \gamma X_{imt} + \varepsilon_{imt}$$

	Dependent variable:			
	Checking deposits	Saving deposits	Time deposits	Total loans
	(1)	(2)	(3)	(4)
Pix · Income	0.043***	−0.015*	−0.306***	−0.061***
	(0.012)	(0.008)	(0.037)	(0.010)
Pix · Small · Income	0.034	0.042**	0.810***	0.098***
	(0.025)	(0.019)	(0.084)	(0.034)
Controls	Yes	Yes	Yes	Yes
Observations	7,123	7,123	7,123	7,123
R^2	0.746	0.684	0.416	0.551

Note: This table provides results of the second stage in the IV estimation of equation (11), including interactions with the small bank dummy and income per capita. The easing of COVID-19 restrictions in Brazil is used as an instrument for Pix usage. The specification uses a heteroskedasticity-based IV approach. Column 1 presents results for checking deposits. Column 2 presents results for saving deposits. Column 3 shows results for time deposits. Column 4 corresponds to total loans. Controls include all interactions in addition to the same variables included in the regressions above. Municipality-time fixed effects are included. Standard errors are clustered at the municipality level and displayed in parentheses. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

invest in them more. In fact, time deposits are more of a substitute for treasuries than cash, as shown in Krishnamurthy and Li (2023).

The proposed channel implies that an increase in deposits of small banks is primarily driven by reallocations from large banks and not by increase in bank accounts from previously unbanked people. In other words, I argue that the margin of the results is intensive, not extensive. To further provide evidence in support of the channel, I test if the results are stronger in the areas with a larger share of the banked population. Specifically, I run the following regression:

$$\log D_{imt} = \alpha \cdot \log \widehat{Pix}_{mt} + \delta \cdot \log \widehat{Pix}_{mt} \cdot S_i + \beta \cdot \log \widehat{Pix}_{mt} \cdot B_m + \theta \cdot \log \widehat{Pix}_{mt} \cdot S_i \cdot B_m + \gamma X_{imt} + \varepsilon_{imt} \tag{12}$$

where B_m is a share of banked population in municipality m as of 2019. Controls include all interactions in addition to other variables includes in regressions above. [32]

Table 11 shows the results. An increase in deposits of small banks is more prevalent in the areas with a larger share of the banked population, consistent with the hypothesis that my main results are due to reallocation from large banks to small banks. In contrast, the increase in deposits of large banks is stronger in areas with a larger unbanked population. This is consistent with the finding that constrained unbanked people do not value high deposit rates but value free services offered by large banks. Although I am not able to show directly that the results are driven by depositors who open new accounts as opposed to existing depositors of small banks, I show in a follow-up work (Liang, Sampaio, and Sarkisyan (2024)) that Brazilians started opening more bank accounts in high-Pix areas after November 2020, consistent with the proposed channel. Overall, the results in this section provide evidence that is in line with the claim that payment and transfer convenience is a crucial driver of the results.

6 Impact of Pix on deposit betas

In the paper, I use deposit market HHI as a measure of deposit market concentration. However, the literature argues that there can be alternative sources of market power for banks (Drechsler et al. (2017, 2021)). One source of market power can come from the payment methods, so analyzing simply deposit market concentration may understate the full effect of Pix on market power.

In this section, I follow the literature and construct the measure of deposit market power – *deposit flow beta*. Specifically, for each bank in the sample, I compute sensitivities of deposits to changes to central bank policy rates, *Selic*, in a ten-month rolling window controlling for bank assets and macro variables. For example, the deposit beta of Caixa Economica for October 2020 is the sensitivity of deposits of Caixa Economica to changes in the policy rate from January to October 2020. I compute deposit betas for up to seven

[32] I thank Bernardo Ricca for making this series available to me.

Table 11: Impact of Pix on Deposits and Loans: Interactions with Share of Banked Population

$$\log D_{imt} = \alpha \cdot \log \widehat{Pix}_{mt} + \delta \cdot \log \widehat{Pix}_{mt} \cdot S_i + \beta \cdot \log \widehat{Pix}_{mt} \cdot B_m + \theta \cdot \log \widehat{Pix}_{mt} \cdot S_i \cdot B_m + \gamma X_{imt} + \varepsilon_{imt}$$

	Dependent variable:			
	Checking deposits	Saving deposits	Time deposits	Total loans
	(1)	(2)	(3)	(4)
Pix · Banked	-0.321^{***}	-0.493^{***}	-2.419^{***}	-0.328^{***}
	(0.044)	(0.049)	(0.194)	(0.050)
Pix · Small · Banked	0.467^{***}	0.488^{***}	3.000^{***}	0.434^{***}
	(0.069)	(0.063)	(0.225)	(0.089)
Controls	Yes	Yes	Yes	Yes
Observations	7,123	7,123	7,123	7,123
R^2	0.744	0.677	0.418	0.579

Note: This table provides results of the second stage in the IV estimation of equation (12), including interactions with the small bank dummy and share of banked population. The easing of COVID-19 restrictions in Brazil is used as an instrument for Pix usage. The specification uses a heteroskedasticity-based IV approach. Column 1 presents results for checking deposits. Column 2 presents results for saving deposits. Column 3 shows results for time deposits. Column 4 corresponds to total loans. Controls include all interactions in addition to the same variables included in the regressions above. Municipality-time fixed effects are included. Standard errors are clustered at the municipality level and displayed in parentheses. *,**, and *** correspond to 10-, 5-, and 1% significance level, respectively.

months after the introduction of Pix. Higher deposit betas imply lower deposit market power.

The regression specification is the following:

$$b_{it} = \delta \cdot \log Pix_{mt} \cdot S_i + \alpha HHI_m + \gamma X_{imt} + \alpha_i + \theta_t + \varepsilon_{imt} \tag{13}$$

where b_{it} is deposit beta of bank i at time t, and HHI_m is HHI of municipality m as of October 2020. I run the regression for time and saving deposit betas because these are the most popular interest-bearing deposits in Brazil. It is important to mention here that banks in Brazil cannot pay interest on saving deposits above the regulated number. The same law does not apply to time deposits.

Table 12 shows the results. Deposit betas increase significantly for larger banks in municipalities with more Pix transactions. This is true for both saving and time deposits. Since deposit beta is a direct measure of market power, the results imply that large banks lose their deposit market power to small banks as a result of the Pix launch. There could be at least two interpretations. First, as the analysis above suggests, deposit market concentration declines – households prefer deposits of smaller banks to larger bank deposits. Second, payment convenience provides an important source of market power to large banks, and instant payment systems allow small banks to compete. The two forces likely impact each other – because small banks offer better payment convenience, they gain significant market power relative to large banks.

Another widely used measure of banks' market power is profitability. If banks hold significant market power over deposits, they are able to extract higher rents from deposits. In Appendix D.4 I show that the profitability of small banks increases relative to large banks, consistent with the finding that small banks' deposit market power rises relative to large banks.

7 Deposit demand model estimation

The empirical results of the paper show that the introduction of instant payment systems available to all banks promotes more competitive deposit markets. Specifically, deposits of small banks increase relative to deposits of large banks. Nevertheless, there are several questions that reduced-form tests do not address. First, Table 5 indicates that banks change their interest rates in response to the launch of Pix, which in turn can affect the equilibrium choices of deposits. In other words, I have so far not separated the deposit demand component. I aim to do so by estimating a structural deposit demand model in the style of industrial organizations literature (Berry et al. (1995); Nevo (2001); Egan et al. (2017); Wang et al. (2022)). Second, the estimated model allows me to analyze welfare and counterfactuals. In particular, I propose two counterfactual scenarios – one in which Pix is not introduced and another in which deposit stickiness remains constant.

Table 12: Impact of Pix on Deposit Betas

$$b_{it} = \delta \cdot \log Pix_{mt} \cdot S_i + \alpha HHI_m + \beta Y_{imt} + \gamma X_{imt} + \theta_t + \varepsilon_{imt}$$

	Dependent variable:			
	Saving deposits		Time deposits	
	(1)	(2)	(3)	(4)
Pix	0.042***	0.043***	0.104***	0.100***
	(0.004)	(0.004)	(0.038)	(0.039)
HHI	0.001***	0.000***	−0.013***	−0.000
	(0.000)	(0.000)	(0.003)	(0.001)
Small	−0.015***		−0.023***	
	(0.000)		(0.001)	
Pix · Small	−0.024***	−0.024***	−0.043***	−0.042***
	(0.000)	(0.000)	(0.002)	(0.002)
Bank FE	No	Yes	No	Yes
Time FE	No	Yes	No	Yes
Controls	Yes	Yes	Yes	Yes
Observations	297,654	297,654	297,654	297,654
R^2	0.211	0.283	0.024	0.148

Note: This table provides results of estimation of equation (13). The dependent variable is deposit beta – the sensitivity of deposits to changes to central bank policy rates, *Selic*, in a ten-month rolling window controlling for bank assets and macro variables. Columns 1 and 2 include saving deposit betas, while columns 3 and 4 include time deposit betas. Standard errors are clustered at the municipality level and included in the parentheses. Bank and time fixed effects are included. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

7.1 Model

The infinite-horizon model features a mass W_t of households, each of which is endowed with one Brazilian real. Households can invest in deposits of any of the J banks in the economy or in cash. I follow Wang et al. (2022) and assume that households can only choose one bank. I denote the set of options by $\mathcal{A}^d = \{0, 1, ..., J\}$ where option 0 corresponds to cash. Since the households' decision is static, I drop the time subscript. I treat the months as a market, not a municipality-month pair, since the number of municipalities makes it computationally intensive to estimate the model otherwise.

Each bank j has certain bank-specific characteristics. First, each bank pays a deposit rate r_j. Second, banks have non-interest rate product characteristics, x_j. Third, some banks are large, and some are small, which captures households' demand for services of large banks (not necessarily limited to payment systems). I denote the dummy for small banks by s_j. Finally, banks benefit from offering payment convenience, p_j, to households. I define p_j as the mean of the log value of transactions in Pix across municipalities where the bank has branches. The measure captures the exposure of banks' clients to the Pix network. I also test if the sensitivity of the demand to deposit rates changes with Pix by interacting interest rates with the Pix variable.

Each household i chooses the bank $j \in \mathcal{A}^d$ to maximize its utility:

$$\max_{j \in \mathcal{A}} u_{i,j}^t = \alpha_i r_j^t + \beta_i p_j^t + \theta_i r_j^t p_j^t + \delta_i p_j^t s_j + \gamma x_j^t + \xi_j + \eta^t + \epsilon_{i,j}^t \tag{14}$$

where ξ_j is a product-specific time-invariant characteristic (bank fixed effect), η^t is a time fixed effect, and $\epsilon_{i,j}$ is a relation-specific shock to the choice of the bank. For example, it can capture the geographic proximity to the bank j. I follow the literature and assume that the shock follows a generalized extreme-value distribution with the function $F(\epsilon) = \exp(-\exp(-\epsilon))$ and random coefficients, α_i and θ_i are normally distributed.

Parameter α_i captures the sensitivity to the interest rate r_j before Pix. Intuition and household finance theory suggest that when banks pay higher deposit rates, households should increase their demand, i.e., $\alpha_i \geq 0$. θ_i captures an additional sensitivity of deposit demand to deposit rates from Pix. β_i is the sensitivity of depositors to the payment technology. δ_i is an additional sensitivity of depositors to the payment system if they choose deposits of small banks. The reduced-form estimates suggest that $\delta_i \leq 0$, so depositors like it more if the bank offering payment systems is small.

The optimal choice of the household i is then defined as follows:

$$\mathbb{I}_{i,j} = \begin{cases} 1, & \text{if } u_{i,j} \geq u_{i,k}, \quad j, k \in \mathcal{A} \\ 0, & \text{otherwise} \end{cases} \tag{15}$$

Household i chooses to invest its Brazilian real in the bank that gives it the largest utility. To compute the deposit share of each bank, I need to integrate (15). The assumption on the distribution of $\epsilon_{i,j}$ allows us to compute the integral in closed form and to show that the deposit share of bank j is[33]

$$
\begin{aligned}
s_j(r_j) &= \int \mathbb{I}_{i,j} dF(\epsilon) \qquad (16)\\
&= \sum_i \mu_i \frac{\exp(\alpha_i r_j + \theta_i r_j p_j + \beta_i p_j + \delta_i p_j s_j + \gamma x_j + \xi_j)}{\exp(\gamma x_c + \xi_c) + \sum_{n=1}^{J} \exp(\alpha_i r_n + \theta_i r_n p_n + \beta_i p_n + \delta_i p_n s_n + \gamma x_n + \xi_n)}
\end{aligned}
$$

where μ_i is the fraction of total wealth held by household i.

7.2 Data and identification

I collect data on bank balance sheets and interest rates from ESTBAN and IF. I calculate deposit rates as interest expense on time deposits divided by time deposits. Note that the IF data only shows the overall interest expense, but the rate on saving deposits in Brazil is fixed by the government (so-called *poupança*). I use the rate on saving deposits and data on the amounts of saving deposits to calculate the interest expense on time deposits.

I split banks into large and small based on the number of depositors, as in Section 3. I construct the measure of Pix as the mean log of the value of Pix transactions across municipalities where bank j has branches. Finally, I include the number of branches of the bank and time fixed effects in non-interest characteristics following Wang et al. (2022) and Whited et al. (2022). Thus, the only unobservable in equation (16) is bank fixed effect, ξ_j. I solve for bank fixed effects using the nested fixed-point procedure following Nevo (2001).

I estimate the deposit demand using GMM following the procedure described in Berry et al. (1995) (henceforth, BLP) and Nevo (2001). The market is Brazil as a whole, where each month constitutes a separate market. Separability and assumptions on distributions allow us to treat (16) as a logistic model with random coefficients.

[33] I drop the time subscript for notational simplicity.

There is a key challenge in identifying the demand parameters in the model – deposit rates are correlated with the unobserved part of the deposit demand. In other words, there are confounding factors that can impact both deposit rates and demand for deposits. Moreover, deposit demand itself influences deposit rates. To address the challenge, I use supply shifters as proposed by Ho and Ishii (2011). Specifically, I use non-interest expenses related to the use of fixed assets and the provision for loan losses as instruments for interest rates. The identifying assumption is that the supply shifters impact banks' deposit rate decisions but not deposit demand, conditional on controls.

An example of fixed costs is the cost of renting a bank building. That cost likely impacts banks' decision to change their deposit rates, but it is unlikely to correlate with unobserved deposit demand. As for the loan loss provision, by assumption, banks should be willing to change their deposit rates when their loan loss provision changes, because they expect to incur bigger losses in lending. The exclusion restriction implies that the loan loss provision should not impact an unobserved deposit demand. In other words, when depositors decide where to put their dollars, they do not take banks' loan loss provisions into account, conditional on observing deposit rates and non-rate characteristics, as well as bank and time fixed effects. The exclusion restriction violation concerns are also partly mitigated, given that Brazil has deposit insurance for deposits under R$ 250 thousand.

The standard approach in the literature is to use fixed costs and salaries as instruments for Pix. I do not use salaries in the main results because of data limitations (70% of the sample is missing because most banks do not have to report the salaries that they pay to the employees). However, in Appendix D.32, I show that my results are robust to including salaries in the instrument set instead of the loan loss provision. I collect salaries prior to 2019 from RAIS, and I hand-collect them from banks' statements after 2019.

An important concern is identification of δ – the sensitivity of the deposit demand for small banks to Pix. There are two broad reasons why the demand for deposits from small banks could react differently to Pix than the deposits from large banks. The first reason is interest rates – large banks tend to pay lower interest rates, so their clients can be more sensitive to developments in technology as compensation for the low interest rates. This reason is captured by the parameter θ. The second reason is non-rate characteristics (partly captured by x_j and bank fixed effects). These can include the quality of the online banking app or the speed of wire transfers. I do not directly observe such characteristics, but they make clients of small banks more sensitive to the introduction of digital payments, thus making δ positive and significant. In other words, a positive δ implies that, conditional on observables, Pix increases the demand for small bank deposits relative to large banks. I show that removing the interaction term between Pix and a small bank dummy makes welfare gains lower but otherwise keeps the results robust in Appendix D.33. In Appendix D.34, I also show that even negative values (down to $\delta = -0.017$) of δ keep the results robust.

7.3 Estimation results

Table 13 shows the results. Column 3 displays the point estimates, and column 4 presents clustered standard errors. The estimates of the demand sensitivity to deposit rates suggest that a 1 s.d. increase in Pix usage leads to a 70 b.p. additional sensitivity of deposit demand to deposit rates. It implies that deposits become less sticky, consistent with intensified competition. Second, deposit demand for small banks increases, implying that the introduction of Pix leads to a demand-driven inflow of deposits into small banks.

7.4 Welfare and counterfactuals

The estimated model allows me to study welfare and counterfactuals. Specifically, I compare measures of consumer surplus and deposit market concentration obtained from the benchmark model with two counterfactuals. I next plot welfare gains and HHI percentage gains to study how the introduction of Pix affected deposit market concentration and how it would be if deposits remained sticky.

For the first counterfactual, I set all parameters related to Pix to zero, so I assume

Table 13: Structural Estimation Results

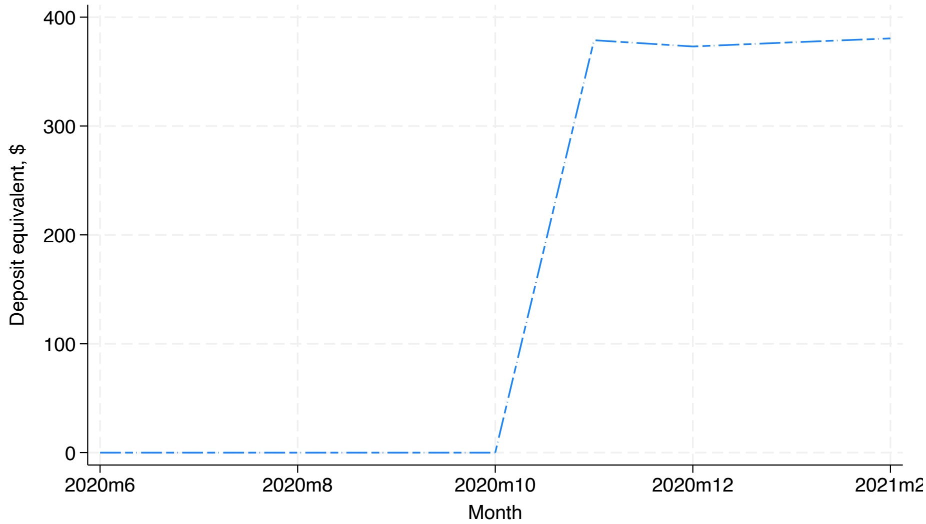
Parameter	Symbol	Estimate	Standard error
Sensitivity to deposit rates	α	0.048***	(0.021)
Sensitivity to deposit rate with Pix	θ	0.007***	(0.003)
Relative sensitivity to Pix for small banks	δ	0.008**	(0.004)
Observations		6,584	
R^2		0.905	

Note: This table provides results of structural estimation of equation (16). 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.

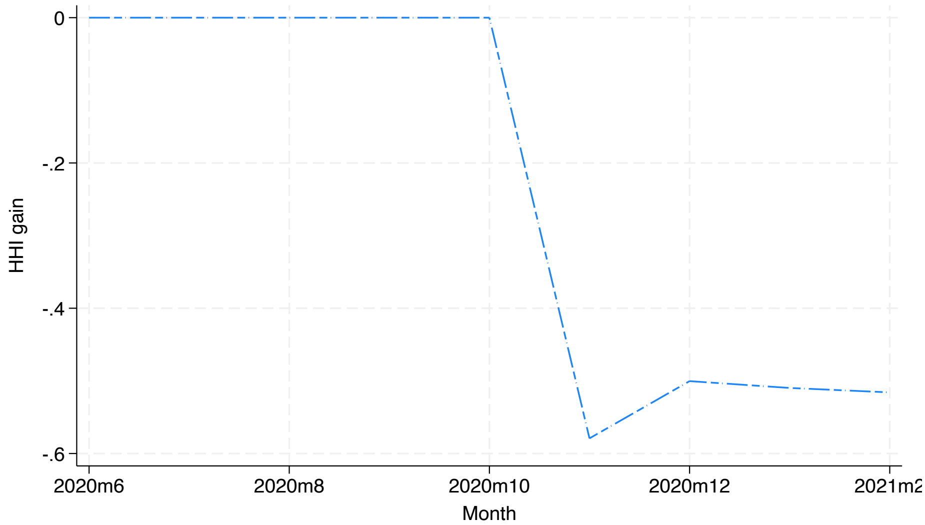
that Pix was never introduced. Panel (a) of Figure 7 shows the results. The variable plotted is the percentage gain in the consumers' surplus in deposit-equivalent terms. Panel (a) compares the benchmark model, where all banks offer Pix, with the scenario in which Pix was never introduced. The deposit-equivalent welfare of an average Brazilian increases by \$380 per quarter. In other words, the average depositor would be willing to sacrifice \$380 from their deposit account to stay in the world with Pix. It implies that depositors are better off with more deposit competition, although interest rates paid by small banks decline, potentially hurting their existing clients.

The estimation results pointed to the reduced stickiness of deposits, so deposits became more sensitive to interest rate changes. Since reduced-form analysis suggests that small banks end up decreasing their deposit rates in response to an inflow of deposits, they are likely to lose some depositors in equilibrium. If deposits remained sticky, small banks might have kept those depositors. Panel (b) of Figure 7 plots the HHI in the counterfactual scenario where deposits remain sticky (i.e., $\theta_i^d = 0$) to the benchmark estimate. The results suggest that deposit markets would have been even more competitive had deposits remained sticky. This means that small banks lose some deposits in equilibrium because they decide to decrease deposit rates.

Figure 7: Welfare and Counterfactuals



(a) Welfare Gain from Pix



(b) Counterfactual: Inelastic Deposit Demand

Note: This figure plots the deposit-equivalent welfare change (panel (a)) and HHI (panel (b)) gain for counterfactuals from the BLP estimation. Figure (a) compares the benchmark model where Pix is offered by all banks with the scenario in which Pix was never introduced. Figure (b) compares the counterfactual where deposits remained sticky with the benchmark model.

8 Conclusion

This paper provides evidence that the implementation of instant payment systems, such as Brazil's Pix, can effectively foster competition in the deposit market, leading to increased deposits and loans and reduced deposit rates. The study demonstrates that Pix's introduction leads to higher deposit market competition, resulting in a surge of checking, saving, and time deposits, particularly in smaller banks. As a result, small banks reduce deposit rates. Consequently, this dynamic contributes to a decline in local deposit market concentration. Additionally, the analysis reveals a significant boost in lending supply following the launch of Pix.

These findings hold significant implications for the advancement of the economy through payment technologies. Enhanced competition in deposit markets has the potential to amplify the transmission channels of monetary policy, influencing the provision of credit. The prevailing market power of large banks has historically hindered the central bank's ability to impact their interest rates despite changes in the policy rate. For instance, even when policy rates are high, large banks in the US seldom adjust their deposit rates. Moreover, deposit market power shapes the lending policies of these larger banks. The increased competition stemming from smaller banks can incentivize larger institutions to respond more effectively to changing economic conditions.

This paper also has implications for consumer welfare. Although the structural model used in this study suggests an increase in welfare, a more comprehensive general equilibrium model is required to assess the overall advantages and disadvantages of this policy. Additionally, the results shed light on the decision-making processes of households and banks when it comes to selecting payment technologies. While smaller banks may initially be slower to adopt new technologies, the introduction of Pix highlights the substantial benefits they can reap from early adoption. In turn, households are willing to alter their investment behavior if small banks can offer convenient payment options. Further research in this field is necessary to provide more comprehensive answers to the questions posed.

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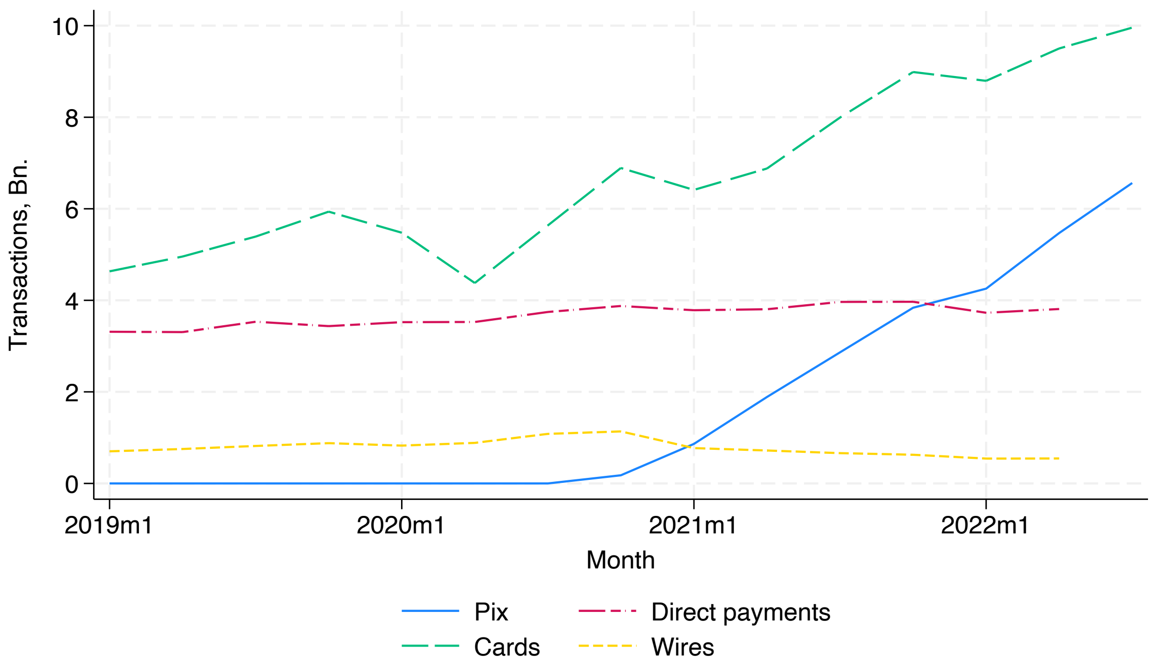
Appendix

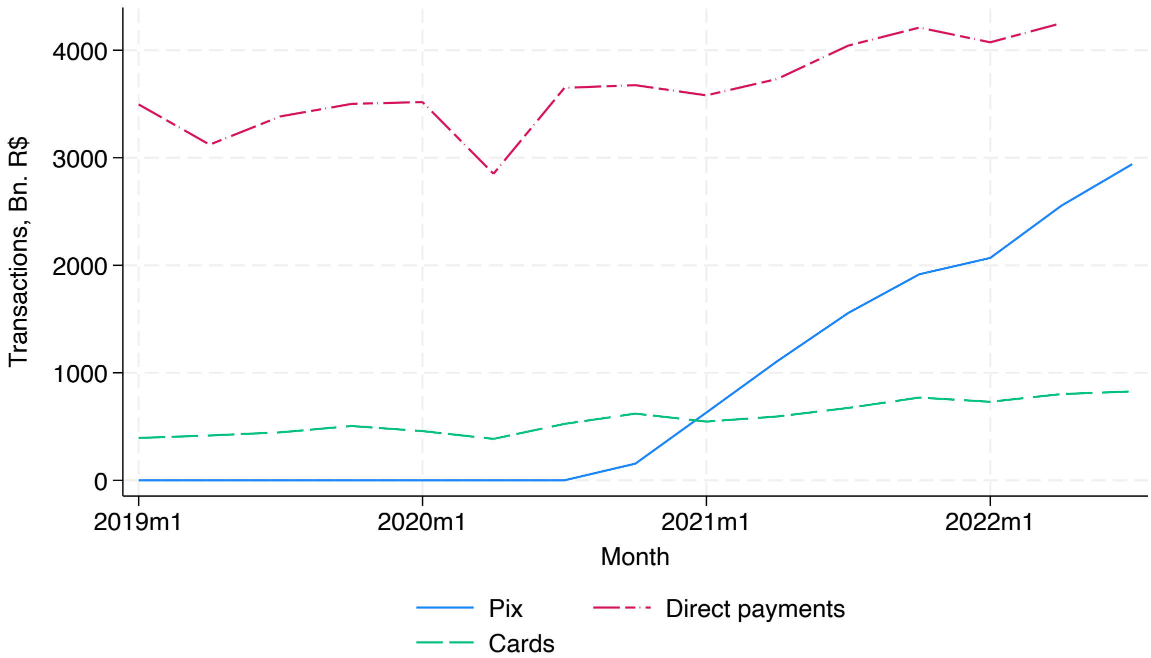
A Additional figures

Figure A.1: Electronic Means of Payment in Brazil, Quantities



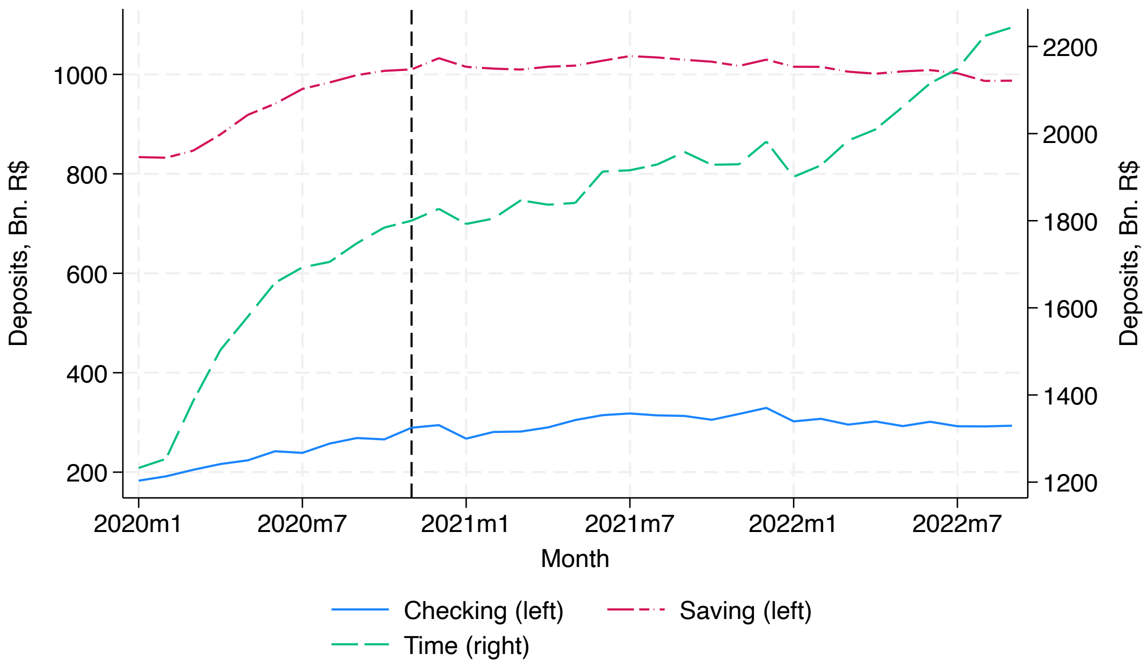
Note: Data is from the Central Bank of Brazil. The graph plots the number of transactions for the main electronic means of payment in Brazil – Pix (instant payment system launched in November 2020), Direct payments (includes Boleto Bancário (payment slip used by the coalition of Brazilian banks since 1993), direct deposit, and others), cards (debit, credit, and pre-paid), and wire transfers (TED, DOC, cheque, and others).

Figure A.2: Electronic Means of Payment in Brazil, Value



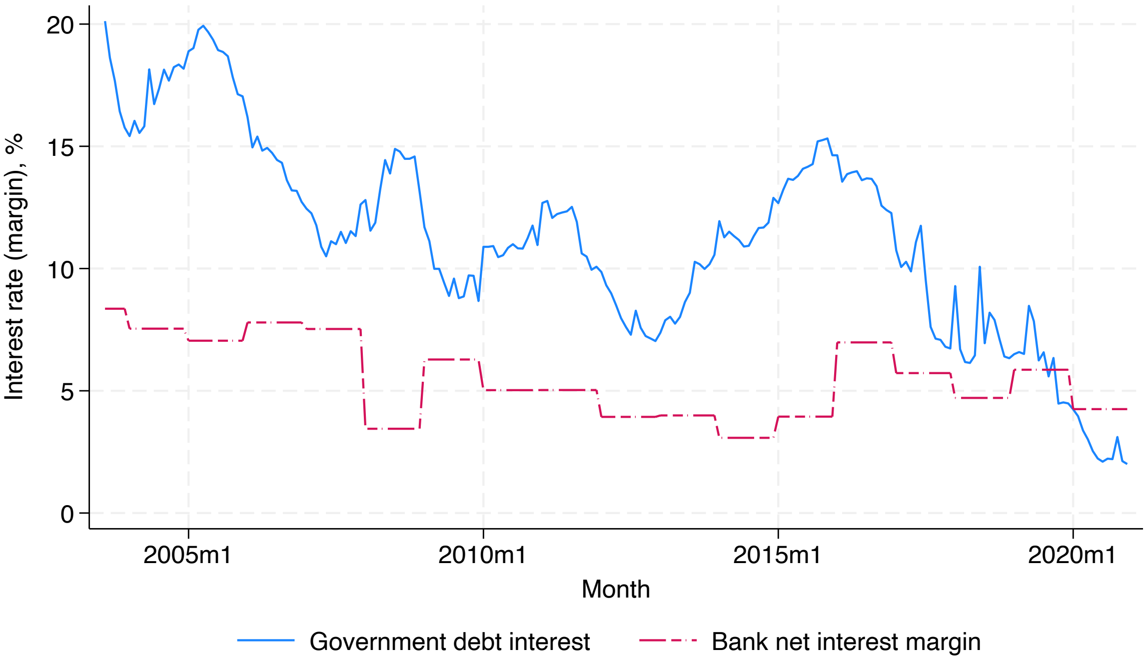
Note: Data is from the Central Bank of Brazil. The graph plots the value of transactions for the main retail electronic means of payment in Brazil – Pix (instant payment system launched in November 2020), Direct payments (includes Boleto Bancário (payment slip used by the coalition of Brazilian banks since 1993), direct deposit, and others), and cards (debit, credit, and pre-paid). All transactions are in billion Brazilian Reals (the exchange rate as of January 2023 is 0.19 USD per 1 BRL).

Figure A.3: Bank Deposits in Brazil



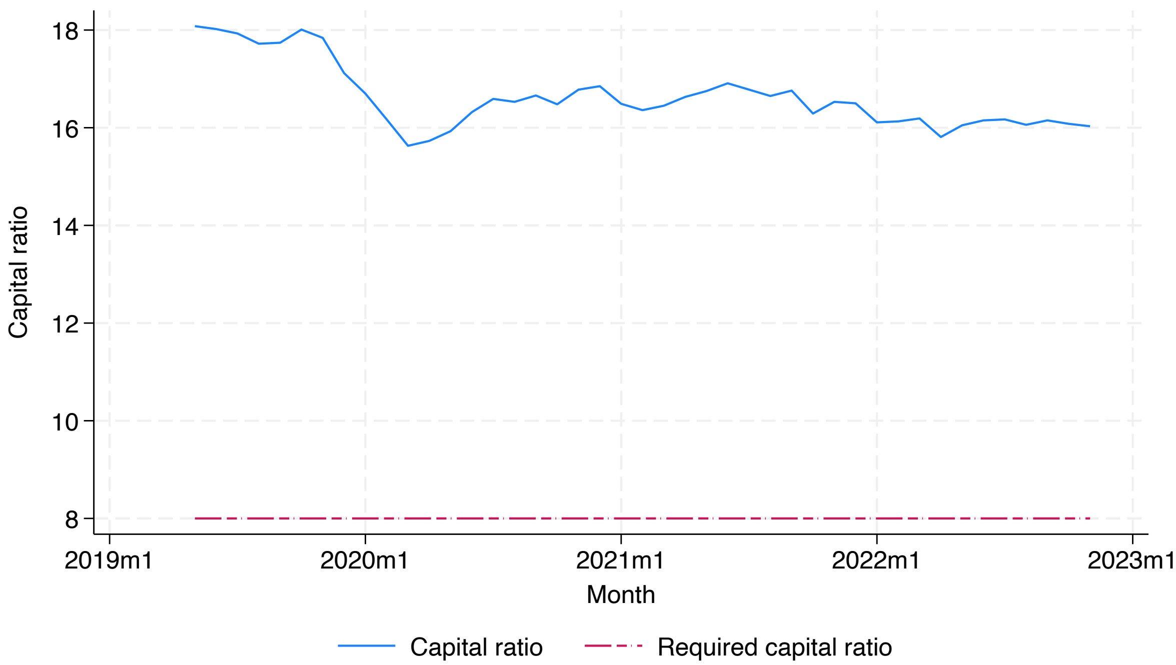
Note: Data is from ESTBAN. The graph plots the checking, saving, and time deposits of Brazilian banks from January 2020 to July 2022. The left axis corresponds to checking and saving deposits, and the right axis – to time deposits. The vertical black line corresponds to November 2020, when Pix was launched. All values are in billion Brazilian Reals (the exchange rate as of January 2023 is 0.19 USD per 1 BRL).

Figure A.4: Net Interest Margin of Brazilian Banks



Note: Data is from FRED – database maintained by St. Louis Fed. The graph plots aggregated net interest margins of Brazilian banks and compares them to government debt interest rates. The solid blue line corresponds to the rate on Brazilian treasuries. The dashed red line is the net interest margin.

Figure A.5: Capital Adequacy Ratio of Brazilian Banks



Note: Data is from the Central Bank of Brazil. The graph plots the aggregated capital ratios of Brazilian banks and compares them to the required capital ratios. The solid blue line corresponds to the capital ratios. The dashed red line is the required capital ratio.

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 is monthly and municipality-level. Bank data is branch-level and also monthly. Such granularity allows me to provide rigorous cross-sectional evidence in the paper.

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	Monthly	Branch
Deposits	ESTBAN	Monthly	Branch
Loans	ESTBAN	Monthly	Branch
Reserves	ESTBAN	Monthly	Branch
Deposit rates	IF	Quarterly	Bank
Loan rates	Banco Central	Monthly	Bank
Investments	IPEA	Annual	Municipality
Savings	IPEA	Annual	Municipality
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

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 municipality office. For example, I observe 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). Although my results are robust to using branch-level data, I choose to use the municipality office one because of the quality of branch-level data and misreporting (Fonseca and Matray (2022)).

C Heteroskedasticity-based identification

Heteroskedasticity-based identification was proposed by Rigobon and Sack (2003) and Rigobon and Sack (2004) and was later used by Hébert and Schreger (2017). Consider the model of simultaneous equations:

$$Pix_{mt} = \delta HHI_{mt} + \gamma_P F_{mt} + u_{mt} \tag{C.1}$$

$$HHI_{mt} = \alpha Pix_{mt} + \gamma F_{mt} + \varepsilon_{mt} \tag{C.2}$$

I consider two months in the sample – October and November. Pix was introduced in November, and COVID-19 restrictions were eased by September. Hence, my identifying assumption is as follows. Denote the standard deviation of u_{mt} by σ^u_{mt}, standard deviation of ε_{mt} by $\sigma^{\varepsilon}_{mt}$, and standard deviation of unobservables by σ^F_{mt}. Further denote municipalities that lifted COVID restrictions by m' and other municipalities by m^0. I assume that $(\sigma^u_{m'Nov})^2 - (\sigma^u_{m'Oct})^2 > (\sigma^u_{m^0Nov})^2 - (\sigma^u_{m^0Oct})^2$, $(\sigma^{\varepsilon}_{m'Nov})^2 - (\sigma^{\varepsilon}_{m'Oct})^2 = (\sigma^{\varepsilon}_{m^0Nov})^2 - (\sigma^{\varepsilon}_{m^0Oct})^2$, $(\sigma^F_{m'Nov})^2 - (\sigma^F_{m'Oct})^2 = (\sigma^F_{m^0Nov})^2 - (\sigma^F_{m^0Oct})^2$. In other words, the variance of Pix shocks increases between October and November in affected municipalities by more than in unaffected municipalities, but the variances of unobservables and deposit shocks change the same way.

Rigobon and Sack (2004) and Hébert and Schreger (2017) show that the heteroskedasticity-based identification can be implemented using a simple IV specification. The second-stage equation is given by (10). The first-stage equation is given by the following expression:

$$PixPerCap_{mt} = \alpha Eased_m + \theta Pix_t + \gamma Eased_m Pix_t + \eta Eased_m PixPerCap_{mt} + u_{mt} \tag{C.3}$$

where $Eased_m$ is equal to one for municipalities that lifted COVID restrictions, and Pix_t is equal to one for November 2020 and zero for October 2020.

D Additional results and robustness tests

D.1 Bank-level statistics

Table D.1 below shows bank-level summary statistics sourced from the bank-level IF data.

Table D.1: Summary Statistics: Banks (IF data)

	Large banks			Small banks		
	Mean	Median	Std. dev.	Mean	Median	Std. dev.
Panel A: Before Pix launch (ESTBAN)						
Checking deposits (bn. R$)	62.8	61.3	11.8	1.28	0.07	5.4
Saving deposits (bn. R$)	290.2	286.9	99.4	4	0	20.5
Time deposits (bn. R$)	205.2	208.7	32.6	13	1.28	52.4
Total loans (bn. R$)	651.7	646	91.3	12.7	1.13	49.4
Total assets (tn. R$)	1.55	1.55	0.12	0.06	0.01	0.21
Checking deposits (% in total)	11	11	3.2	23	6.3	33
Saving deposits (% in total)	51	50	13	4.5	0	15
Time deposits (% in total)	37	38	9.6	73	91	35
Banks		2			98	
Panel B: After Pix launch (ESTBAN)						
Checking deposits (bn. R$)	67.7	70.3	18.8	1.47	0.1	6.1
Saving deposits (bn. R$)	299.2	293.9	92.7	4.32	0	22
Time deposits (bn. R$)	205.4	203.4	52.3	14.3	1.31	56.1
Total loans (bn. R$)	693.4	694.1	105	14.4	1.39	54.1
Total assets (tn. R$)	1.57	1.55	0.15	0.06	0.01	0.21
Checking deposits (% in total)	12	12	3.7	22	6.4	32
Saving deposits (% in total)	52	52	14	4.5	0	15
Time deposits (% in total)	36	36	11	74	91	34
Banks		2			98	

Note: This table provides descriptive statistics for the bank data sourced from the bank-level IF data. Panel A shows statistics for two quarters before introduction of Pix. Panel B provides means, medians, and standard deviations for two quarters after introduction of Pix. The table splits the sample of banks into large and small. Large banks are defined as intermediaries with more than 50 million depositors.

D.2 Impact of instant payments on investments

Pix facilitates transactions in Brazil and mitigates payment frictions that existed before. I hence find that Pix leads to an increase in deposits and loans and a reduction in deposit market concentration. Therefore, the introduction of Pix should boost the economy by impacting investments. In this Section, I show that Pix leads to growth in investments and, to a lesser extent, in savings.

D.2.1 Empirical strategy

Since data on investments and savings are annual, I collapse observations to the level of municipalities at the time of Pix's introduction. I hypothesize that larger initial use of Pix leads to growth in investments and savings in 2020 and 2021. To test the hypotheses, I run the following regression for investments:

$$\log Inv_{m,T+1} = \eta_I \log Pix_{m,T} + \rho_I \log Inv_{m,T} + \mu_I X_{m,T} + v_{m,T} \tag{D.1}$$

where $Pix_{m,T}$ is Pix transaction value for municipality m in November 2020, $Inv_{m,T}$ and $Inv_{m,T+1}$ are capital investments in municipality m in 2020 and 2021, respectively, $X_{m,T}$ is a vector of demographic and economic controls including average household income, municipality status, literacy ratio, gender and age ratios, deposit market concentration, and average bank assets. I cluster standard errors at the municipality level to account for potential unobservable correlations within areas.

I run a similar regression for savings:

$$\log Sav_{m,T+1} = \eta_S \log Pix_{m,T} + \rho_S \log Sav_{m,T} + \mu_S X_{m,T} + u_{m,T} \tag{D.2}$$

where $Sav_{m,T}$ and $Sav_{m,T+1}$ are personal savings in municipality m in 2020 and 2021, respectively. I include the same set of control variables as in (D.1).

I also include the Herfindahl-Hirschman index in both regressions to compare municipalities with high and low deposit market concentration. I demean HHI and interact with the Pix value to compare the impact of Pix on investments and savings in municipalities with market concentrations. I discuss the necessity of the exercise and its implications in detail in Section 4.

D.2.2 Results

Table D.2 shows the results. The introduction of Pix is associated with a significant increase in investments and savings in 2020 and 2021. Specifically, a 100% increase in initial Pix transactions is associated with an investment growth of 14.5% in 2021 and 13.6% in 2020. A one s.d. increase in Pix transactions is also associated with an increase in savings by 3% in 2021 and a reduction in savings by 1.3% in 2021. Results on investments support the hypothesis. However, the impact on savings is economically small. A savings reduction can indicate more spending due to mitigated payment frictions in the Brazilian economy.

Deposit market concentration dampens the impact of Pix on investments and savings. For example, if HHI increases by 0.1 units, investment in 2021 increases by 13.3% instead of 14.5% following a doubling in Pix transactions. Both HHI and its interaction with Pix are statistically significant, implying an essential role of deposit market concentration in transmitting the effect of Pix on the real economy.

D.3 Impact of Pix on equity prices

Since large banks lose retail deposits relative to small banks and substitute them with uninsured funds, equity prices might be affected. I collect equity price data of the Brazilian bank stocks traded on the B3 stock exchange from Bloomberg. I then restrict the sample to the period between November 1, 2020, and November 30, 2020, and analyze daily returns. Table D.3 shows that the stock returns of small banks rise on average by 30 b.p. daily after the introduction of Pix. However, the effects are insignificant, reflecting that large banks replaced insured deposits with uninsured funds without raising fear of potential default, since large banks are systemically important.

Table D.2: Impact of Pix on Capital Investments and Savings

$$\log Inv_{m,T+1} = \eta_I \log Pix_{m,T} + \rho_I \log Inv_{m,T} + \mu_I X_{m,T} + v_m$$
$$\log Sav_{m,T+1} = \eta_S \log Pix_{m,T} + \rho_S \log Sav_{m,T} + \mu_S X_{m,T} + u_m$$

	Dependent variable:			
	Investments 2021	Investments 2020	Savings 2021	Savings 2020
	(1)	(2)	(3)	(4)
Pix	0.145***	0.136***	0.030***	−0.013***
	(0.018)	(0.018)	(0.006)	(0.003)
Lag	0.545***	0.584***	1.002***	0.936***
	(0.021)	(0.018)	(0.009)	(0.007)
HHI	−0.544***	−0.332***	−0.000	0.076***
	(0.123)	(0.113)	(0.041)	(0.029)
Pix · HHI	−0.110***	−0.103***	−0.041***	0.007
	(0.026)	(0.023)	(0.007)	(0.005)
Demographic controls	Yes	Yes	Yes	Yes
Economic controls	Yes	Yes	Yes	Yes
Observations	3,152	3,166	3,089	3,178
R^2	0.727	0.756	0.984	0.994

Note: This table provides results of estimation of equations (D.1), and (D.2). Columns 1 and 2 show results for investments in 2021 and 2020, respectively. Columns 3 and 4 show results for savings in 2021 and 2020, respectively. Demographic and economic control variables are included. Herfindahl-Hirschman index is demeaned. Standard errors are clustered at the municipality level and displayed in parentheses. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

D.4 Impact of Pix on profitability

Small banks increase deposits and are able to reduce their deposit rates. It means that small banks can increase their returns on assets. I collect data on profits of banks from the Central Bank of Brazil and divide them by total assets to obtain the panel of profitability. I then test how ROA changes with Pix. Table D.4 shows that the expected profitability of small banks increases relative to large banks in areas with more usage of Pix.

Table D.3: Impact of Pix on Equity Returns
$R_{it} = \eta \cdot Pix_t \cdot S_i + \alpha_i + \theta_t + v_{it}$

	Dependent variable:			
	Equity returns			
	(1)	(2)	(3)	(4)
Pix	−0.009	−0.025*	−0.009	−0.026*
	(0.012)	(0.014)	(0.013)	(0.014)
Small	−0.001	−0.001	−0.000	−0.001
	(0.010)	(0.009)	(0.012)	(0.010)
Pix · Small	0.003	0.003	0.002	0.003
	(0.013)	(0.011)	(0.013)	(0.012)
Constant	0.011	0.010	0.011	0.010
	(0.009)	(0.010)	(0.010)	(0.010)
Bank FE	No	No	Yes	Yes
Time FE	No	Yes	No	Yes
Observations	314	314	314	314
R^2	0.015	0.254	0.053	0.292

Note: This table provides results of the estimation of the effect of Pix introduction on bank equity returns. Returns are defined as daily growth rates in equity prices collected from Bloomberg. Pix_t is a dummy for the time after November 15, 2020. The time range is from November 1 to November 30, 2020. Bank and time fixed effects are included. Standard errors are displayed in parentheses. *,**, and *** correspond to 10-, 5-, and 1% significance level, respectively.

D.5 New bank branches

Reduction in deposit market power can be either on the intensive or extensive margin. In other words, it is possible for households to move their deposits from large banks to small banks or for banks to open new branches in a less competitive environment. I show that Pix launch did not lead to the opening of new branches in Brazil. I collect bank-level data on agencies from the Central Bank of Brazil to check if they increased for small banks. I run the following regression:

$$\log NumAgencies_{it} = \delta \cdot \log Pix_{mt} \cdot S_i + \gamma X_{imt} + \theta_t + \alpha_i + o_{imt} \tag{D.3}$$

where $NumAgencies_{it}$ is number of agencies of bank i at time t.

Table D.4: Impact of Pix on Return on Assets

$$ROA_{it} = \alpha \cdot Pix_t \cdot S_i + \alpha_i + \theta_t + \eta_{mt} + v_{imt}$$

	Dependent variable:	
	Return on assets	
	(1)	(2)
Pix · Small	0.128***	0.132***
	(0.003)	(0.003)
Bank FE	No	Yes
Muni-Time FE	Yes	Yes
Observations	15,986	15,986
R^2	0.486	0.646

Note: This table provides results of the estimation of the effect of Pix introduction on bank profitability. Profitability is defined as the return on assets. Bank and municipality-time fixed effects 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.5 shows that the number of agencies of small banks did not rise. Instead, I find a decline in the number of small banks' agencies relative to large banks.

D.6 Alternative definitions of HHI

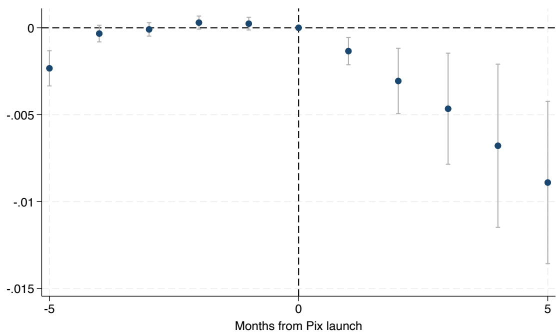
In this section, I show that the results in Figure 3 are robust to measuring HHI using checking, saving, or time deposits instead of total private deposits. The results are presented in Figure D.1.

D.7 Alternative definitions of large banks

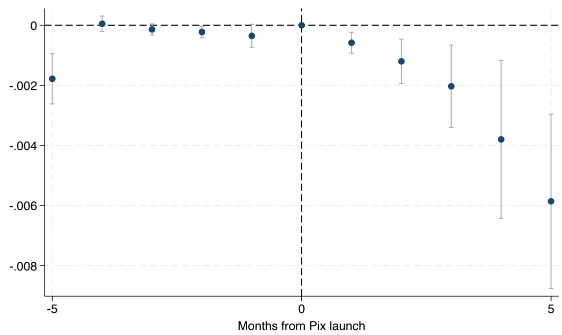
I consider three different definitions of large banks. The first is to define large banks as the ones with more than 40 million depositors, which will leave me with top-3 largest banks (including Itau) that control 56% of branches in Brazil. The second is to consider top-4 largest banks (including Bradesco) that control 75% on branches in Brazil. In column 5, I consider top-5 banks (including Santander) that control more than 90% of branches in Brazil, leaving the small bank group very tiny. Finally, I exclude two banks where the

Figure D.1: Impact of Pix on Deposit Market Concentration: Different Definitions of HHI

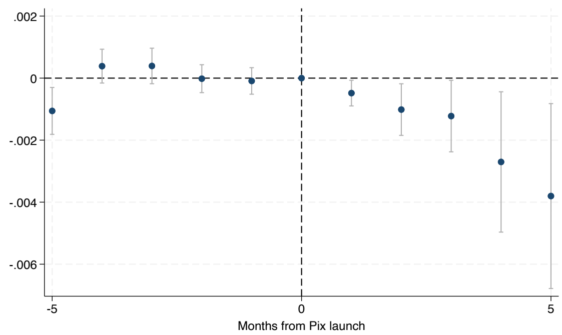
$$HHI_{m,t+s} = \theta PixPerCap_{mt} + \delta HHI_{m,t-1} + \gamma X_{mt} + \varepsilon_{mt}$$



(a) Checking deposits



(b) Saving deposits



(c) Time deposits

Note: This figure plots results of estimation of equation (3). HHI is defined using checking deposits (a), saving deposits (b), or time deposits (c). The vertical axis corresponds to θ – sensitivity of future deposit market concentration to per capita Pix transactions. The horizontal axis corresponds to months since t. Blue dots are coefficients, whereas grey lines are 95% confidence intervals constructed by clusterization on the municipality level.

Table D.5: Impact of Pix on Number of Banking Agencies

$$\log NumAgencies_{it} = \delta \cdot \log Pix_{mt} \cdot S_i + \gamma X_{imt} + \theta_t + \alpha_i + o_{imt}$$

	Dependent variable:			
	Number of agencies			
	(1)	(2)	(3)	(4)
Pix	0.044***	0.042	0.044***	0.042
	(0.008)	(0.027)	(0.008)	(0.027)
Pix · Small	−0.042***	−0.073***	−0.042***	−0.073***
	(0.001)	(0.011)	(0.001)	(0.011)
Bank FE	Yes	No	Yes	No
Time FE	Yes	Yes	No	No
Controls	Yes	Yes	Yes	Yes
Observations	18,283	18,283	18,283	18,283
R^2	0.999	0.593	0.999	0.593

Note: This table provides results of the estimation of the effect of Pix on the number of agencies. Standard errors are clustered at the municipality level and displayed in parentheses. Bank and time fixed effects are included. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

government is the largest shareholder – Caixa and Banco do Brasil. Table D.6 shows that the deposits of small banks increase relative to large banks for all specifications.

D.8 Bank-level deposit rate regressions

In the main part, I assume that banks follow uniform pricing of deposits and the deposit rates are the same in all municipalities. In this section, I estimate deposit rate regressions at the bank level by aggregating the Pix variable. Table D.7 shows that the results are robust.

D.9 Placebo IV tests

In this section, I repeat the analysis that produces Figure 5, but instead of using 2020 data, I exploit the 2018, 2019, and 2021 series. Figure D.2 shows that HHI does not decline if 2018, 2019, and 2021 data is used. Hence, the results in the paper are likely

Table D.6: Impact of Pix on Deposits and Loans of Small Banks: Different Definitions of Large Banks

$$\log D_{imt} = \delta \cdot \widehat{\log Pix}_{mt} \cdot S_i + \gamma X_{imt} + \eta_{mt} + \varepsilon_{imt}$$

	Large bank definition:				
	Benchmark	Top-3	Top-4	Top-5	Only private
	(1)	(2)	(3)	(4)	(5)
Pix · Small	0.174***	0.150***	0.213***	0.108*	0.025***
	(0.021)	(0.020)	(0.027)	(0.059)	(0.007)
Muni × Time FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Observations	7,123	6,905	6,150	5,429	6,797
R^2	0.039	0.006	0.036	0.588	0.314

Note: This table provides results of the second stage in the IV estimation of equation (10), including interactions with the small bank dummy. The dependent variable is time deposits. The easing of COVID-19 restrictions in Brazil is used as an instrument for Pix usage. The specification uses a heteroskedasticity-based IV approach. Column 1 presents results where large banks are defined as banks with more than 50 million depositors (Banco do Brasil and Caixa). Column 2 presents results where Itau is added to the list of large banks. Column 3 shows results where Bradesco is also in the list of large banks. Column 4 corresponds to the results where the five largest banks are included in the list of large banks. Column 5 excludes Caixa and Banco do Brasil, where the government is the largest shareholder. Municipality-time fixed effects are included. Standard errors are clustered at the municipality level and displayed in parentheses. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

not driven by seasonality in market power or municipality-specific reasons. A decline in HHI in pre-trends of the 2021 graph is likely still a decline caused by Pix.

D.10 Branch-level lending results

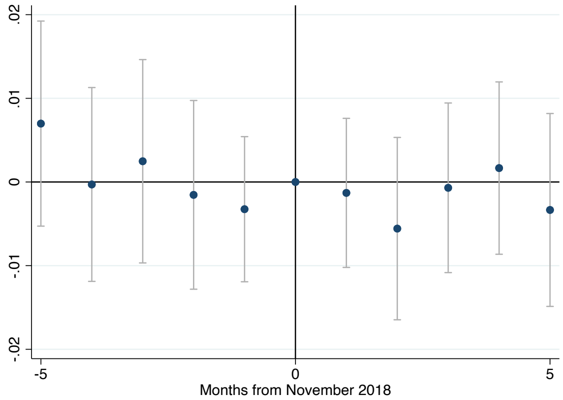
In this section, I show that the lending results hold if I use branch-level data from ESTBAN and regressions. I estimate the following regression:

$$\log Y_{imt} = \delta \cdot \log Pix_{mt} \cdot S_i + \gamma X_{imt} + \theta_t + \alpha_i + \eta_{mt} + o_{imt} \tag{D.4}$$

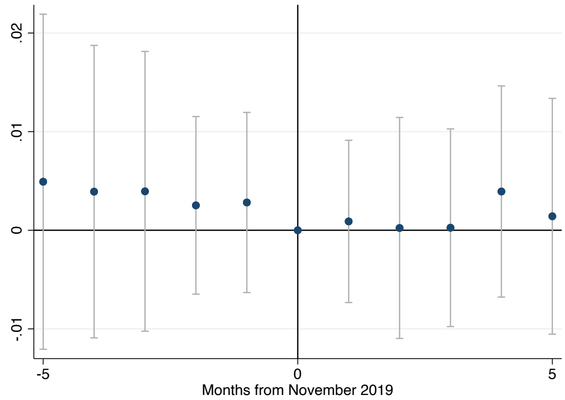
where Y_{imt} are either loans or financing of bank i in municipality m at month t. Control variables include deposits, demographic and economic controls, and fixed effects. Table D.8 shows the results.

Figure D.2: Impact of Pix on Deposit Market Concentration: Placebo Tests

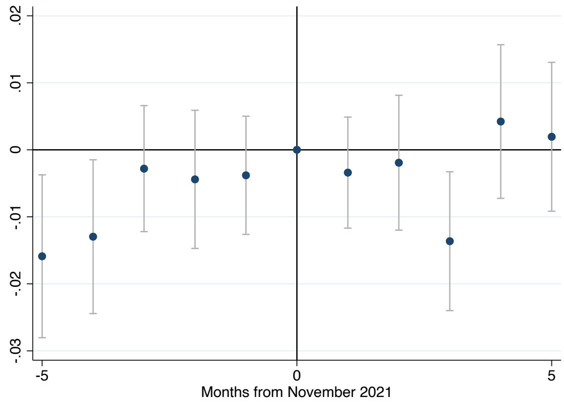
$$HHI_{m,T+s} = \theta Pix\widehat{PerCap}_{mT} + \delta HHI_{m,T} + \gamma X_{mT} + \eta_m$$



(a) 2018 Placebo



(b) 2019 Placebo



(c) 2021 Placebo

Note: This figure plots the results of the second stage in the IV estimation of equation (10) using data from 2018, 2019, and 2021 as a placebo test. The vertical axis corresponds to θ – sensitivity of future deposit market concentration to per capita Pix transactions predicted by the COVID-19 restrictions easing using heteroskedasticity-based estimation. The horizontal axis corresponds to months since Pix launch denoted by T, but instead of 2020, I use 2018, 2019, and 2021, respectively. Blue dots are coefficients, whereas grey lines are 95% confidence intervals constructed by clusterization on the municipality level.

Table D.7: Impact of Pix on Bank-Level Deposit and Loan Rates

$$IntRate_{imt} = \delta \cdot \log Pix_{it} \cdot S_i + \gamma X_{it} + o_{it}$$

	Dependent variable:			
	Deposit rates		Public loans	Private loans
	(1)	(2)	(3)	(4)
Pix	-0.084^{**}	-0.254	0.023	-0.020
	(0.002)	(0.054)	(0.020)	(0.032)
Pix · Small	-0.709^{**}	-0.419^{**}	-0.070	-0.019
	(0.053)	(0.021)	(0.030)	(0.015)
Denominator	All deposits	Time deposits	–	–
Controls	Yes	Yes	Yes	Yes
Observations	209	178	120	69
R^2	0.027	0.059	0.172	0.098

Note: This table provides results of estimation of the effect of Pix on deposit rates and personal loan rates – equation (4) at the bank level. The Pix variable is aggregated to the bank level. Column 1 shows results for deposit rates computed as an interest expense divided by total deposits, while Column 2 uses time deposits as a denominator. Column 3 corresponds to public payroll loans. Column 4 represents private payroll loans. Standard errors are clustered at the month level and displayed in parentheses. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

D.11 Impact of Boleto Bancário

The impact of instant payments on bank competition generally depends on the specific design. Larger banks might adopt certain types of technologies faster than smaller banks. For example, Zelle and Swish are mainly used by large banks. I argue in the paper that Pix's success is determined by its availability to all financial intermediaries in Brazil.

To justify the claim, I study the impact of Boleto Bancário on deposit market concentration in Brazil. Boleto was created by the association of Brazilian banks, which only includes less than 20% of all intermediaries in the country. It then should provide more market power to larger banks since they offer better payment convenience. I run the following regression:

$$\log D_{it} = \delta \cdot \log Boleto_t \cdot L_i + \gamma X_{imt} + \theta_t + \alpha_i + \varepsilon_{imt} \tag{D.5}$$

Table D.8: Impact of Pix on Branch-Level Loans, Financing, and Alternative Funds

$$\log Y_{imt} = \delta \cdot \log Pix_{mt} \cdot S_i + \gamma X_{imt} + \theta_t + \alpha_i + \eta_{mt} + o_{imt}$$

	Dependent variable:		
	Loans	Financing	Alternative funding
	(1)	(2)	(3)
Pix · Small	−0.005	0.019**	−0.198***
	(0.004)	(0.008)	(0.017)
Bank FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Muni × Time FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	32,097	32,097	27,840
R^2	0.928	0.949	0.733

Note: This table provides branch-level results of estimation of equation (D.4). Column 1 shows results for traditional loans. Column 2 shows results for financing. Column 3 presents results for reserves. Standard errors are clustered at the municipality level and displayed in parentheses. Bank, time and municipality-time fixed effects are included. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

where $Boleto_t$ is equal to one after January 1993 – the date of the Boleto launch. I restrict the sample to one year before and after the introduction of Boleto. I use a dummy instead of the cross-sectional measure due to data availability constraints.

Table D.9 shows the results. Estimates in Columns 1 and 2 demonstrate that the introduction of Boleto had a significant positive impact on checking and saving deposits of larger banks compared to smaller banks.[34] In other words, deposit markets became more concentrated after the launch of Boleto. Column 3 shows the opposite result for time deposits, but it is economically smaller than the effect on saving deposits. The outflow of time deposits is likely associated with the deposit tax introduced by the Brazilian government shortly before the introduction of Boleto. The evidence suggests that the broad availability of Pix is key to promoting more competitive deposit markets.

[34] I define large and small banks based on the asset size in 1992.

Table D.9: Impact of Boleto Bancário on Bank Deposits

$$\log D_{it} = \delta \cdot \log Boleto_t \cdot S_i + \gamma X_{imt} + \theta_t + \alpha_i + \varepsilon_{imt}$$

	Dependent variable:		
	Checking deposits	Saving deposits	Time deposits
	(1)	(2)	(3)
Boleto · Small	-0.0279^{*}	-0.758^{***}	0.265^{***}
	(0.0160)	(0.236)	(0.0952)
Bank FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	509,245	509,245	509,245
R^2	0.895	0.859	0.812

Note: This table provides results of estimation of equation (D.5). The column corresponds to checking deposits. Column 2 shows results for saving deposits. Column 3 corresponds to time deposits. Standard errors are clustered at the municipality level and displayed in parentheses. Bank and time fixed effects are included. *,**, and *** correspond to 10-, 5-, and 1% significance level, respectively.

D.12 Cross-municipality transfers

In this section, I show that part of an increase in deposits of small banks can be attributed to facilitation of cross-municipality banking, i.e., usage of accounts in other municipalities. I measure Pix transfers to other municipalities using data on Pix value separated by senders and receivers. If there is a gap, it means that part of the Pix usage happened outside of the municipality. I also classify municipalities as Net Receivers ($NetRec_{mt} = 1$) if they received more Pix transactions than sent or Net Payers ($NetRec_{mt} = -1$) otherwise. Table D.10 shows the results of regressing deposits of the Pix gap interacted with the Net Receiver variable and a small bank dummy. Deposits of small banks are growing in the areas with a larger gap that are also net receivers. This is consistent with some households opening accounts in small banks in other municipalities.

A possible reason for opening a bank account in another municipality is that a household lives in a relatively rural area. With Pix, they can open an account in a bank in a nearby urban area and transfer funds for free. To validate the hypothesis, I add another interaction to the regression – a dummy variable equal to 1 if a municipality's

Table D.10: Impact of Cross-Municipality Transfers on Bank Deposits

$$\log D_{it} = \delta \cdot \log MuniGap_{mt} \cdot S_i \cdot NetRec_{mt} + \gamma X_{imt} + \theta_t + \alpha_i + \eta_{mt} + \varepsilon_{imt}$$

	Dependent variable:		
	Checking deposits	Saving deposits	Time deposits
	(1)	(2)	(3)
MuniGap · Small	-0.006^{***}	-0.003^{*}	-0.007^{***}
	(0.002)	(0.002)	(0.002)
NetRec · Small	-0.693^{***}	-0.710^{***}	-1.031^{***}
	(0.084)	(0.133)	(0.168)
MuniGap · NetRec · Small	0.064^{***}	0.062^{***}	0.092^{***}
	(0.007)	(0.012)	(0.014)
Bank FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Muni × Time FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	32,097	32,097	32,097
R^2	0.882	0.961	0.923

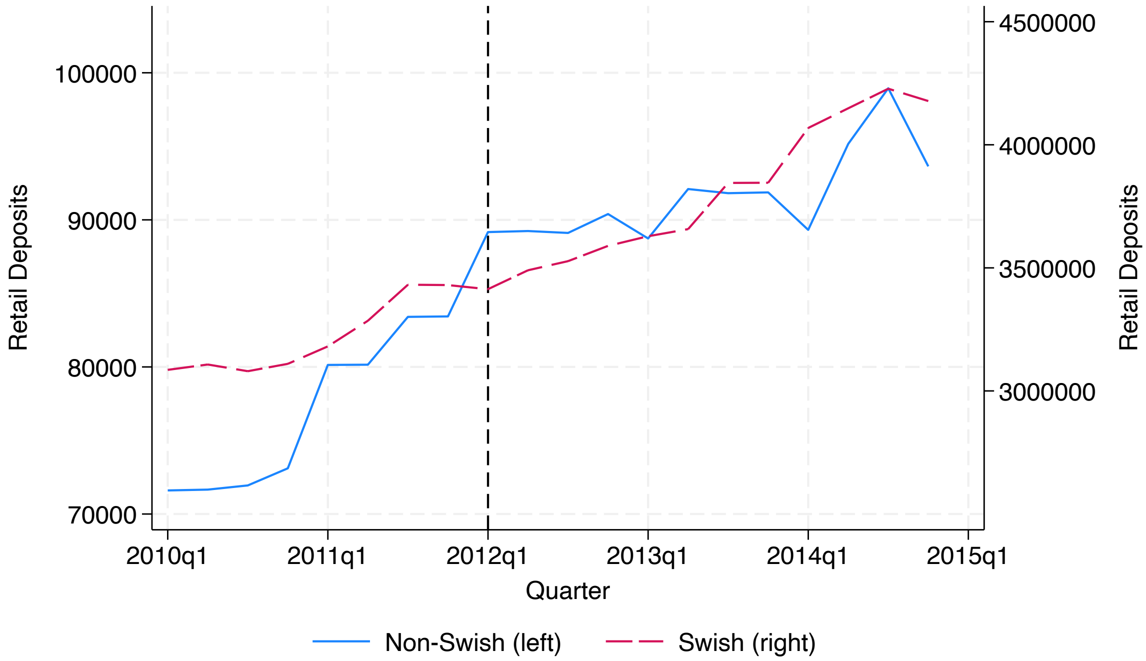
Note: This table provides results of the regression of deposits on cross-municipality transfers measured as the gap between received Pix payments and sent Pix payments. The first column corresponds to checking deposits. Column 2 shows results for saving deposits. Column 3 corresponds to time deposits. Standard errors are clustered at the municipality-level and included in the parentheses. Bank, time, and municipality-time fixed effects are included. *,**, and *** correspond to 10-, 5-, and 1% significance level, respectively.

90% of more of the population lives in urban areas. Table D.11 shows that the dummy for urban areas explains nearly all of the effect found in Table D.10. Finally, I restrict the sample to municipalities that had strict travel restrictions due to COVID-19 and show in Table D.12 that most results turn insignificant – it is arguably difficult to travel to another municipality to open a deposit account if there are travel restrictions in place.

D.13 Impact of Swish

Swish in was launched by six large banks in Sweden in 2012. The entry costs for other banks are substantial (the participants must approve all applications). Initially, Swish was designed to be a peer-to-peer payment application but later became a payment method.

Figure D.3: Impact of Swish on Deposit Market Concentration



Note: This figure plots the deposits of Swedish banks. The blue line (left axis) plots retail deposits of banks that were not Swish participants as of 2012. The red line (right axis) plots retail deposits of banks that were original Swish participants. All numbers are in millions SEK. The vertical black line corresponds to January 2012, when Swish was introduced.

I hand-collect data on ten banks in Sweden from their quarterly financial reports – six original participants of Swish and four large banks that were not part of Swish.

Figure D.3 plots the retail deposits. First, the deposit market concentration increases after the introduction of Pix, because participating banks now offer greater payment convenience than before.[35] Second, the effect of Swish is not economically large because Swish was initially a peer-to-peer payment application. The result suggests that instant payment systems impact customers' deposit choices most when they mitigate *retail payment* frictions, as Pix did. Finally, the figure only plots deposits of the ten largest banks. Since Sweden has over 90 banks, the results can be stronger.

[35]Sveriges Riksbank is designing a retail instant payment system, *Rix*, that will be available to all banks in Sweden. One motivation can be the monopoly power of Swish participants.

D.14 Summary statistics across treatment and control groups

Table D.13 provides descriptive statistics for the demographic and economic data separately for municipalities that eased COVID-19 restrictions by September 2020 (treated) and those that did not (control). Generally, demographics and deposits per capita are not very different across the groups of municipalities. However, population and total deposits are different. There are also likely differences in unobservables. For example, more conservative areas in Brazil are more likely to lift COVID restrictions given political pressure. As I discuss in Section 5, such differences are unlikely toviolate the exclusion restriction, because for differences to violate the exclusion restriction, it is necessary for them to impact the demand for small bank deposits exactly when Pix is introduced.

D.15 COVID-19 and deposit markets in Brazil

The Pix launch took place during the COVID-19 pandemic. Although by November, most restrictions were lifted, and I use the easing of COVID-19 restrictions to identify the impact of Pix on deposits and market power in Section 5, there are still concerns that bank deposits could have increased in municipalities with strict COVID restrictions.

In this section, I use data on COVID restrictions by municipalities provided by de Souza Santos et al. (2021) to show how two types of COVID restrictions impacted bank deposits. Specifically, I run the following regression:

$$\log D_{mT} = \delta Restr_m + \gamma X_{mT} + \varepsilon_{mT} \tag{D.6}$$

where T is November 2020, and $Rest_m$ is equal to one if COVID restrictions were implemented in municipality m. I consider two types of COVID restrictions – mask mandates and isolation requirements.

Table D.14 shows the results. It is clear that deposits did not rise in municipalities with strict COVID-19 restrictions. Moreover, there was a reduction in checking deposits in municipalities with self-isolation in place and an outflow of saving deposits in municipalities with mask mandates. Therefore, the main results of the paper cannot be driven by an increase in deposits during the COVID-19 pandemic.

D.16 Heterogeneity in severity of COVID restrictions

This section explores heterogeneity in COVID restrictions. In the main results, I require municipalities to have imposed mask mandates to consider them having COVID restrictions in place. Panel B of Table D.15 also requires gathering restrictions to be in place in addition to mask mandates. Finally, Panel C further restricts the sample by requiring isolation mandates to be in place. As expected, stricter requirements make the results of the paper stronger – bigger increases in checking and time deposits, as well as loans, of small banks relative to large banks.

Another concern is that some municipalities do not comply with the health mandate. Although direct data on health mandate enforcement is not available, I am using Hepatitis B vaccination coverage as a proxy of compliance. Hepatitis B is a vaccine that is generally highly recommended by the Ministry of Health, but many households choose not to vaccinate. I collect the data from the Ministry of Health's DataSUS database. In Table D.16, I restrict the sample to only keep municipalities where the coverage is above the median as of 2022. The results are significant and, for checking deposits and loans, even stronger than in the benchmark case.

D.17 Placebo: second wave of relaxation of COVID restrictions

In this section, I show the results of the placebo first stage, where I use the second wave of the relaxation of the COVID restrictions. By then, Pix has already been introduced, and I do not expect to find a strong increase in its use in the areas that relax COVID restrictions. The results in Table D.17 confirm the hypothesis.

D.18 Standard IV

In the main section, I use heteroskedasticity-based identification. Table D.18 below shows that the results are robust. There are more observations that in the tables with the heteroskedasticity-based IV because the standard IV does not require aggregation to the municipality level.

D.19 Impact of initial stimulus payments

A potential identification concern is that the results are affected by the distribution of the COVID stimulus in Brazil, which was mostly conducted through the large banks. It is possible that many households opened bank accounts there to receive their paychecks. However, the bias in this case would not be in my favor – opening accounts at large banks would make the effects I find smaller, if anything. In addition, major waves of stimulus payments in Brazil were between April and August of 2020 and later in April of 2021. In Table D.19, I run an event study around the first wave of COVID stimulus payments. The results are mostly insignificant – there was no significant change in deposits of small banks relative to large banks in high-Pix areas around COVID stimulus payments. Most of the significant values are negative – they imply an increase in deposits of large banks consistent with household opening accounts to withdraw their checks.

D.20 IV results without municipality-time fixed effects

Table D.20 shows the results of the estimation without including municipality-time fixed effects. As column 1 shows, checking and saving deposits of large banks increase while time deposits decrease.

D.21 Insured banks only

In this section, I show that if I limit the sample to the banks that are insured by FGV (analog of FDIC), the results hold. Table **??** shows the main coefficients.

D.22 Bootstrapping standard errors

In Table 4 standard errors are clustered at the municipality level to account for potential correlation between the residuals within the same municipality (Petersen (2009); Abadie et al. (2022)). The correlation between the residuals across municipalities is also possible, and it would require clustering standard errors at the time level. Since my sample in the regressions includes only two months pre-Pix and two after, clusterization can bias standard errors (Bertrand et al. (2004)). In this Section, I follow Bertrand et al. (2004) and bootstrap standard errors. I also include municipality fixed effects to account for regional unobservables. Table D.22 shows that the main results are robust.

D.23 Impact on municipality-level income

One identification concern is that COVID restrictions can impact income and, thus, violate the exclusion restriction. Table **??** shows that Pix usage does not predict an increase in municipality-level GDP per capita in 2020.

I also collect bimonthly data on expenditures and investments for each municipality to run an event study around the easing of COVID restrictions. I show the results in Table D.24. Expenditures were not different across the two groups of municipalities, and they were not affected by the easing of COVID restrictions. There was an increase in economic activity – a rise in investments with a two-month lag but the effect reversed two months later.

D.24 Discussion of parallel trends

In the main part of the paper, I show that deposits of small banks increase in areas with more Pix transactions predicted by the easing of COVID restrictions. The main parallel trend assumption is that, absent Pix, areas that relaxed COVID restrictions were on a similar track to areas that kept COVID restrictions. This assumption cannot be directly tested, but I show that there were no pre-trends in HHI or deposits of small banks prior to November 2020. In this section, I provide more evidence in support of the parallel trend assumption.

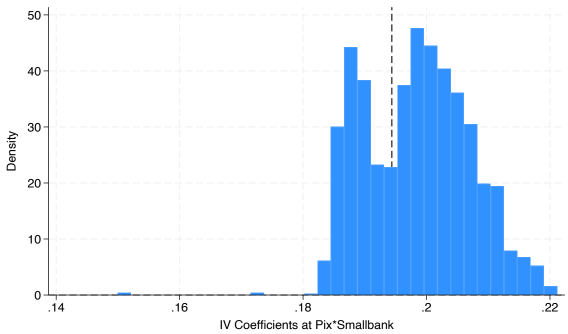
Although I do not observe pre-trends, what if there are unobservables with pre-trends, and these unobservables explain the results? To address the concern, I follow Altonji et al. (2005) and add supporting evidence to the following two assumptions: 1) observables are drawn randomly from the large set of possible variables; 2) sets of observables and unobservables are large enough. These two assumptions lead to the result that the part of deposits of small banks explained by observables is as related to Pix as the part explained by unobservables. In that case, selection on observables is indicative of the selection on unobservables.

To validate the point of Altonji et al. (2005), I run 2053 specifications of the IV regression of checking and time deposits on Pix interacted with small banks, where I include or exclude different control variables (including lending) and fixed effects. I plot the distribution of the point estimates and t-stats in Figure D.4 for time deposits and Figure D.5 for checking deposits. The results are highly stable, which suggests that the selection on observables is indicative of the selection on unobservables. I also follow Altonji et al. (2005) and calculate that the shift in the distribution of unobservables must be at least 3.94 times as large as the shift in the distribution of observables to explain away my results. Such a difference seems unlikely.

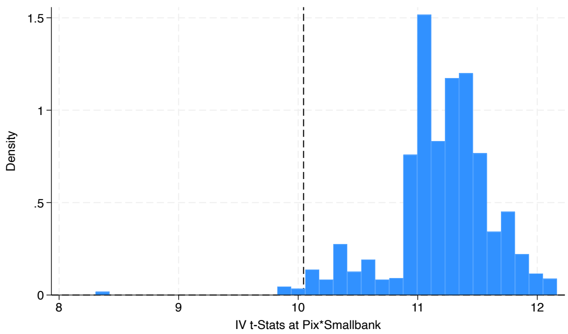
In addition, I follow Rambachan and Roth (2023) and allow for violations of the parallel trend assumption. I allow for different magnitudes of the violation of the parallel trend assumption relative to pre-trends. For example, $M = 0$ implies no violation of parallel trends, and $M = 0.5$ implies that violations of parallel trends are half as large as the average violation in the pre-treatment period. Figure D.6 shows the results. For even reasonably large values of M, the estimated coefficient is still positive and significant. The significance breaks if the violations of parallel trends are 130% of the average violation in the pre-treatment period.

Finally, I follow Roth (2022) and calculate several statistics that compare two hypotheses: 1) the trends are parallel, 2) there is a linear trend that fits pre-trends. The

Figure D.4: Distributions of Point Estimates and t-Statistics from Time Deposit IV Regressions



(a) Estimates



(b) t-Statistics

Note: This figure plots histograms of point estimates (panel (a)) and t-stats (panel (b)) from 2,053 specifications of the IV regressions of time deposits on Pix interacted with a small bank dummy. Different specifications have different control variables and fixed effects.

parallel trend assumption cannot be tested directly, but looking at the likelihood ratio and Bayesian statistics can still be insightful. Specifically, the Bayes ratio is 0.37, which is relatively small, indicating that we should update our priors in favor of the parallel trend assumption. Similarly, the likelihood ratio is 0.004, also consistent with the parallel trend assumption.

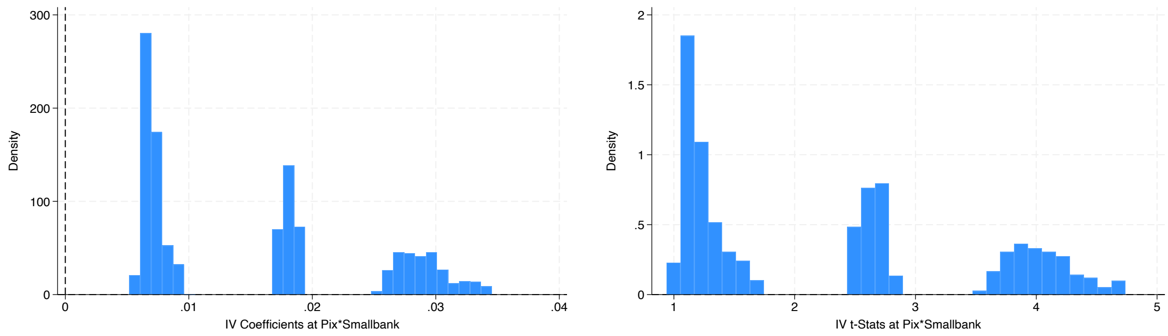
D.25 Robustness to controls and fixed effects

In this section, I show that the OLS results are robust to various sets of controls and fixed effects. First, Table D.25 shows that the results are robust to excluding controls, municipality-time fixed effects, or time fixed effects. In addition, I run more than 20 thousand specifications and plot estimates and t-stats for time deposits in Figure D.7 and for checking deposits in Figure D.8. Most of the coefficients are positive and significant, as in the specification with all controls and fixed effects showed in Table 4.

D.26 Different scaling of Pix

Table D.26 shows that both OLS and IV results are robust to using log of Pix, Pix value per capita, or Pix quantity per capita as an independent variable.

Figure D.5: Distributions of Point Estimates and t-Statistics from Checking Deposit IV Regressions



(a) Estimates

(b) t-Statistics

Note: This figure plots histograms of point estimates (panel (a)) and t-stats (panel (b)) from 2,053 specifications of the IV regressions of checking deposits on Pix interacted with a small bank dummy. Different specifications have different control variables and fixed effects.

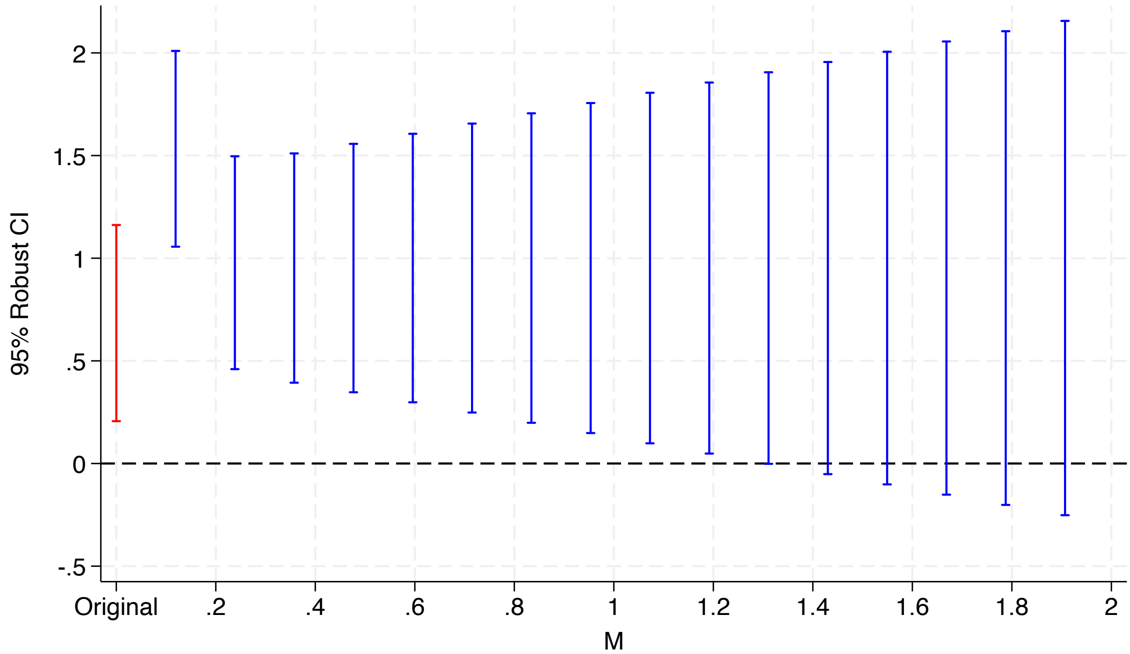
D.27 OLS in a six-month window

In this section, I show that my results are robust to extending the sample period to include August 2020 and January 2021. Table D.27 shows the results.

D.28 Various difference-in-differences methods

Table D.28 provides results of the OLS regression of time deposits on Pix interacted with small bank and post-November dummies where the Pix variable is fixed either in November 2020 (columns 1 and 2) or averaged across November and December (columns 3 and 4). This is in some ways a more standard difference-in-differences approach. Deposits of small banks increase relative to large banks in all specifications. Table D.29 shows the results of a similar analysis for deposit rates – small banks reduce deposit rate relative to large banks. Table D.31 shows the results for the IV regressions (first-stage results are in Table D.30). Finally, Figures D.9 and D.10 show the results for HHI regressions.

Figure D.6: Honest Difference-in-Differences: Violations of Parallel Trend Assumption



Note: This figure plots confidence intervals for the reduced-form version of the IV regressions of time deposits on Pix (fixed at November 2020), interacted with a post-Pix dummy and a small bank dummy. The left line is a benchmark that assumes no violation of the parallel trend assumption. Values of M allow violations of parallel trends to be M times as large as the average violation in the pre-treatment period.

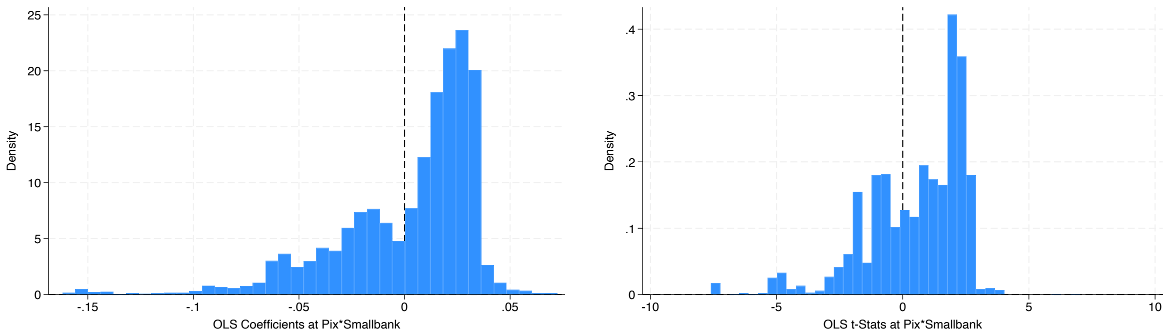
D.29 Instrumenting Pix with high-speed internet access

I collect municipality-level data on access to high-speed internet from Anatel. In the first stage, I regress the value of per capita Pix transactions on the index of high-speed internet access. Table D.32 shows that Pix is used more in areas with better access to high-speed internet. The results indicate that the relevance assumption is likely satisfied.

The exclusion restriction implies that the only way access to high-speed internet can impact change in deposit market concentration between October and November is through its impact on access to Pix. Figure D.11 shows the results. First, there is almost no pre-trend.[36] Second, there is a significant reduction in HHI following the introduction of Pix. Economic impact is comparable to effects found when COVID-19 restrictions are

[36]Small pre-trend likely implies that small banks had an advantage in areas with bad access to the internet during COVID-19 restrictions since they are mainly not digital.

Figure D.7: Distributions of Point Estimates and t-Statistics from Time Deposit OLS Regressions



(a) Estimates (b) t-Statistics

Note: This figure plots histograms of point estimates (panel (a)) and t-stats (panel (b)) from 10,242 specifications of the OLS regressions of time deposits on Pix interacted with a small bank dummy. Different specifications have different control variables and fixed effects.

used as instruments.

D.30 Impact of political views, mortality, and age

Table D.33 shows that political views (the results of the elections), mortality, and age do not impact the easing of COVID restrictions and usage of Pix.

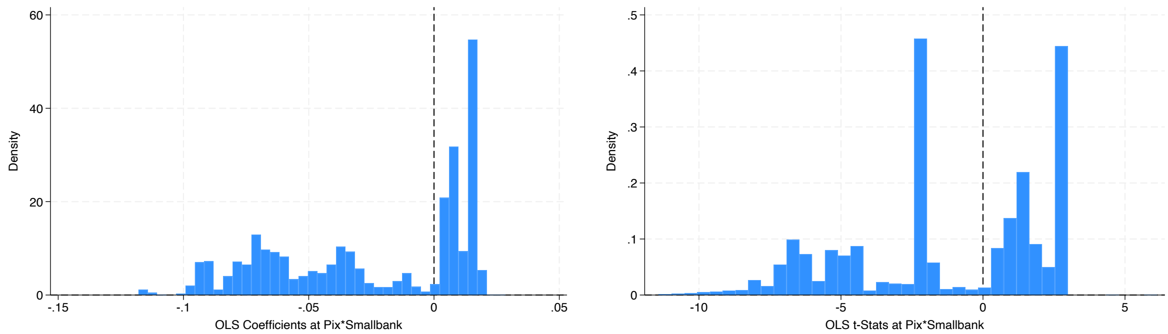
D.31 Sample of direct Pix participants

The results in Table 4 include the sample of 119 banks during the analyzed period. Account holders at most of those banks can use Pix but not always through the banks' mobile app directly. 64 out of 119 banks allow to use Pix directly through their apps and they are listed as Pix participants on the Central Bank's website. This section shows that the main results hold in the sample of banks that directly participate in Pix.

D.32 Using salaries as an instrument

This section estimates the model but uses fixed costs and salaries as instruments for deposit rates.

Figure D.8: Distributions of Point Estimates and t-Statistics from Checking Deposit OLS Regressions



(a) Estimates

(b) t-Statistics

Note: This figure plots histograms of point estimates (panel (a)) and t-stats (panel (b)) from 10,242 specifications of the OLS regressions of checking deposits on Pix interacted with a small bank dummy. Different specifications have different control variables and fixed effects.

D.33 BLP without small bank interaction

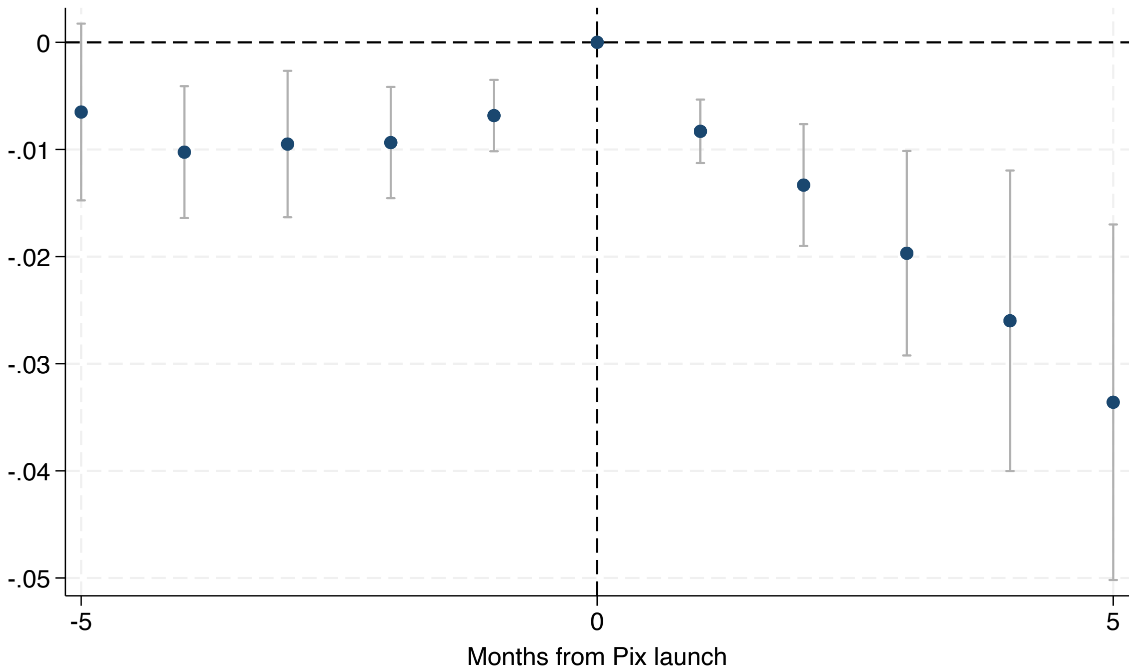
Table D.37 presents the results of the BLP estimation without including the term that interacts Pix with a small bank dummy. Figure D.12 shows counterfactuals. The results are very similar to the ones in the main section. The welfare implications are, however, mitigated – the deposit-equivalent change in welfare in this case is around \$250 instead of \$380.

D.34 BLP with negative δ

In this section, I show that even some negative values of the parameter at the interaction of Pix with a small bank dummy yield welfare gains. I also show that for sufficiently negative values of the parameter, welfare gains transform into welfare losses. Figure D.13 shows the results. Panel (a) sets $\delta = -0.008$ – a value negative to an actual estimate of δ. Welfare gains from Pix are reduced but are still positive at about \$130. Panel (c) sets $\delta = -0.017$, which is just negative enough to erase welfare gains. Finally, panel (e) sets $\delta = -0.05$, which yields welfare losses of \$600. Panels (b), (d), and (f) show that HHI counterfactuals are not very sensitive to changes in δ.

Figure D.9: Impact of Pix on Deposit Market Concentration: Pix Fixed in November

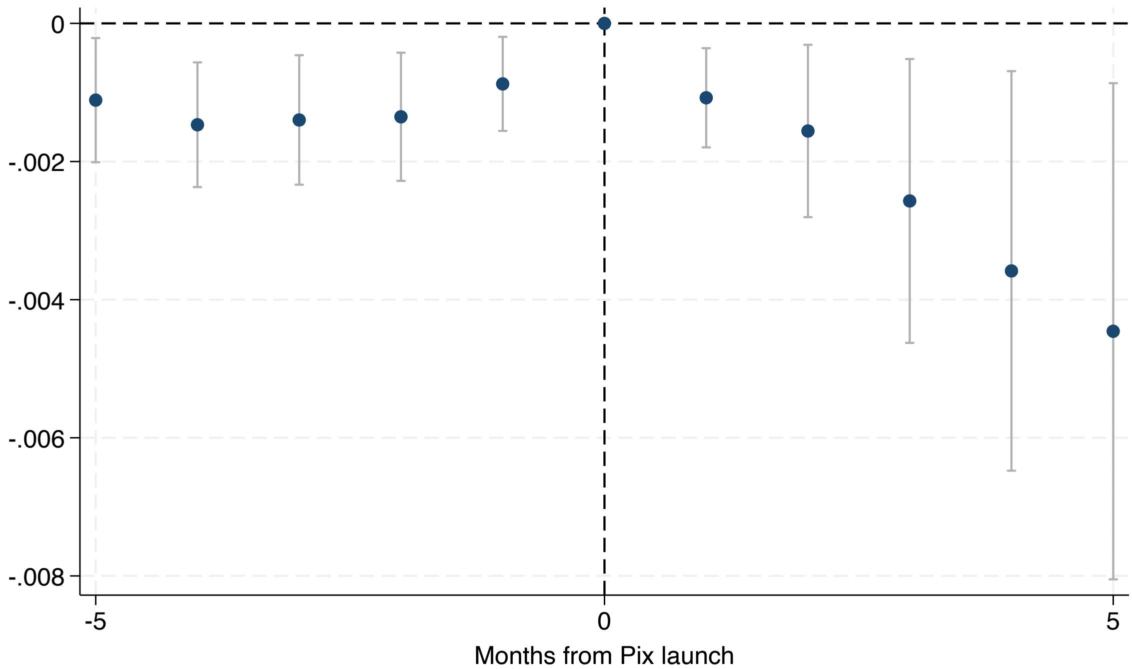
$$HHI_{m,t+s} = \theta PixPerCap_{mt} + \delta HHI_{m,t-1} + \gamma X_{mt} + \varepsilon_{mt}$$



Note: This figure plots results of estimation of equation (3). The vertical axis corresponds to θ – sensitivity of future deposit market concentration to per capita Pix transactions. The horizontal axis corresponds to months since t. Pix per capita is fixed at its value in November 2020. Blue dots are coefficients, whereas grey lines are 95% confidence intervals constructed by clusterization on the municipality level.

Figure D.10: Impact of Pix on Deposit Market Concentration: Pix Averaged across Post-Period

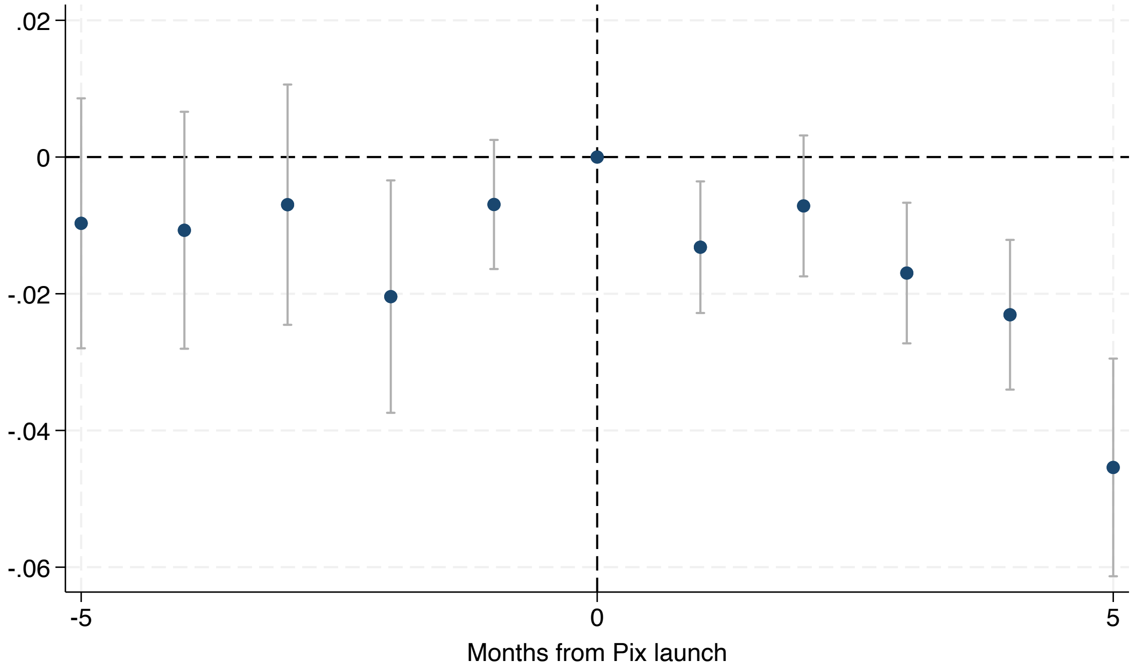
$$HHI_{m,t+s} = \theta PixPerCap_{mt} + \delta HHI_{m,t-1} + \gamma X_{mt} + \varepsilon_{mt}$$



Note: This figure plots results of estimation of equation (3). The vertical axis corresponds to θ – sensitivity of future deposit market concentration to per capita Pix transactions. The horizontal axis corresponds to months since t. Pix per capita is fixed at its average value during the post-period. Blue dots are coefficients, whereas grey lines are 95% confidence intervals constructed by clusterization on the municipality level.

Figure D.11: Impact of Pix on Deposit Market Concentration: IV with Access to High-Speed Internet

$$HHI_{m,t+s} = \theta Pix\widehat{PerCap}_{mt} + \delta HHI_{m,t} + \gamma X_{mt} + \eta_{mt}$$



Note: This figure plots the results of the second stage in the IV estimation of equation (10) where access to high-speed internet is used as an instrument. The vertical axis corresponds to θ – sensitivity of future deposit market concentration to per capita Pix transactions predicted by the access to high-speed internet. The horizontal axis corresponds to months since Pix launch. Blue dots are coefficients, whereas grey lines are 95% confidence intervals constructed by clusterization on the municipality level.

Table D.11: Impact of Cross-Municipality Transfers on Bank Deposits: Interaction with Urban Areas

$$\log D_{it} = \delta \cdot \log MuniGap_{mt} \cdot S_i \cdot NetRec_{mt} \cdot Urban_m + \gamma X_{imt} + \theta_t + \alpha_i + \eta_{mt} + \varepsilon_{imt}$$

	Dependent variable:		
	Checking deposits	Saving deposits	Time deposits
	(1)	(2)	(3)
MuniGap · Small	0.001	0.004**	0.001
	(0.002)	(0.002)	(0.002)
NetRec · Small	−0.031	0.111	−0.101
	(0.103)	(0.135)	(0.218)
MuniGap · NetRec · Small	0.003	−0.013	0.010
	(0.009)	(0.012)	(0.019)
Small · Urban	0.310***	0.279***	0.206***
	(0.032)	(0.044)	(0.062)
MuniGap · Small · Urban	−0.013***	−0.014***	−0.019***
	(0.003)	(0.005)	(0.006)
NetRec · Small · Urban	−0.763***	−1.161***	−1.915***
	(0.178)	(0.300)	(0.350)
MuniGap · NetRec · Small · Urban	0.070***	0.102***	0.157***
	(0.015)	(0.025)	(0.030)
Bank FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Muni × Time FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	32,097	32,097	32,097
R^2	0.883	0.962	0.923

Note: This table provides results of the regression of deposits on cross-municipality transfers measured as the gap between received Pix payments and sent Pix payments. The variables are interacted with a dummy for a highly urban area. The first column corresponds to checking deposits. Column 2 shows results for saving deposits. Column 3 corresponds to time deposits. Standard errors are clustered at the municipality-level and included in the parentheses. Bank, time, and municipality-time fixed effects are included. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

Table D.12: Impact of Cross-Municipality Transfers on Bank Deposits: Interaction with Urban Areas with Travel Restrictions

$$\log D_{it} = \delta \cdot \log MuniGap_{mt} \cdot S_i \cdot NetRec_{mt} \cdot Urban_m + \gamma X_{imt} + \theta_t + \alpha_i + \eta_{mt} + \varepsilon_{imt}$$

	Dependent variable:		
	Checking deposits	Saving deposits	Time deposits
	(1)	(2)	(3)
MuniGap · Small	−0.001	−0.000	−0.014
	(0.005)	(0.004)	(0.010)
NetRec · Small	−0.247	0.329	0.009
	(0.308)	(0.438)	(0.808)
MuniGap · NetRec · Small	0.024	−0.023	0.024
	(0.028)	(0.040)	(0.074)
Small · Urban	0.417***	0.434***	0.244
	(0.085)	(0.132)	(0.188)
MuniGap · Small · Urban	−0.005	−0.010	0.003
	(0.007)	(0.010)	(0.014)
NetRec · Small · Urban	−0.479	−2.194***	−1.905*
	(0.498)	(0.738)	(1.102)
MuniGap · NetRec · Small · Urban	0.040	0.174***	0.128
	(0.043)	(0.062)	(0.096)
Bank FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Muni × Time FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	3,282	3,282	3,282
R^2	0.903	0.951	0.933

Note: This table provides results of the regression of deposits on cross-municipality transfers measured as the gap between received Pix payments and sent Pix payments. The variables are interacted with a dummy for a highly urban area. The sample is restricted to only municipalities with COVID travel restrictions. The first column corresponds to checking deposits. Column 2 shows results for saving deposits. Column 3 corresponds to time deposits. Standard errors are clustered at the municipality-level and included in the parentheses. Bank, time, and municipality-time fixed effects are included. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

Table D.13: Summary Statistics: Treatment and Control Groups

	Eased restrictions			Kept restrictions		
	Mean	Median	Std. dev.	Mean	Median	Std. dev.
Population (th.)	48	19	134	37	15	90
% under 40 y.o.	57	57	5.1	56	56	4.8
% females	50	50	1.4	50	50	1.7
% single responsible	72	72	8.4	71	72	8.6
% urban	73	77	20	72	76	20
% illiterate	14	11	9.6	14	11	9.1
Checking deposits per capita (m. R$)	0.57	0.5	0.38	0.56	0.48	0.41
Saving deposits per capita (m. R$)	1.4	0.81	2.6	1.5	0.73	2.4
Time deposits per capita (m. R$)	3.4	3	2.4	3.4	2.8	2.4
Loans per capita (m. R$)	1.6	1.5	1.1	1.6	1.3	1.1
Total deposits (bn. R$)	204	85	292	166	64	240
Number of munis		1,541			715	

Note: This table provides descriptive statistics for the demographic and economic data separately for municipalities that eased COVID-19 restrictions by September 2020 (treated) and those that did not (control). Panel A shows statistics for the treatment group as of October 2020. Panel B provides means, medians, and standard deviations for the control group as of October 2020.

Table D.14: Impact of COVID-19 Restrictions on Bank Deposits

$$\log D_{mT} = \delta Restr_m + \gamma X_{mT} + \varepsilon_{mT}$$

	Dependent variable:					
	Checking deposits		Saving deposits		Time deposits	
	(1)	(2)	(3)	(4)	(5)	(6)
Masks	-0.048		-0.152^{**}		-0.371	
	(0.092)		(0.076)		(0.287)	
Isolation		-0.098^{***}		-0.014		-0.142
		(0.034)		(0.032)		(0.129)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,326	2,331	2,326	2,331	2,326	2,331
R^2	0.773	0.774	0.792	0.793	0.486	0.487

Note: This table provides results of estimation of equation (D.6). The first two columns correspond to checking deposits. Columns 3 and 4 show results for saving deposits. Columns 4 and 5 correspond to time deposits. Standard errors are clustered at the municipality level and displayed in parentheses. *,**, and *** correspond to 10-, 5-, and 1% significance level, respectively.

Table D.15: Impact of Pix on Deposits and Loans of Small Banks: IV with Easing of COVID Restrictions of Various Severity

$$\log D_{imt} = \delta \cdot \log \widehat{Pix}_{mt} \cdot S_i + \gamma X_{imt} + \eta_{mt} + \varepsilon_{imt}$$

	Panel A: Mask mandate			
	Checking deposits	Saving deposits	Time deposits	Total loans
	(1)	(2)	(3)	(4)
Pix · Small	0.019***	−0.008	0.174***	0.046***
	(0.007)	(0.006)	(0.021)	(0.008)
Muni × Time FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	7,123	7,123	7,123	7,123
R^2	0.636	0.545	0.072	0.289

	Panel B: Gathering restrictions			
	Checking deposits	Saving deposits	Time deposits	Total loans
	(1)	(2)	(3)	(4)
Pix · Small	0.019***	−0.009	0.175***	0.047***
	(0.007)	(0.006)	(0.021)	(0.009)
Muni × Time FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	6,939	6,939	6,939	6,939
R^2	0.634	0.541	0.072	0.290

	Panel C: Isolation mandate			
	Checking deposits	Saving deposits	Time deposits	Total loans
	(1)	(2)	(3)	(4)
Pix · Small	0.021***	-0.002	0.179***	0.042***
	(0.006)	(0.004)	(0.023)	(0.006)
Muni × Time FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	5,193	5,193	5,193	5,193
R^2	0.603	0.521	0.078	0.289

Note: This table provides results of the second stage in the IV estimation of equation (10), including interactions with the small bank dummy. The easing of COVID-19 restrictions in Brazil is used as an instrument for Pix usage. Panel A is the benchmark results where mask mandates qualify as COVID restrictions. In Panel B, I require gathering restrictions to be in place as well. Panel C also includes isolation mandates. The specification uses a heteroskedasticity-based IV approach. Column 1 presents results for checking deposits. Column 2 presents results for saving deposits. Column 3 shows results for time deposits. Column 4 corresponds to total loans. Municipality-time fixed effects 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.16: Impact of Pix on Deposits and Loans of Small Banks: IV with Easing of COVID Restrictions in Areas with High Vaccination Rates

$$\log D_{imt} = \delta \cdot \widehat{\log Pix}_{mt} \cdot S_i + \gamma X_{imt} + \eta_{mt} + \varepsilon_{imt}$$

	Dependent variable:			
	Checking deposits	Saving deposits	Time deposits	Total loans
	(1)	(2)	(3)	(4)
Pix · Small	0.020***	−0.005	0.141***	0.055***
	(0.007)	(0.004)	(0.027)	(0.008)
Muni × Time FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	3,606	3,606	3,606	3,606
R^2	0.645	0.579	0.046	0.332

Note: This table provides results of the second stage in the IV estimation of equation (10), including interactions with the small bank dummy. The easing of COVID-19 restrictions in Brazil is used as an instrument for Pix usage. The sample is restricted to municipalities with above-median hepatitis B vaccination as of 2022. The specification uses a heteroskedasticity-based IV approach. Column 1 presents results for checking deposits. Column 2 presents results for saving deposits. Column 3 shows results for time deposits. Column 4 corresponds to total loans. Municipality-time fixed effects 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.17: Impact of the Second Wave of the Easing of the COVID-19 Restrictions on Pix

$$\log Pix_{mt} = \alpha Eased_m + \theta Placebo_t + \gamma Eased_m Placebo_t + \theta X_{mt} + \theta_t + \upsilon_m + \varepsilon_{mt}$$

	Dependent variable:			
	Pix			
	(1)	(2)	(3)	(4)
Eased	-0.129^{***}	-0.129^{***}		
	(0.021)	(0.021)		
Post Placebo	0.195^{***}		0.195^{***}	
	(0.017)		(0.003)	
Eased · Post Placebo	0.011	0.011	0.012^{**}	0.012^{**}
	(0.030)	(0.030)	(0.005)	(0.005)
Municipality FE	No	No	Yes	Yes
Time FE	No	Yes	No	Yes
Controls	Yes	Yes	Yes	Yes
Observations	6,887	6,887	6,885	6,885
R^2	0.857	0.857	0.996	0.996

Note: This table provides results of the first stage in the IV estimation, where the second wave of the relaxation of COVID restrictions is used. $Eased_m = 1$ for municipalities that eased COVID-19 restrictions following the introduction of the vaccine in Spring 2021. $Placebo_t = 1$ for April 2021. Columns 2-3 include time and/or municipality fixed effects. Robust standard errors are displayed in parentheses. *,**, and *** correspond to 10-, 5-, and 1% significance level, respectively.

Table D.18: Impact of Pix on Deposits and Loans of Small Banks: Standard IV with Easing of COVID Restrictions

$$\log D_{imt} = \delta \cdot \widehat{\log Pix}_{mt} \cdot S_i + \gamma X_{imt} + \eta_{mt} + \varepsilon_{imt}$$

	Dependent variable:			
	Checking deposits	Saving deposits	Time deposits	Total loans
	(1)	(2)	(3)	(4)
Pix · Small	0.009*	0.024***	0.021**	0.023***
	(0.005)	(0.009)	(0.010)	(0.005)
Muni × Time FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	12,207	12,207	12,207	12,207
R^2	0.641	0.256	0.070	0.148

Note: This table provides results of the second stage in the IV estimation of equation (10), including interactions with the small bank dummy. The easing of COVID-19 restrictions in Brazil is used as an instrument for Pix usage. The specification uses a standard IV approach. Column 1 presents results for checking deposits. Column 2 presents results for saving deposits. Column 3 shows results for time deposits. Column 4 corresponds to total loans. Municipality-time fixed effects 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.19: Impact of Stimulus Payments on Bank Deposits

$$\log D_{imt} = \delta_s \cdot PixPerCap_m \cdot S_i \cdot \sum_{s=-3}^{4} Stim_{t+s} + \gamma X_{imt} + \theta_t + \alpha_i + \eta_{mt} + \varepsilon_{imt}$$

	Dependent variable:		
	Checking deposits	Saving deposits	Time deposits
	(1)	(2)	(3)
$\text{Stim}_{(-3)} \cdot \text{Pix} \cdot \text{Small}$	-0.002	0.000	-0.007
	(0.008)	(0.002)	(0.005)
$\text{Stim}_{(-2)} \cdot \text{Pix} \cdot \text{Small}$	0.024^{***}	0.002	0.009
	(0.008)	(0.003)	(0.008)
$\text{Stim}_{(-1)} \cdot \text{Pix} \cdot \text{Small}$	0.002	-0.004^{**}	-0.004
	(0.007)	(0.002)	(0.005)
$\text{Stim} \cdot \text{Pix} \cdot \text{Small}$	-0.011	-0.009^{***}	-0.012^{**}
	(0.007)	(0.002)	(0.006)
$\text{Stim}_{(1)} \cdot \text{Pix} \cdot \text{Small}$	0.002	0.005	0.024^{**}
	(0.007)	(0.003)	(0.011)
$\text{Stim}_{(2)} \cdot \text{Pix} \cdot \text{Small}$	-0.003	-0.013^{*}	-0.007
	(0.006)	(0.008)	(0.005)
$\text{Stim}_{(3)} \cdot \text{Pix} \cdot \text{Small}$	-0.023^{***}	0.011^{*}	0.004
	(0.007)	(0.007)	(0.007)
Bank FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Muni $\times$ Time FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	98,636	98,636	98,636
R^2	0.896	0.962	0.916

Note: This table provides results of the estimation of the event study around COVID stimulus payments that were primarily distributed through large banks. The payments were mostly delivered between April 2020 (Stim) and August of 2020. I also include 3 months before April in the event study. The Pix variable is fixed to November 2020 value so that it does not vary over time. The first column corresponds to checking deposits. Column 2 shows results for saving deposits. Column 3 corresponds to time deposits. Standard errors are clustered at the municipality level and displayed in parentheses. Bank, time, and municipality-time fixed effects are included. *,**, and *** correspond to 10-, 5-, and 1% significance level, respectively.

Table D.20: Impact of Pix on Deposits and Loans of Small Banks: No Municipality-Time Fixed Effects

$$\log D_{imt} = \delta \cdot \widehat{\log Pix_{mt}} \cdot S_i + \gamma X_{imt} + \varepsilon_{imt}$$

	Dependent variable:			
	Checking deposits	Saving deposits	Time deposits	Total loans
	(1)	(2)	(3)	(4)
Pix	0.022***	0.009***	−0.054***	−0.012
	(0.003)	(0.001)	(0.008)	(0.002)
Pix · Small	0.006	−0.011**	0.203***	0.058*
	(0.006)	(0.005)	(0.018)	(0.034)
Muni × Time FE	No	No	No	No
Controls	Yes	Yes	Yes	Yes
Observations	7,123	7,123	7,123	178
R^2	0.746	0.683	0.411	0.239

Note: This table provides results of the second stage in the IV estimation of equation (10) without municipality-time fixed effects. The easing of COVID-19 restrictions in Brazil is used as an instrument for Pix usage. The specification uses a heteroskedasticity-based identification strategy conditional on the information in October 2020. Column 1 presents results for checking deposits. Column 2 presents results for saving deposits. Column 3 shows results for time deposits. Column 4 corresponds to bank-level total loans. Municipality-level variables for the loan regression are aggregated using time deposits as weights. The loan regression is estimated in a four-month window because the bank-level data is quarterly. Standard errors are clustered at the municipality level (at the bank level for the loan regression) and displayed in parentheses. Time fixed effects are included in the panel regression. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

Table D.21: Impact of Pix on Deposits and Loans of Small Banks in the Sample of Insured Banks: IV with Easing of COVID Restrictions

$$\log D_{imt} = \delta \cdot \widehat{\log Pix}_{mt} \cdot S_i + \gamma X_{imt} + \eta_{mt} + \varepsilon_{imt}$$

	Dependent variable:			
	Checking deposits	Saving deposits	Time deposits	Total loans
	(1)	(2)	(3)	(4)
Pix · Small	0.019***	−0.009	0.178***	0.048***
	(0.007)	(0.006)	(0.021)	(0.009)
Muni × Time FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	7,063	7,063	7,063	7,063
R^2	0.640	0.554	0.079	0.303

Note: This table provides results of the second stage in the IV estimation of equation (10), including interactions with the small bank dummy. The sample is restricted to insured banks only. The easing of COVID-19 restrictions in Brazil is used as an instrument for Pix usage. The specification uses a heteroskedasticity-based IV approach. Column 1 presents results for checking deposits. Column 2 presents results for saving deposits. Column 3 shows results for time deposits. Column 4 corresponds to total loans. Municipality-time fixed effects 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.22: Impact of Pix on Bank Deposits: Bootstrapped Standard Errors

$$\log D_{it} = \delta \cdot \log Pix_{mt} \cdot S_i + \gamma X_{imt} + \theta_t + \alpha_i + \eta_{mt} + \varepsilon_{imt}$$

	Dependent variable:		
	Checking deposits	Saving deposits	Time deposits
	(1)	(2)	(3)
Pix · Small	0.030***	0.032***	0.043***
	(0.004)	(0.005)	(0.006)
Bank FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Muni × Time FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	32,097	32,097	32,097
R^2	0.882	0.961	0.923

Note: This table provides results of estimation of equation (2) with bootstrapped standard errors and municipality fixed effects. The first column corresponds to checking deposits. Column 2 shows results for saving deposits. Column 3 corresponds to time deposits. Standard errors are bootstrapped and displayed in parentheses. Bank, time, and municipality-time fixed effects are included. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

Table D.23: Impact of Pix on Municipality-Level GDP per Capita

$$\log GDPpc_{mt} = \delta \widehat{\log Pix}_{mt} + \theta X_{mt} + o_{mt}$$

	Dependent variable:	
	GDP per capita	
	(1)	(2)
Pix	-0.004^{*}	-0.005^{***}
	(0.002)	(0.002)
Method	HC	IV
Controls	Yes	Yes
Observations	7,124	7,124
R^2	0.426	0.426

Note: This table provides results of the IV estimation of the impact of Pix on GDP per capita across municipalities. The first column estimates the causal effect using heteroskedasticity-based estimation. Column 2 shows results using standard IV. Standard errors are clustered at the municipality level and displayed in parentheses. *,**, and *** correspond to 10-, 5-, and 1% significance level, respectively.

Table D.24: Impact of Easing of COVID Restrictions on Investments and Spending

$$\log Sp_{mt} = \delta \cdot Eased_m \cdot \sum_{s=-4}^{4} Cov_{t+s} + \gamma X_{mt} + \varepsilon_{mt}$$

	Dependent variable:	
	Expenditures	Investments
	(1)	(2)
$\text{Cov}_{(-4)} \cdot$ Eased	-0.017	-0.062
	(0.013)	(0.053)
$\text{Cov}_{(-2)} \cdot$ Eased	0.017	-0.005
	(0.013)	(0.048)
Cov $\cdot$ Eased	-0.006	-0.053
	(0.023)	(0.054)
$\text{Cov}_{(2)} \cdot$ Eased	-0.045	0.226^{***}
	(0.040)	(0.080)
$\text{Cov}_{(4)} \cdot$ Eased	0.034	-0.143^{**}
	(0.030)	(0.067)
Controls	Yes	Yes
Observations	21,729	20,468
R^2	0.414	0.226

Note: This table provides results of the estimation of the event study around the easing of COVID-19 restrictions by September 2020. I include 4 months before and after September in the event study. The first column corresponds to expenditures. Column 2 shows results for investments. Data is bimonthly. Standard errors are clustered at the municipality level and displayed in parentheses. *,**, and *** correspond to 10-, 5-, and 1% significance level, respectively.

Table D.25: Impact of Pix on Deposits of Small Banks: Different Controls and Fixed Effects

	Panel A: OLS without controls		
	Checking deposits	Saving deposits	Time deposits
	(1)	(2)	(3)
Pix · Small	0.025***	0.030***	0.039***
	(0.006)	(0.006)	(0.006)
Time FE	Yes	Yes	Yes
Muni × Time FE	Yes	Yes	Yes
Controls	No	No	No
Observations	32,218	32,218	32,218
R^2	0.795	0.948	0.897

	Panel B: OLS witout muni-time FEs		
	Checking deposits	Saving deposits	Time deposits
	(1)	(2)	(3)
Pix	0.027	−0.103**	0.237***
	(0.029)	(0.042)	(0.048)
Pix · Small	0.016**	0.025***	0.019*
	(0.006)	(0.006)	(0.010)
Time FE	Yes	Yes	Yes
Muni × Time FE	No	No	No
Controls	Yes	Yes	Yes
Observations	36,496	36,496	36,496
R^2	0.852	0.945	0.900

	Panel C: OLS without time FEs		
	Checking deposits	Saving deposits	Time deposits
	(1)	(2)	(3)
Pix	−0.012**	−0.030***	-0.017**
	(0.005)	(0.006)	(0.007)
Pix · Small	0.018***	0.021***	0.032***
	(0.006)	(0.005)	(0.013)
Time FE	No	No	No
Muni × Time FE	No	No	No
Controls	Yes	Yes	Yes
Observations	36,496	36,496	36,496
R^2	0.852	0.945	0.900

This table provides results of the OLS estimation of the effect of Pix on deposits of small banks. Column 1 presents results for checking deposits. Column 2 presents results for saving deposits. Column 3 shows results for time deposits. Panel A excludes control variables, Panel B excludes municipality-time FEs, Panel C also excludes time FEs. Bank FEs 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.26: Impact of Pix on Bank Deposits: OLS and IV with Different Scaling

	Dependent variable:					
	Time deposits					
	(1)	(2)	(3)	(4)	(5)	(6)
Pix · Small	0.043***	0.093***	0.181***	0.174***	0.388***	3.610***
	(0.006)	(0.020)	(0.028)	(0.021)	(0.125)	(0.341)
Specification		OLS			IV	
Pix variable	Log Value	Value Per Capita	Quantity Per Capita	Log Value	Value Per Capita	Quantity Per Capita
Muni × Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	32,097	32,097	15,957	7,123	7,123	3,556
R^2	0.923	0.923	0.924	0.039	0.033	0.041

Note: This table provides results of OLS (columns 1-3) and IV (columns 4-6) of the effect of Pix on time deposits of small banks. Columns 1 and 4 use log of Pix as an independent variable. Columns 2 and 5 use Pix value per capita. Columns 3 and 6 use Pix quantity per capita. Standard errors are clustered at the municipality level and displayed in parentheses. Bank, time, and municipality-time fixed effects are included for OLS, and municipality-time fixed effects are included for the IV. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

Table D.27: Impact of Pix on Bank Deposits: Six-Month Window

$$\log D_{imt} = \delta \cdot \log Pix_{mt} \cdot S_i + \gamma X_{imt} + \theta_t + \alpha_i + \eta_{mt} + \varepsilon_{imt}$$

	Dependent variable:		
	Checking deposits	Saving deposits	Time deposits
	(1)	(2)	(3)
Pix · Small	0.029***	0.034***	0.046***
	(0.004)	(0.005)	(0.006)
Bank FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Muni × Time FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	48,237	48,237	48,237
R^2	0.880	0.961	0.922

Note: This table provides results of estimation of equation (2) in a six-month window. The first column corresponds to checking deposits. Column 2 shows results for saving deposits. Column 3 corresponds to time deposits. Standard errors are clustered at the municipality level and displayed in parentheses. Bank, time, and municipality-time fixed effects are included. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

Table D.28: Impact of Pix on Bank Deposits: OLS Difference-in-Differences with Fixed Pix

$$\log D_{imt} = \delta \cdot \log Pix_m \cdot S_i \cdot Pix_t + \gamma X_{imt} + \theta_t + \alpha_i + \eta_{mt} + \varepsilon_{imt}$$

	Dependent variable:			
	Time deposits			
	(1)	(2)	(3)	(4)
$\text{Pix}_m \cdot \text{Small}$	0.422***	0.152***	0.397***	0.156***
	(0.065)	(0.034)	(0.061)	(0.035)
$\text{Small} \cdot \text{Pix}_t$	0.062***	0.030***	0.065***	0.031***
	(0.012)	(0.008)	(0.013)	(0.009)
$\text{Pix}_m \cdot \text{Small} \cdot \text{Pix}_t$	0.053***	0.001	0.051***	0.004
	(0.016)	(0.006)	(0.015)	(0.010)
Pix variable	Log fixed in Nov	PixPerCap fixed in Nov	Log averaged	PixPerCap averaged
Bank FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Muni × Time FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	32,097	32,097	32,097	32,097
R^2	0.883	0.923	0.924	0.923

Note: This table provides results of the OLS estimation where the Pix variable is fixed either in November 2020 (columns 1 and 2) or averaged across November and December (columns 3 and 4). Columns 1 and 3 use log of Pix as a measure of Pix usage, while columns 2 and 4 use Pix per capita. Standard errors are clustered at the municipality level and displayed in parentheses. Bank, time, and municipality-time fixed effects are included. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

Table D.29: Impact of Pix on Deposit Rates: OLS Difference-in-Differences with Fixed Pix

$$IntRate_{imt} = \delta \cdot \log Pix_m \cdot S_i \cdot Pix_t + \gamma X_{imt} + \theta_t + \alpha_i + o_{imt}$$

	Dependent variable:			
	Deposit rates			
	(1)	(2)	(3)	(4)
Pix_m	-0.021^{**}	-0.006^{*}	-0.020^{**}	-0.006^{**}
	(0.009)	(0.003)	(0.009)	(0.003)
$\text{Pix}_m \cdot \text{Pix}_t$	0.033^{***}	0.006^{***}	0.031^{***}	0.006^{***}
	(0.002)	(0.001)	(0.002)	(0.001)
$\text{Pix}_m \cdot \text{Small}$	0.134^{**}	0.064^{**}	0.125^{**}	0.063^{**}
	(0.053)	(0.026)	(0.049)	(0.025)
$\text{Small} \cdot \text{Pix}_t$	-0.422^{***}	-0.316^{***}	-0.430^{***}	-0.316^{***}
	(0.082)	(0.048)	(0.085)	(0.047)
$\text{Pix}_m \cdot \text{Small} \cdot \text{Pix}_t$	-0.252^{***}	-0.119^{***}	-0.235^{***}	-0.118^{***}
	(0.096)	(0.045)	(0.089)	(0.043)
Pix variable	Log fixed in Nov	PixPerCap fixed in Nov	Log averaged	PixPerCap averaged
Bank FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	18,247	18,241	18,243	18,243
R^2	0.123	0.121	0.129	0.121

Note: This table provides results of the OLS estimation of deposit rates on Pix where the Pix variable is fixed either in November 2020 (columns 1 and 2) or averaged across November and December (columns 3 and 4). Columns 1 and 3 use log of Pix as a measure of Pix usage, while columns 2 and 4 use Pix per capita. Standard errors are clustered at the municipality level and displayed in parentheses. Bank and time fixed effects are included. *,**, and *** correspond to 10-, 5-, and 1% significance level, respectively.

Table D.30: Impact of the Easing of COVID-19 Restrictions on Pix: Fixed Pix without Pre-Period

$$\log Pix_m = \alpha Eased_m + \theta X_m + \varepsilon_m$$

	Dependent variable:			
	Pix			
	(1)	(2)	(3)	(4)
Eased	0.095***	0.100***	0.256***	0.407***
	(0.024)	(0.025)	(0.062)	(0.071)
Bank Controls	Yes	No	Yes	No
Muni Controls	Yes	Yes	No	No
Observations	3,557	3,557	3,574	3,574
R^2	0.844	0.841	0.291	0.010

Note: This table provides results of the first stage in the IV estimation where Pix usage is fixed at its November value. $Eased_m = 1$ for municipalities that eased COVID-19 restrictions by September 2020. Robust standard errors are displayed in parentheses. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

Table D.31: Impact of Pix on Deposits and Loans of Small Banks: IV with Easing of COVID Restrictions, Difference-in-Differences with Fixed Pix

$$\log D_{imt} = \delta \cdot \log \widehat{Pix_m \cdot} Pix_t \cdot S_i + \gamma X_{imt} + \eta_{mt} + \varepsilon_{imt}$$

	Panel A: Log of Pix			
	Checking deposits	Saving deposits	Time deposits	Total loans
	(1)	(2)	(3)	(4)
$\text{Pix}_m \cdot \text{Small}$	0.269^{***}	-0.175^{***}	4.211^{***}	1.051^{***}
	(0.062)	(0.068)	(0.341)	(0.103)
$\text{Small} \cdot \text{Pix}_t$	0.093^{***}	0.035^{***}	0.073^{***}	0.020^{*}
	(0.016)	(0.007)	(0.017)	(0.011)
$\text{Pix}_m \cdot \text{Small} \cdot \text{Pix}_t$	0.108^{***}	0.047^{***}	0.128^{***}	0.018
	(0.024)	(0.016)	(0.036)	(0.026)
Muni × Time FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	7,121	7,121	7,121	7,121
R^2	0.653	0.506	0.151	0.150

	Panel B: Pix Per Capita			
	Checking deposits	Saving deposits	Time deposits	Total loans
	(1)	(2)	(3)	(4)
$\text{Pix}_m \cdot \text{Small}$	0.013	-0.054^{**}	0.545^{**}	0.191^{***}
	(0.039)	(0.021)	(0.217)	(0.070)
$\text{Small} \cdot \text{Pix}_t$	0.012	0.000	-0.012	0.014
	(0.011)	(0.006)	(0.013)	(0.009)
$\text{Pix}_m \cdot \text{Small} \cdot \text{Pix}_t$	0.014	0.008	0.026^{**}	0.011
	(0.012)	(0.005)	(0.011)	(0.007)
Muni × Time FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	7,121	7,121	7,121	7,121
R^2	0.620	0.525	0.020	0.031

Note: This table provides results of the second stage in the IV estimation of equation (10), including interactions with the small bank dummy. The Pix variable is fixed in November and interacted with the post-November dummy. The easing of COVID-19 restrictions in Brazil is used as an instrument for Pix usage. Panel A uses log of Pix, while Panel B uses Pix per capita. The specification uses a heteroskedasticity-based IV approach. Column 1 presents results for checking deposits. Column 2 presents results for saving deposits. Column 3 shows results for time deposits. Column 4 corresponds to total loans. Municipality-time fixed effects 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.32: Impact of the Access to High-Speed Internet on Pix

$$\log PixPerCap_{mt} = \alpha HighSpeed_m + \theta Pix_t + \gamma HighSpeed_m Pix_t + \theta X_{mt} + \theta_t + v_m + \varepsilon_{mt}$$

	Dependent variable:	
	Per Capita Pix	
	(1)	(2)
High Speed	-0.017^{***}	-0.017^{***}
	(0.001)	(0.001)
Post Pix	12.87^{***}	
	(0.036)	
High Speed · Post Pix	0.057^{***}	0.057^{***}
	(0.002)	(0.002)
Time FE	No	Yes
Controls	Yes	Yes
Observations	5,719	5,719
R^2	0.985	0.985

Note: This table provides results of the first stage in the IV estimation where access to high-speed internet is used as an instrument for Pix access. $Pix_t = 1$ for November 2020. Column 2 includes time fixed effects. Robust standard errors are displayed in parentheses. *,**, and *** correspond to 10-, 5-, and 1% significance level, respectively.

Table D.33: Impact of Demographic, Economic, and Political Factors on Easing of COVID Restrictions and Pix Usage

	Dependent variable:	
	Easing	Pix per Capita
	(1)	(2)
Right	0.068	0.013
	(0.069)	(0.011)
Vote percentage	0.030	0.030***
	(0.071)	(0.011)
Right · Vote percentage	−0.047	−0.028
	(0.124)	(0.019)
Old	−0.002	0.000
	(0.003)	(0.000)
Mortality January	−0.001	−0.000***
	(0.001)	(0.000)
Mortality September	-0.000	0.000***
	(0.001)	(0.000)
Mortability November	0.001	−0.000
	(0.001)	(0.000)
Population	0.031**	0.010***
	(0.013)	(0.002)
Capital	0.077	0.031**
	(0.170)	(0.015)
Urban	−0.000	0.001***
	(0.000)	(0.000)
Male	−0.006	0.002**
	(0.006)	(0.001)
Illiterate	0.000	0.001***
	(0.002)	(0.000)
Sole responsible	−0.001	−0.000***
	(0.001)	(0.000)
Income per capita	0.000	0.000***
	(0.000)	(0.000)
GDP growth	0.005	0.003***
	(0.010)	(0.001)
Observations	3,455	4,849
R^2	0.009	0.140

Note: This table provides results of regressing easing of COVID restrictions (Column 1) or Pix per Capita (Column 2) on a battery of demographic, economic, and political variables. Standard errors are displayed in parentheses. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

Table D.34: Impact of Pix on Deposits and Deposit Rates: OLS in the Sample of Direct Participants

$$\log D_{imt} = \delta \cdot \log Pix_{mt} \cdot S_i + \gamma X_{imt} + \theta_t + \alpha_i + \eta_{mt} + \varepsilon_{imt}$$

	Dependent variable:			
	Checking deposits	Saving deposits	Time deposits	Deposit rates
	(1)	(2)	(3)	(4)
Pix · Small	0.032***	0.033***	0.042***	−0.121***
	(0.005)	(0.005)	(0.006)	(0.004)
Bank FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Muni × Time FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	31,745	31,745	31,745	15,851
R^2	0.880	0.955	0.925	0.949

Note: This table provides results of regressions of deposits and deposit rates on the value of Pix transactions in the sample that only includes direct Pix participants. Column 1 presents results for checking deposits. Column 2 presents results for saving deposits. Column 3 shows results for time deposits. Column 4 corresponds to deposit rates. Standard errors are clustered at the municipality level and displayed in parentheses. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

Table D.35: Impact of Pix on Deposits and Loans: IV with Easing of COVID Restrictions in the Sample of Direct Participants

$$\log D_{imt} = \delta \cdot \log \widehat{Pix}_{mt} \cdot S_i + \gamma X_{imt} + \eta_{mt} + \varepsilon_{imt}$$

	Dependent variable:			
	Checking deposits	Saving deposits	Time deposits	Total loans
	(1)	(2)	(3)	(4)
Pix · Small	0.019***	−0.008	0.173***	0.045***
	(0.007)	(0.006)	(0.021)	(0.008)
Muni × Time FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	7,123	7,123	7,123	7,123
R^2	0.619	0.528	0.038	0.018

Note: This table provides results of the second stage in the IV estimation of equation (10) in the sample that only includes direct Pix participants. The easing of COVID-19 restrictions in Brazil is used as an instrument for Pix adoption. The specification uses a heteroskedasticity-based identification strategy conditional on the information in October 2020. Column 1 presents results for checking deposits. Column 2 presents results for saving deposits. Column 3 shows results for time deposits. Column 4 corresponds to total loans. Standard errors are clustered at the municipality level and displayed in parentheses. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

Table D.36: Structural Estimation Results: Salaries in the Supply Shifter Set

Parameter	Symbol	Estimate	Standard error
Sensitivity to deposit rates	α	0.010	(0.026)
Sensitivity to deposit rate with Pix	θ	0.004**	(0.002)
Relative sensitivity to Pix for small banks	δ	0.007**	(0.003)
Observations		6,584	
R^2		0.922	

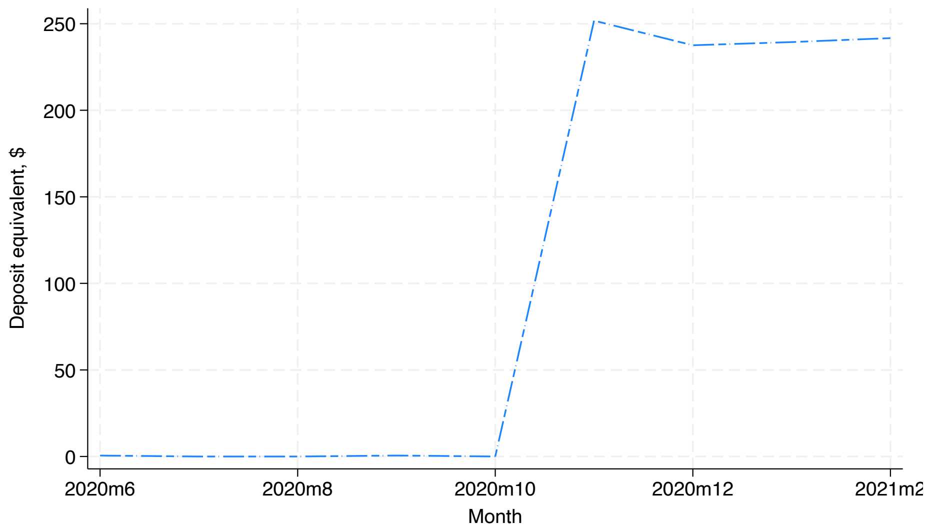
Note: This table provides results of structural estimation of equation (16). The method used is GMM following the random coefficient logit procedure described in Berry et al. (1995). The estimated time period is from January 2015 to December 2021. Bank and time fixed effects are included. Deposit rates are instrumented with supply shifters (fixed costs and salaries). 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.37: Structural Estimation Results: No Small Bank Dummy

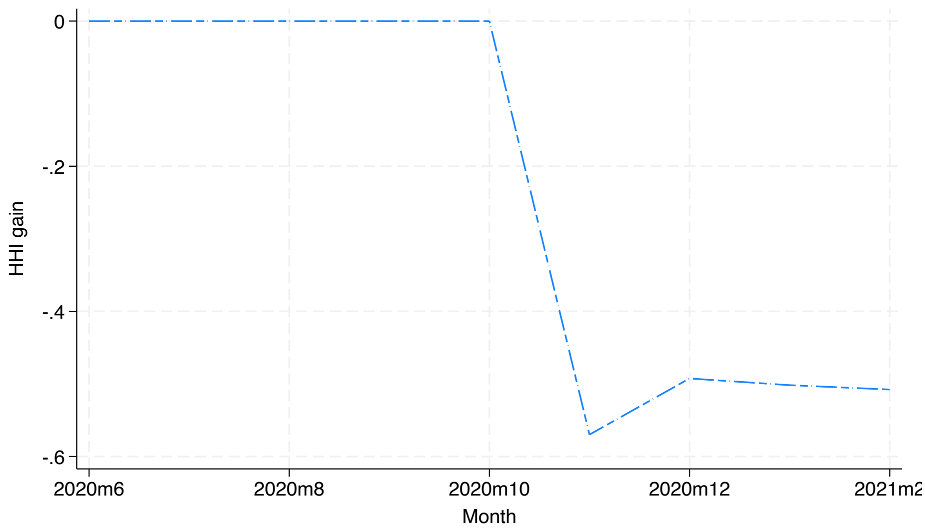
Parameter	Symbol	Estimate	Standard error
Sensitivity to deposit rates	α	0.047***	(0.021)
Sensitivity to deposit rate with Pix	θ	0.007***	(0.002)
Observations		6,584	
R^2		0.905	

Note: This table provides results of structural estimation of equation (16) without an interaction term with small bank dummy. 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.

Figure D.12: Welfare and Counterfactuals: No Small Bank Dummy



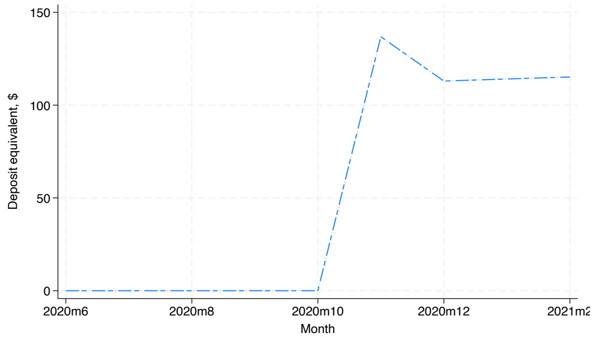
(a) Welfare Gain from Pix



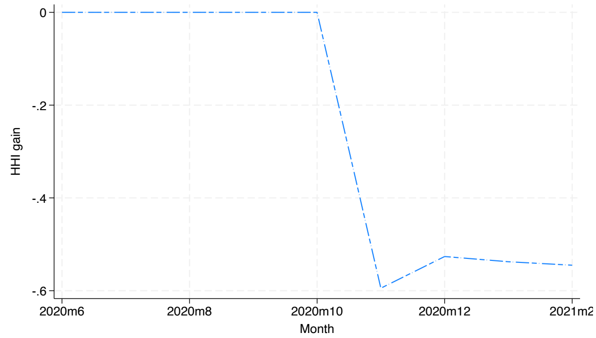
(b) Counterfactual: Inelastic Deposit Demand

Note: This figure plots the deposit-equivalent welfare change (panel (a)) and HHI (panel (b)) gain for counterfactuals from the BLP estimation without an interaction term with small bank dummy. Figure (a) compares the benchmark model where Pix is offered by all banks with the scenario in which Pix was never introduced. Figure (b) compares the counterfactual where deposits remained sticky with the benchmark model.

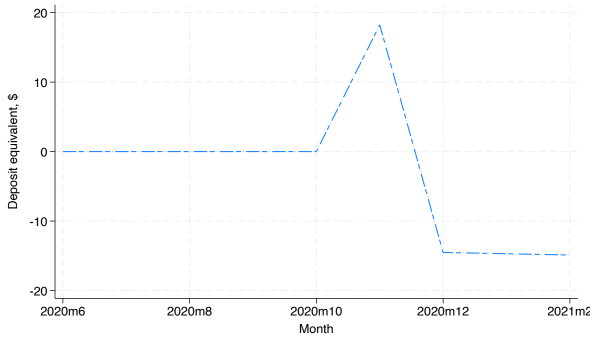
Figure D.13: Welfare: Negative Values of δ



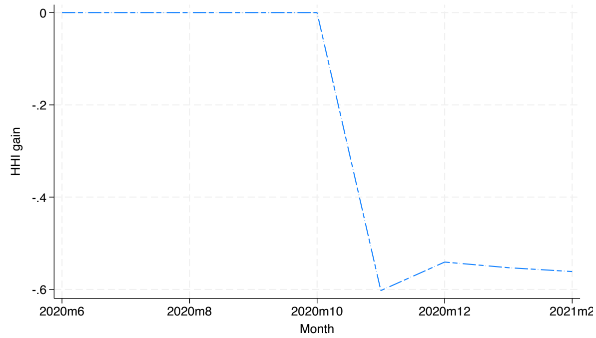
(a) Welfare Gain from Pix with $\delta = -0.008$



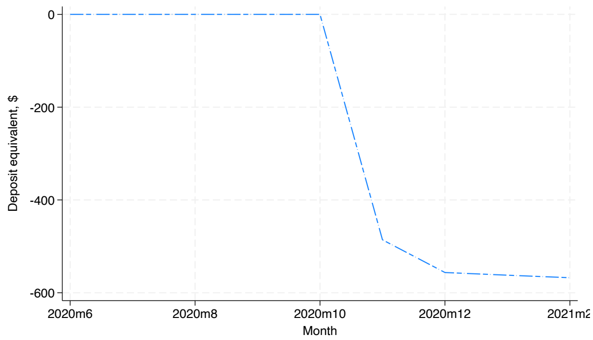
(b) Counterfactual: Inelastic Deposit Demand with $\delta = -0.008$



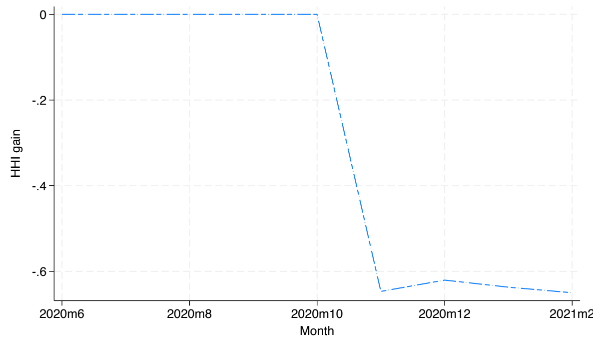
(c) Welfare Gain from Pix with $\delta = -0.017$



(d) Counterfactual: Inelastic Deposit Demand with $\delta = -0.017$



(e) Welfare Gain from Pix with $\delta = -0.05$



(d) Counterfactual: Inelastic Deposit Demand with $\delta = -0.05$

Note: This figure plots the deposit-equivalent welfare change and HHI counterfactuals where the parameter at the interaction of Pix with a small bank dummy is set to negative values. Figures (a) and (b) set $\delta = -0.008$, Figures (c) and (d) set $\delta = -0.017$, and Figures (e) and (f) set $\delta = -0.05$.